UNDERSTANDING DISPARITIES IN PUNISHMENT: REGULATOR PREFERENCES AND EXPERTISE

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Abstract. We exploit institutional changes in the enforcement of water quality regulations in California, and study regulatory discretion by identifying and estimating a structural model of strategic interactions between a regulator and a privately-informed discharger. We find that even if the regulator's objective function were the same across dischargers, differences in the punishment of violations would mostly persist. Moreover, we quantify the extent to which employing regulators' knowledge about dischargers can be beneficial. Specifically, we find that limiting regulatory discretion would, on average, raise enforcement costs and increase violations by dischargers with relatively high benefits of compliance.

Keywords: Adverse Selection, Nonparametric Identification, Optimal Regulation Enforcement, Regulatory Discretion, Regulator Preferences, Water Quality Regulation

JEL Classification: D78, K42, L51, L95

1. Introduction

Regulations are often written flexibly so that the authorities in charge of enforcing them can do so judiciously. For example, following a particular violation, enforcement authorities may be able to choose from a range of possible punishments, considering a host of aggravating and mitigating factors that are, at times, subjective. One reason to allow discretion in enforcement is that it might be impossible, in practice, for the written regulation to specify all possible contingencies—especially when the

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circumstances surrounding any given violation, such as the compliance costs borne by the regulated entity and the resource-constraints faced by the enforcement authority, can vary considerably from one case to another. However, without proper incentives, regulators may pursue their own interests rather than applying their expertise to make an appropriate judgment as a social planner (Stigler, 1971; Peltzman, 1976). In this paper we identify and estimate a game-theoretic model of regulation to empirically evaluate regulatory discretion in the context of the enforcement of water quality regulation in California.

To begin with, we argue that the enforcement policies of the Clean Water Act and California's Porter-Cologne Water Quality Control Act leave room for regulatory discretion, giving rise to concerns over inconsistencies in the enforcement of these laws within the state. We then provide empirical evidence that regulators use their discretion, by documenting *disparities* in penalties—that is, variation in penalties, conditional on violation attributes. To do so, we employ our unique data containing the universe of recorded water quality violations in 2000–2014, as well as all monetary penalties associated with each individual violation. By linking violations and penalties, these data allow us to gauge regulation enforcement standards, without having to make an assumption on the time lag between violations and enforcement actions.[1] In our analysis, we focus on domestic wastewater treatment facilities, which are among the most important violators of water quality regulation in California. We find that the penalty disparities are correlated with two important sets of variables: (i) various facility and local attributes, such as the facility's size and age, and demographic, economic, and environmental attributes of the location; and (ii) other concurrent violations by the facility.

Becker (1968) provides a theoretical justification for disparities in punishment, by considering the optimal amount of enforcement when it is costly to impose sanctions. In the absence of such costs, the optimal punishment induces an offense level that equates the marginal private gain by the offender and the marginal social harm from the offense. With costly punishment, the optimal offense level also depends on the extent to which offenders respond to changes in penalties. Under this framework, disparities in punishment may have a few, non-exclusive sources: heterogeneity in the private violation gains, the social harms of violations, and the costs of punishment.

[1]This feature of our data is an important advantage, relative to the data sets employed by the existing literature on the enforcement of the Clean Water Act (Magat and Viscusi, 1990; Earnhart, 2004a,b; Shimshack and Ward, 2005; Gray and Shimshack, 2011), where the link between an enforcement action and a violation is not observed.

In a related contribution, Mookherjee and Png (1994), show that, in a setting in which the offender has private information on the costs of complying with regulation, penalties associated with any given violation may also depend on other violations by the same offender.

Our structural approach helps disentangling these sources of disparities in regulation enforcement and better understanding regulatory discretion. Our model works as follows: For each facility, the regulator sets a penalty schedule, and, given that schedule, the facility exerts costly effort to affect the extent of compliance. The regulator knows the distribution of compliance cost types of each facility, but observes neither the realized compliance cost type nor the facility's effort, so the penalty is a function of the violations only. In determining the penalty schedule, the regulator minimizes the sum of the facility's expected compliance costs, the cost from environmental hazards of violations, and the enforcement costs associated with assessing and imposing penalties. Departing from the normative framework of Becker (1968) and Mookherjee and Png (1994), we allow the latter two costs to partially reflect the regulator's private concerns, and we refer to these costs as the *regulator preferences*.

We use data on violations and penalties to identify and estimate the model, exploiting a set of institutional changes in the mid-2000s, which were aimed at reducing the administrative burden of enforcement and making the compliance information more accessible to the public. These changes include: the launch of a new computerized system to track and manage information about violations and enforcement; and the establishment of a new statewide office to support enforcement activities. We document that, after these changes, the average amount of penalties increased and violations became less frequent. Moreover, we find little evidence that the compliance cost structure changed during the period. This institutional feature provides a unique opportunity to identify the dischargers' compliance cost function.

We provide conditions under which the model is non-parametrically identified. Our identification strategy is closely related to two recent papers, d´Haultfoeuille and Février (forthcoming) and Luo, Perrigne and Vuong (2018), both of which address the identification and estimation of adverse selection models. The former study focuses on the informed party, and employs exogenous variation in the contracts (which, in our application, is provided by the mid-2000s institutional changes) to identify that party's distribution of types (the distribution of facilities' compliance costs). This approach does not rely on the regulator's optimality. Conversely, the latter paper builds upon the optimality conditions of both the informed and non-informed parties to identify the model primitives without necessarily relying on any external variation. By combining both approaches, we identify a more general model than the ones considered by these two papers. We develop a multi-step estimator that closely follows the constructive identification strategy. In this regard, our paper relates to the structural empirical literature on regulation (Wolak, 1994; Thomas, 1995; Timmins, 2002; Gagnepain and Ivaldi, 2002; Brocas, Chan and Perrigne, 2006; Ryan, 2012; Gagnepain, Ivaldi and Martimort, 2013; Oliva, 2015; Fowlie, Reguant and Ryan, 2016; Lim and Yurukoglu, 2018; Abito, forthcoming).

We find suggestive evidence that the regulators tailor the enforcement policies to local residents' preferences. Specifically, the estimation results indicate that the regulators tend to consider the violations by a facility located in a county with a high average household income as more environmentally damaging and less costly to punish than those by other facilities. To the extent that environmental goods or amenities are a normal good, this finding is consistent with the idea that regulators may reflect local preferences on water quality when they enforce the water regulation. Moreover, we find that the estimated enforcement costs are negatively correlated with the percentage of voters supporting California Proposition 84 in 2006, which authorized the issuing of bonds to fund water quality improvement projects, at the county where the facility is located.

Given our estimates of both the compliance cost structure and the regulator preferences, we quantify the extent to which the heterogeneity in regulator preferences explains the observed disparities in penalty stringency. In doing so, we consider a hypothetical scenario in which all facilities are subject to a regulator with the same preferences—set at the median across our preference estimates. Not surprisingly, we find that, relative to the current regime, homogenizing the regulator's preferences would reduce the dispersion of penalty stringency across facilities. However this reduction is by a moderate extent, 11 percent.

We also assess the implications of limiting regulatory discretion. As discussed earlier, our descriptive data analyses reveal two main channels through which regulatory discretion in enforcement manifests itself: penalty adjustments that vary with (i) facility and local attributes and (ii) the violator's conduct in terms of other violations during the period. In light of these findings, we consider two counterfactual scenarios, limiting each of these channels at a time. First, we evaluate a *one-size-fits-all policy*, where all facilities face the same penalty schedule. Then we examine a *linear policy*, in which the regulator is constrained to set a per-violation penalty amount. We find that violations, on average, would slightly decrease under both scenarios (roughly six percent), but at the expense of an increase in total penalties. More importantly, we measure the penalty savings associated with allowing for each type of regulatory discretion; for example, we show that a linear penalty policy that would induce facilities to adhere to the compliance level of the full discretion scenario would lead to 12 percent higher penalties in total. We also find that implementing the one-size-fits-all policy would lead to more violations by facilities perceived to have high benefits of compliance, such as those posing a high treat to water quality.

One of the perils of regulatory discretion stems from the potential misalignment between the preferences of the regulator and those of the social planner. In the absence of external estimates of the latter, we cannot quantify the effects of such misalignment on enforcement and compliance. Instead, we assess an upper bound of the amount of violations that might be associated with inappropriately low perceptions of the benefits of compliance by the regulator, possibly driven by corruption or lack of dedication. To do so, we consider an alternative regulator whose preferences are at the extreme, towards the maximum stringency in enforcement. We find that under such a scenario, the number of violations would fall by half and the assigned penalties would increase by 77 percent.

Our paper contributes to the empirical literature on regulatory mechanisms and the incentives of regulators. Existing studies show evidence on various determinants of enforcement stringency, including local economic conditions, public health risk, pressure from special interest groups, the political ideology of the government, and the agency budget.[2] Because the benefits and costs of a regulation are not directly observed, it is difficult to empirically evaluate the regulatory mechanism using a reduced-form approach. Our analysis, along with the recent papers by Duflo, Greenstone, Pande and Ryan (2018) and Blundell, Gowrisankaran and Langer (2019), provides a step forward to this end, by identifying and estimating a regulation model. The former study uses data from a field experiment in India that doubled the inspection frequency for a random group of manufacturing plants, and quantifies the extent to which regulator's discretion over what plants to target helps enforcement. The latter assesses the gains from the Clean Air Act's dynamic enforcement, where repeat

[2]See Scholz (1986); Deily and Gray (1991); Cropper, Evans, Berardi, Ducla-Soares and Portney (1992); Gray and Deily (1996); Helland (1998); Agarwal, Lucca, Seru and Trebbi (2014); Gordon and Hafer (2014); Holland (2016). Recently, Burgess, Olken and Sieber (2012), and Jia and Nie (2017) provide suggestive evidence of regulatory capture in developing countries, and Leaver (2009) shows that regulators' desire to avoid public criticism can lead to inefficiency even without capture.

offenders are placed in high priority violator status and receive more frequent inspections and higher penalties. The results of these papers, consistent with ours, indicate that limiting regulatory discretion may increase penalties and enforcement costs. Unlike theses two recent papers, we estimate regulator preferences. Having estimates of these preferences allows us to examine their determinants, investigate their role in explaining penalty disparities, and predict how regulators would respond to policies limiting their discretion.

The rest of the paper is organized as follows: Section 2 describes how the water quality regulations in California are enforced and provides details of the institutional changes. In Section 3, we present the data and some descriptive statistics. Section 4 contains the theoretical model, and Section 5 describes the identification and estimation of the structural model. Section 6 presents the estimation and counterfactual results. We conclude in Section 7.

2. Institutional Background

2.1. **Water Quality Regulation and Enforcement.** Both the Clean Water Act and the state's Porter-Cologne Water Quality Control Act govern the water quality regulation in California. The former act created the National Pollutant Discharge Elimination System (NPDES) to regulate facilities that discharge pollutants from any point source, such as a pipe or a ditch, into surface waters, including lakes, rivers and the ocean. Although the program is federal, the state government has administered it since the authorization by the Environmental Protection Agency in 1973. An NPDES permit is typically a license for a facility to discharge a specified amount of a pollutant into a receiving water under certain conditions, where the limits on the concentration of the pollutants are based on both the availability of pollution control technologies and the water quality standards of the receiving water.

Both laws require that permittees periodically submit discharge monitoring reports with information about the quantity and quality of their effluents. They are required to sample receiving waters, to perform bioassays, and to measure and report the toxicity potential of the discharges. Enforcement actions are mostly based on these reports. Our data regarding all NPDES violations in the state during the period of 2000-2014 indicate that 95 percent of the recorded violations were detected from permittees' self-reports, while the remaining 5 percent were detected during an inspection or triggered by a complaint, referral, or sewer overflow.

The California Water Boards, consisting of the State Water Resources Control Board and nine Regional Water Quality Control Boards, are in charge of enforcing the water quality regulations in the state. The state board oversees the regional boards, and the regional boards have primary jurisdiction in issuing permits, monitoring water quality, and taking enforcement actions against violating dischargers. The boundaries of the regional boards follow mountain chains and ridges that define watersheds.

Each regional water board consists of seven board members, who are appointed by the governor to serve four-year terms once they are confirmed by the state senate. Members of a regional water board serve part-time and conduct their business at regular meetings, which are normally held ten times per year to make decisions on water quality matters.[3] The board members rely on the staff, most of whom are engineers, geologists, and biologists, to conduct the day-to-day tasks associated with water quality management, such as setting water quality standards, drafting permits, and conducting enforcement activities.

Policies have been proposed to reduce the autonomy of the regional water boards. Specifically, there are concerns that the oversight of the regional boards by the state government might be insufficient, leading to inconsistencies in the implementation of the regulation across the different regions (Little Hoover Commission, 2009). To address these concerns, there have been several reform proposals aiming at greater centralization of water quality regulation decisions at the state level. For example, in 2005, Assembly Bill 1727 would let the state board appoint the executive officer of each regional board. More drastically, the California Performance Review, a task force assembled in the 2004 by the state government to restructure the state administration, proposed to abolish both the state and the regional boards, and shift their environmental regulation duties to a new, centralized division of the California Environmental Protection Agency (California Legislative Analyst's Office, 2004).

2.2. **Penalty Determination.** For an initial determination of compliance, the regional board' staff screens the self-monitoring reports. When a violation is identified, the staff issues a formal notice of violation, which is critical in determining violations and clarifying errors, vague permit language, or other areas of disagreement between the discharger and the staff. If a violation is confirmed, the case is then evaluated for

[3]Regional board members must reside in, or have a principal place of business within, the region that a given board covers. Based on the short biographical description of each regional board member available online, we find that, on average, a regional board consists of 4 members from the private sector (e.g., a law firm partner or a farm owner), 1-2 members from the public sector (e.g., a mayor), and 1-2 members from the academia.

enhanced enforcement, such as an administrative civil liability (ACL), which might result in a monetary penalty. To impose an ACL, the staff must make an ACL complaint, followed by a 30-day public comment period. The notice for the comment period is posted on the water board's website and may also be mailed to interested parties or published in a local newspaper. The discharger may waive its right to a board hearing and pay the liability, negotiate a settlement, or appear at the hearing to dispute the ACL.

The enforcement policy (California State Water Resources Control Board, 2002, 2010b), provides a detailed penalty calculation methodology. It involves determining the initial penalty amount and then adjusting it to address various factors. The initial penalty amount is based on the extent and severity of the violation, the sensitivity of the receiving water, and any impacts of the violation on beneficial uses of the affected water. The enforcement policy provides guidelines for calculating the initial penalty amount, but these guidelines leave room for discretion by the water board staff in defining and quantifying each factor in the calculation of the initial penalty amount.

The initial penalty amount is then adjusted to reflect a number of factors. Some of the factors are associated with the violator's conduct, such as whether the violation was accidental as opposed to intentional or negligent; and if there is a pattern of (intentional) repeat violations. The remaining adjustment factors are: the violator's ability to pay and continue in business; the economic benefit of the violations; costs of investigation and enforcement including any expert witness expenses; environmental justice issues related to whether the violations have a disproportionate impact on a particular disadvantaged group of people; and the maximum/minimum liability amounts. After these adjustments by the water board staff, the final penalty amount may be further modified by the water board, possibly as a result of negotiations with the violator.

An important regulation associated with a minimum liability amount is that serious or multiple non-serious NPDES violations are subject to a mandatory minimum penalty (MMP) of $3,000 per violation. A *serious* violation is associated with a discharge above limits of a Group I (Group II) pollutant by 40 percent (20 percent) or more.[4] As for non-serious violations, the minimum penalty applies when such violations occur four or more times in any period of six consecutive months.

[4]The list of the pollutants of Groups I and II is in Appendix A to Section 123.45 of Title 40 of the Code of Federal Regulations. Group I pollutants include biological oxygen demand and total suspended solids; and chlorine, copper, and cyanide are examples of Group II pollutants.

2.3. **Institutional Changes in Enforcement.** In 1999, the Clean Water Enforcement and Pollution Prevention Act (SB 709) amended the California Water Code. To implement this new law, the state and regional water boards undertook various administrative efforts. Two of the major changes during our period of study are the launch of the California Integrated Water Quality System (CIWQS) in July 2005 and the establishment of the Office of Enforcement in July 2006.[5] For convenience, we often refer to these two changes as the *2006 institutional changes*.

These changes have decreased the administrative costs borne by the regional water boards in enforcing the water quality regulations. First, the new computer system, CIWQS, tracks and manages information about permittees, permits, inspections, violations, and enforcement activities. It also allows for the online submittal of self-monitoring data by permittees. Previously, dischargers would submit hard copies of the self-monitoring reports, which would then need to be manually entered into the system and reviewed by the boards' staff. This system dramatically increased efficiency and enabled more resources to be devoted to enforcement.[6] Second, the Office of Enforcement was established to provide statewide enforcement and to support the regional water boards' enforcement programs. The staff of the office regularly meet with representatives from the regional water boards to discuss enforcement matters and give feedback on enforcement approaches. Besides providing support to the regional water boards, the office has the authority to perform independent enforcement actions.

2.4. **Wastewater Treatment Facilities.** We focus on the facilities that treat domestic wastewater and discharge the treated water. Based on our data, there are in total 288 such facilities that had an active NPDES permit during 2000–2014. They are responsible for the vast majority (73 percent) of effluent and water quality violations statewide during the period of study. A clear assessment of the compliance behavior of these facilities is thus particularly important for the better understanding of water pollution regulation in general.

[5]In November 2006, Governor Schwarzenegger was reelected. The timing of these two administrative actions by the state government may be potentially related to the incumbent governor's reelection motives (List and Sturm, 2006), but this is beyond the scope of our analysis.

[6]The introduction of the computerized system did not lead to a decrease in the government budget for the water boards. Based on the historical budget publications, made available online by the state department of finance, the annual budget allocated for the support of the water boards regarding water quality issues (the item numbered as 3940-001-0001 until the 2008–9 budget or 3940-001-0439 after) has been steady at around $480 million in 2010 dollars.

Wastewater treatment facilities reduce the amount of oxygen-demanding substances, such as organic matter and ammonia, disinfect and chlorinate wastewater to decrease the concentration of infectious micro-organisms, and remove phosphorus, nitrogen, and inorganic or synthetic organic chemicals. The process for treating wastewater includes a primary stage, in which solids are removed, and a secondary stage, which treats biological and dissolved organics. In addition, a tertiary stage may be used for disinfection and treatment of nitrogen, phosphorus, and other pollutants. The Clean Water Act requires municipal wastewater treatment plants to implement at least secondary stage treatment.

Even after all three stages, facilities do not always comply with the water quality regulations. The causes of violations include improper maintenance and operation, as well as insufficient investment. Both the EPA and the California water boards stress the importance of the former factor for explaining violations.[7] We also find evidence corroborating this view by analyzing the description of corrective measures that were planned or taken following the detection of a violation in the data: out of 3,504 violations with such a description, only 30 percent of them are associated with a need for investment—in the sense that the corrective measure description contains words related to capital investment—while the rest of the violations are associated with short-term measures.[8]

A number of factors make it harder for some facilities to comply with the permit conditions than others. Facilities differ substantially in age, size, treatment technology, and capacity utilization rate (see Table 1 in Section 3). They also differ in their finances. For example, although the state and the federal governments provide subsidized financing to water treatment projects through the Clean Water State Revolving Fund (CWSRF), facilities located in small or disadvantaged communities often lack the resources and in-house expertise necessary to apply for grants and determine which types of project are the most appropriate for their needs (California State Water Resources Control Board, 2008). Moreover, weather conditions and existing pollution levels, which can substantially obstruct compliance efforts, vary both across facilities and over time.

[7]For details, see US Environmental Protection Agency (2004) and California State Water Resources Control Board (2010a). For example, the latter document provides details of a case in which a facility administrator employed uncertified operators and failed to provide adequate supervision to trainees, leading to permit violations.

[8]The keywords used to classify corrective measure descriptions into capital investment are: *capital; construct; design; fund; grant; install; invest; new; project;* and *upgrade.*

3. Descriptive Statistics

3.1. **Data Sources and Variables.** We draw data from the California Integrated Water Quality System (CIWQS) database for the universe of NPDES violations and enforcement actions during 2000–2014.[9] The database provides various attributes of each facility, which we include as control variables in our analyses: the EPA designation of the facility as a *major* facility;[10] the water board designation of the extent of threat that the facility poses to the receiving water, ranging from 1 to 3;[11] the starting year of its operation; and the unit of the local government that runs the facility (a county or city government or a special district). We collect further facility-level attributes from the Clean Watersheds Needs Survey data from the US Environmental Protection Agency: the treatment level or technology (primary, secondary, or advanced); the extent of capacity utilization, defined by the ratio of the actual flow to the designed flow; and the size of population served by the facility.[12]

We complement our data with the attributes of the county or the watershed in which the facility is located. As for the county-level attributes, we use various sources: the American Community Survey for average household income; the Census for population and water use; and the California Irrigation Management Information System for precipitation. The precipitation data are provided at the 253 weather stations level, which we aggregate at the county level based on the stations' locations. From the California Secretary of State website, we obtain the vote shares for the 2006 ballot proposition 84 to authorize $5.4 billion in bonds to fund various water projects. Lastly, we employ water pollution data from the STORET and National Water Information System, provided by the US Geological Survey. We focus on the dissolved oxygen (DO) saturation of water, which represents the dissolved oxygen level divided by the maximum oxygen level given the water temperature. This is one of the most common omnibus measures of water quality because, among other reasons, it responds to a

[9]Data from prior to July 2005, when the water boards launched the CIWQS, were imputed retroactively into the CIWQS.

[10]For the NPDES program, the EPA designates certain facilities as major, depending on their industrial category or the amount of flow, generally flow greater than 1 million gallons per day or a discharge that poses a substantial threat to water quality.

[11]Category 1 for the extent of threat to water implies that discharges of waste could cause the long-term loss of a designated beneficial use of the receiving water, such as the loss of drinking water supply and the closure of an area used for water contact recreation. The other two categories are less serious, either short-term (Category 2) or minor (Category 3).

[12]Both treatment level and capacity utilization have been considered as important factors for compliance costs of wastewater treatment facilities in the engineering literature (Weirich et al., 2011; Suchetana et al., 2016; Rahm et al., 2018).

Table 1. Summary Statistics: Wastewater Treatment Facilities

	Before (2000-2005)		After (2009-2014)	
	Mean	SD	Mean	SD
Quarterly Compliance and Enforcement				
Any effluent MMP violation	0.23	0.42	0.17	0.37
Number of effluent MMP violations	1.39	8.30	1.10	5.49
Any penalty upon effluent MMP violation	0.59	0.49	0.77	0.42
Penalty per effluent MMP violation ($)†	2,249	4,721	2,624	4,641
Facility Technological/Cost Attributes				
Major facility	0.74	0.44	0.75	0.43
Design flow (million gallons per day)	17.82	52.32	19.24	54.88
First year of operation	1982.8	5.23	1982.9	5.30
1982-1987	0.69	0.46	0.70	0.46
1988-	0.06	0.23	0.05	0.23
Advanced or tertiary treatment	0.33	0.47	0.40	0.49
Capacity utilization rate (%)	76.15	38.84	72.62	17.72
Over 87%	0.26	0.44	0.24	0.43
Resident population within the service area	94,858	297,458	157,321	476,886
Below 10,000	0.36	0.48	0.34	0.47
Run by a special district	0.39	0.49	0.40	0.49
High threat to water quality (by the Board)	0.53	0.50	0.54	0.50
Time-varying Quarterly Local Attributes				
Precipitation (inches)	6.40	7.49	5.05	6.05
Below 25% of historic quarterly averages	0.21	0.41	0.28	0.45
Over 75% of historic quarterly averages	0.28	0.45	0.22	0.41
Average dissolved oxygen saturation (%)	10.83	12.92	12.62	13.44
Below 17%, "swimmable"	0.71	0.45	0.55	0.50
Time-invariant County Attributes				
Fresh water use for irrigation in 2010 (%)	0.54	0.32	0.54	0.32
Average household income in 2010 ($K)	59,256	14,041	59,125	14,167
Population density per miles^2 in 2010	764.99	1,754.8	762.87	1,788.8
Vote share for the 2006 water proposition (%)	50.21	8.93	50.24	9.06
Number of observations	6,159		6,620	
Number of facilities	228		215	

Notes: For the statistics on violations, we use the sample of 2002–2005 for the period before the 2006 institutional changes and 2009–2014 for the post-change period. We do not use the observations of 2000–2001 for analyzing the extent of compliance because we suspect that not all violation records are in the database for this early period. As for the penalty statistics, we employ the effluent MMP violations of 2000–2001 and 2009–2010 and the follow-up penalty actions for four years. Acknowledging that the 2006 institutional changes may take time to be fully incorporated, we do not employ the observations of 2006–2008. The key patterns found in the table are robust to our choice of the periods. †. The average amount of total penalty per effluent or water quality MMP violation that occurred during three months, accounting for the penalties assessed within four years of the occurrence of the violation.

wide variety of pollutants (Keiser and Shapiro, 2018). We closely follow the details and steps taken to clean the water pollution data in Keiser and Shapiro (2018) and construct the DO saturation measures for each facility by taking the average of water pollution readings within the area that shares the same 5-digit hydrologic unit code as the facility during the previous two years. Following the same reference, we use the DO saturation cutoff of 17 percent to define surface water as "swimmable." Table 1 provides summary statistics of all variables mentioned above for the 228 wastewater treatment facilities used in our analysis.[13]

3.2. **Scope of Analysis.** We focus on effluent or water quality violations subject to the mandatory minimum penalty (MMP) of $3,000. During the period of study, there are in total 48,155 violation records by domestic wastewater treatment facilities, and 19,740 (41 percent) of these records are categorized as MMP violations. Almost the entirety (99 percent) of the MMP records are associated with effluent or water quality violations.[14] Some MMP violations are exempt from penalty under specified conditions in the State Water Code. We focus on non-exempt MMP violations only. As described in Section 2.2, MMP violations are either serious in the violation extent or chronic. Therefore, the violations that are not subject to the MMP regulation are relatively insignificant violations that were not repeated more than three times within six months.

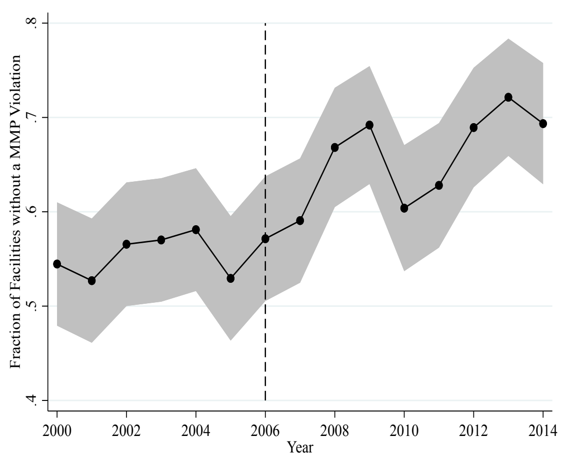
3.3. **Compliance and Enforcement Over Time.** Following the literature on water quality regulation (Magat and Viscusi, 1990; Earnhart, 2004a,b; Shimshack and Ward, 2005; Gray and Shimshack, 2011), we assess compliance using the self-reported data. Two important features of the NPDES program ensure the reliability of the self-monitoring reports. First, the water boards conduct frequent inspections on the facilities. The inspection records show that 86 percent of the wastewater treatment facilities in our data received at least one inspection per year. Second, intentional misreporting can be punished by criminal sanctions to the responsible employees.[15] If

[13]Among the 288 domestic wastewater treatment facilities active during 2000-2014 in our dataset, we exclude the following 60 from our analysis: (i) 48 facilities that were not matched to the Clean Watersheds Needs Survey Data; (ii) the only two facilities in Region 6 (Lahontan); and (iii) ten facilities owned by business, community organization, or the federal government.

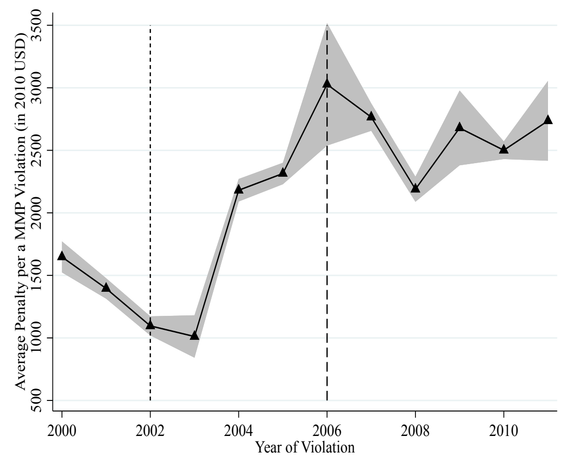
[14]The remaining 142 MMP violation records are regarding the timing of self-reports (126), order conditions (12), deficient monitoring (2), and enforcement actions (2).

[15]According to Section 122.22(d) of Title 40 of the Code of Federal Regulations, employees signing any report required by the permits must make a certification that they are aware of significant penalties for submitting false information, including the possibility of fines and imprisonment for misreporting violations.

Figure 1. Compliance and Enforcement



(a) Fraction of Facilities in Compliance



(b) Average Penalty per MMP Violation

Notes: Panel (A) shows the fraction of the domestic wastewater treatment facilities without an effluent MMP violation for a given year. In Panel (B), we provide the average penalty per effluent MMP violation assessed within 4 years of the occurrence of the violation. Note that the 2006 institutional changes affected the within-4-year penalty for the violations that occurred in 2002 and after. The shaded areas represent the 95 percent confidence intervals.

an employee has accurately reported operation conditions not in compliance with the NPDES permit, he/she cannot be held liable in a civil suit because meeting the permit requirements is the responsibility of the permitted facility, not of that employee.

Table 1 shows that both compliance and enforcement stringency are higher after the institutional changes which we described in Section 2.3. The average number of MMP violations per quarter by a domestic wastewater treatment facility decreased from 1.39 in the 2002-2005 period to 1.10 in 2009-2014, and the average penalties per MMP violation within four years of the violation's occurrence increased from \$2,249 in 2000-2001 to \$2,624 in 2009-2010.[16] The CIWQS database links each enforcement action with all associated violation records, which allows us to measure the enforcement stringency without having to make an assumption on the length of a lag before an enforcement action is taken.[17]

[16]Penalties may occur even after four years of the occurrence of a violation, but given the length of our panel data (fifteen years) and the usual length of a permit (five years), we focus on the four-year window. A large fraction of penalty actions occurs within four years: for example, based on 937 effluent or water quality MMP violations that occurred in 2005 and were penalized by the end of 2014, the average lag before the first penalty record is 2.56 years, with a 90 percentile of 3.93 and a 99th percentile of 7.60 years.

[17]When a penalty action is associated with multiple violation records, we divide the amount by the number of the linked violations to calculate the penalty amount for each individual record.

Figure 1 provides suggestive evidence that the aggregate changes in compliance and enforcement are associated with the institutional changes in 2006. First, Panel (A) in the figure shows that the faction of the facilities without an effluent MMP violation per year is relatively stable up until 2006, and then it substantially increases. Second, Panel (B) shows that, focusing on penalties imposed within four years of the occurrence of a violation, the average penalty for a violation of 2006–2011 ($2,669) is greater than the counterpart for a violation of 2000-2002 by $1,300, which is a 95 percent increase. For violations that occurred in 2003–2005, the average penalty per violation is increasing, which is expected because the 2006 institutional changes were *retroactive*—a large fraction of the *backlogged* MMP violations that had not yet been penalized were penalized after the changes. Because the length of the period affected by the 2006 institutional changes within the four-year penalty window increases as the violation date approaches 2006, we observe that the average penalty per violation increases during 2003–2005 and then is constant from 2006 onward.

These changes may have been driven by time-varying factors which may have coincided with the institutional changes. Table 1 shows that some facilities expanded their capacity (i.e., the average design flow increased) and/or adopted advanced or tertiary treatment technology after the institutional changes. Furthermore, Table 1 documents that California became much drier during the period of study, and that there was an increase in water pollution as measured by dissolved oxygen saturation levels.[18] We find, however, that both compliance rates and penalties increased after the 2006 institutional changes, even after controlling for various time-varying facility and local attributes, including weather conditions (see Table A1 and Figure A1 in Appendix A.1).

3.4. **Determinants of Penalty in the Data.** Under the enforcement policy, as described in Section 2.2, the penalties for violations with the same attributes by different facilities may not be the same. California State Water Resources Control Board (2010b) even recognizes, on page 10, that "the need to assess all of the applicable factors in liability determinations may yield different outcomes in cases that may have many similar facts." There are three main reasons why different penalties may arise. First, the penalty amount is supposed to reflect the local beneficial use of the affected water, the violator's ability to pay, and the economic benefit of the violation,

[18]According to National Integrated Drought Information System, the longest drought in California since 2000 began in late December 2011 and ended on early March 2019, and the most intense period of drought occurred in October 2014. For more information on droughts in California, refer to https://www.drought.gov/drought/states/california.

Table 2. Determinants of Penalty for Effluent MMP Violations

	Penalized			Log (Penalty Amount + 1)		
	(1)	(2)	(3)	(4)	(5)	(6)
Violation attributes						
Priority violation†	0.059	0.030	-0.001	0.506	0.292	0.032
	(0.051)	(0.040)	(0.033)	(0.398)	(0.314)	(0.262)
Group I pollutant	0.066	0.059	0.049	0.489	0.416	0.336
	(0.050)	(0.038)	(0.030)	(0.383)	(0.302)	(0.237)
Group II pollutant	0.040	0.030	-0.012	0.325	0.237	-0.074
	(0.074)	(0.062)	(0.054)	(0.585)	(0.489)	(0.427)
Current violations						
Any violations (quarter)	0.061	0.087**	0.093***	0.599**	0.779***	0.817***
	(0.038)	(0.037)	(0.033)	(0.291)	(0.284)	(0.256)
Past violations						
Any violations (semester)	-0.013	-0.003	0.047	-0.068	0.012	0.430
	(0.063)	(0.055)	(0.044)	(0.501)	(0.443)	(0.349)
Facility attributes						
Major facility		0.195***	0.103		1.402***	0.692
		(0.065)	(0.065)		(0.519)	(0.499)
Started in 1982-87		0.222***	0.167**		1.616**	1.267***
		(0.086)	(0.068)		(0.683)	(0.543)
Started in 1988-		0.213	0.029		1.492	0.164
		(0.173)	(0.114)		(1.319)	(0.869)
Advanced/tertiary		-0.036	-0.038		-0.381	-0.246
		(0.072)	(0.068)		(0.566)	(0.531)
Capacity utilization$>87\%$		0.005	-0.065		-0.064	-0.628
		(0.079)	(0.058)		(0.634)	(0.453)
Service population$<10K$		-0.057	-0.042		-0.545	-0.477
		(0.069)	(0.078)		(0.534)	(0.603)
Special district		0.142**	0.116**		1.014**	0.817**
		(0.061)	(0.046)		(0.489)	(0.369)
High threat		-0.081	-0.002		-0.697	-0.097
		(0.077)	(0.078)		(0.596)	(0.618)

(Continued)

all of which can differ across facilities. Second, the violator's conduct is considered in penalty assessment so that per-violation penalty may depend on the concurrent violations; i.e., penalty can be nonlinear in the number of violations. Third, the violator's past compliance history is another factor in penalty assessment.

Table 2 shows the extent to which of these sources matter in practice, if any. First, we find that some facility and local characteristics further explain the penalty variation, even after controlling for violation attributes and current and past compliance behavior. For example, major facilities and facilities located in a county with high

Table 2. Determinants of Penalty (Continued)

	Penalized			Log (Penalty Amount + 1)		
	(1)	(2)	(3)	(4)	(5)	(6)
Weather & pollution						
Precipitation $> 75^{th}$ pct.	-0.130**	-0.126***	-0.028	-1.112***	-1.080***	-0.248
	(0.050)	(0.042)	(0.038)	(0.396)	(0.330)	(0.274)
Precipitation $< 25^{th}$ pct.	-0.057	-0.038	-0.005	-0.402	-0.251	-0.0124
	(0.048)	(0.036)	(0.029)	(0.379)	(0.290)	(0.231)
Swimmable		0.013	0.069		0.089	0.572
		(0.065)	(0.056)		(0.523)	(0.429)
County attributes						
Irrigation water use>67%			0.134*			1.119*
			(0.073)			(0.583)
Household income >$57K			0.158**			1.133*
			(0.076)			(0.594)
Pop. density $> 722/mi^2$			0.078			0.568
			(0.089)			(0.726)
Pop. density $< 80/mi^2$			-0.133*			-0.990
			(0.077)			(0.603)
Prop. approval >50%			0.118*			1.015**
			(0.063)			(0.505)
Regional water board FE	No	No	Yes	No	No	Yes
Year FE; Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean dependent variable	0.678	0.678	0.678	5.239	5.239	5.239
Number of observations	15,827	15,827	15,827	15,827	15,827	15,827
Adjusted R^2	0.167	0.245	0.400	0.174	0.245	0.406

Notes: This table reports OLS estimates. The unit of observation is a violation; all non-exempt effluent MMP violations of 2000–2010 by the facilities in our sample are included. Standard errors are adjusted for clustering at the facility level, and are provided in parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. † : The water boards may categorize a violation as *priority*, based on the violation's significance and severity (see California State Water Resources Control Board (2002, 2010b) for the criteria for a priority violation).

average household income or high approval rate for the 2006 proposition 84 for water quality projects are more likely to receive a penalty and tend to receive a larger penalty than other facilities. These patterns are possibly due to such facilities having relatively high marginal compliance costs. Alternatively, the regulator may consider violations by these facilities to be particularly serious, because, for example, of their larger potential harm to nearby residents or their potential political repercussions. The structural analysis developed in the next sections decomposes these distinct explanations.

Second, both the probability and the amount of penalty for a violation increase when there are other concurrent violations by the same facility. For example, based on Column (3) in Table 2, the probability of getting penalized within 4 years increases, on average, by 9.3 percentage points if there are other violations during the quarter when the given violation occurred. Moreover, the average penalty amount also increases significantly when there are other concurrent violations (Columns (4)-(6)). In our facility-quarter level analysis presented in Section 5, we find that the expected per-violation penalty increases as the number of violations during a quarter increases.[19] Our structural analysis allows us to study the effects of this nonlinearity of the penalty schedule on compliance.

Third, we do not find that past violations matter for penalty actions. In all specifications in Table 2, the effects of having any other violation in the six months prior to a violation on penalty are statistically insignificant, and also much smaller in magnitude than the counterpart effects of having any concurrent violations. Table A2 in Appendix A.2 shows that these patterns persist even with an enriched set of variables based on current and past compliance behavior, following Blundell et al. (2019). Granted, neither the Clean Water Act nor the California Water Code have an institutionalized dynamic deterrence mechanism, in contrast to the Clean Air Act (Blundell, 2019; Blundell et al., 2019). This motivates us to assume that the regulator sets a static penalty schedule in the analysis.[20]

In Appendix A.3, we provide evidence that these three empirical patterns are not necessarily driven by the violation attributes that are not controlled for. First, when we consider violations that are identical in terms of the pollutant, the emission standards, and the actual emission amounts, not only there is a large dispersion in penalties but also the three patterns described here persist. Second, focusing on penalty actions for which we observe both the initial penalty assessed by the staff and the final penalty set by the water board, we find that the penalty adjustment by the board varies with local attributes, in particular water use for irrigation and income.

4. Theoretical model

4.1. **Setup.** In this section, we present our theoretical model of the interaction between a regulator and a single facility. Section 5.1 clarifies how we employ this model

[19]We specify and estimate the penalty schedule as a function of the number of violations and various facility attributes (see Equation (12) in Section 5). The penalty is allowed to be nonlinear in the number of violations, and our estimates provide evidence that the penalty is increasing and strictly convex in the number of violations (Figure 2 in Section 5; Table A5 in Appendix E.1).

[20]In the California Water Code, the mandatory minimum penalty (MMP) regulations have a partial feature of dynamic incentives in that if four or more non-serious violations happen in six consecutive months, then the facility is subject to an MMP. Reflecting this, we employ six months as a unit of period instead of three months, and find our results to be robust (see the results for alternative specification 3 in Tables A9-A12 in Appendix F.2).

to analyze the heterogeneity in enforcement standards across different facilities. We model regulation enforcement as an adverse selection problem, as in Mookherjee and Png (1994).[21] Consider a wastewater treatment facility that chooses the extent to which it complies to regulations given a penalty schedule.[22] We assume that the facility benefits from avoiding both compliance costs and penalty, following the evidence from Section 3.3 that the facilities reduced the frequency of violations in response to an increase in penalty. The facility is better informed than the regulator about its compliance costs. Specifically, each facility is endowed with a type, θ, which is known to the facility only. The regulator knows that θ is the realization of a random variable Θ that follows a strictly increasing and continuously differentiable distribution function $F(\cdot)$ with support $(0, \bar{\theta})$. Let $f(\cdot)$ be the associated density.

The facility sets a negligence level $a \in [0, \overline{a}]$, which is not observed by the regulator and affects the facility's compliance status in the following manner: let K be a random variable representing the number of emission violations incurred by the facility, and assume that K follows a Poisson distribution with mean a.[23] By setting the negligence level a, the facility derives private benefit $\theta b(a)$, which reflects the operation cost savings associated with lower compliance. In the reminder of the paper, we refer to this private benefit as the facility's compliance costs.[24] Because the facilities in our data are often publicly owned, $\theta b(a)$ could be different from the actual operational cost savings from emitting more pollutants to the waters, reflecting the career concerns of the facility administrators and the scrutiny from the public.

[21]In Mookherjee and Png (1994), the regulators choose both a (random) monitoring frequency and a penalty schedule. Our model abstracts away from monitoring decisions and focuses on the penalty schedule. Implicitly, we assume that exogenously determined inspection activities provide incentives for firms to truthfully self-report any violation. The model is identical to the one in Mookherjee and Png (1994) with zero monitoring costs. This contrasts to the models estimated by Duflo et al. (2018) and Blundell et al. (2019) where the inspection actions of the regulator and the associated costs are studied.

[22]We consider a continuous action for compliance, such as operation and maintenance of the existing pollution abatement equipment, as opposed to a discrete action, such as a large investment for a new piece of equipment. This assumption is suitable in our setting, given the discussion on the main causes of violation in Section 2.4.

[23]The stochastic nature of the number of violations, given a negligence level, reflects that violations may occur due to circumstances outside of a facility's control, such as unexpected weather conditions and varying qualities of incoming water to the treatment facility.

[24]Let us denote the benefit from maximum negligence or no compliance efforts as $\theta\bar{b}$. This means that no negligence or full compliance efforts would cost the facility $\theta\bar{b}$. By choosing some negligence level a, the facility avoids incurring some compliance costs, $\theta b(a)$, leading to the total compliance cost of $\theta[\bar{b} - b(a)]$.

Because the realization θ and the consequent negligence level a are not known by the regulator, a penalty schedule depends on the realized number of violations only. Specifically, given k violations, the facility has to pay the penalty according to a function $\epsilon(k)$. Assuming that the facility is risk-neutral, we can restrict our attention to the expected penalty, conditional on a, which we denote by

$$e(a) \equiv \exp(-a)\sum_{k=0}^{\infty}\frac{\epsilon(k)}{k!}a^k. \tag{1}$$

The payoff to a facility setting the negligence level a is

$$\theta b(a) - e(a). \tag{2}$$

We define that a negligence schedule, $a(\cdot)$, is *implemented* by a penalty schedule $e(\cdot)$ if $a(\theta)$ maximizes (2) for all $\theta \in \Theta$. If $a(\cdot)$ is implemented by $e(\cdot)$, we have that

$$\theta b'\left[a(\theta)\right] = e'\left[a(\theta)\right], \tag{3}$$

whenever $a(\theta) > 0$.

Given a penalty schedule $e(\cdot)$, the regulator's expected costs are

$$\int_0^{\overline{\theta}} \left\{h\left[a(\theta)\right] + \psi e\left[a(\theta)\right] - \theta b\left[a(\theta)\right]\right\} f(\theta)d\theta, \tag{4}$$

where $\psi > 0$ denotes the marginal cost of imposing penalty, and $h(\cdot)$ represents the regulator's perceived environmental costs related to the facility emission violations.[25] The enforcement costs, given by $\psi e[a(\theta)]$, comprise the administrative and political costs associated with taking formal actions against a facility.[26,27]

[25]In our model, we assume that the regulator regards all violation by the same facility as identical to each other. In Appendix F.1, we re-estimate the model, allowing for heterogeneity in the perceived harm of violations within a facility. Our key empirical findings persist.

[26]We assume that the marginal enforcement cost (ψ) is exogenous, i.e., not affected by the aggregate frequency of violations in equilibrium. The literature on crime, conversely, often treats these costs as endogenously determined by the policy maker's allocation of resources to law enforcement and the individuals' choices on criminal activities (see Fu and Wolpin (2018) and the references therein). In environmental regulation, non-administrative costs that might be out of the regulator's control, such as those associated with the political repercussions of enforcement actions, may explain a large part of the enforcement costs.

[27]Money raised from penalties is generally deposited in the Cleanup and Abatement Account, a fund managed by the state board from which the regional boards may request money for a project. Alternatively, publicly owned wastewater treatment facilities in small communities may be allowed to recover part of the amount they pay in penalties for compliance or supplemental environmental projects. Our analysis does not distinguish between these potential destinations of the penalties, since all facilities are liable to pay the penalty amount regardless. However, the possibility that some facilities are able to partially recover the penalties is one of the reasons why, in the empirical model

Lemma A1 in Appendix B shows that, by appropriately selecting the function $\epsilon(\cdot)$, the regulator is able to implement any continuous penalty schedule $e(\cdot)$ with a bounded domain. In the reminder of the paper, we define the regulator's problem as choosing $e(\cdot)$, subject to the constraint that the expected penalty for any a must be nonnegative and not exceed the facility's maximum amount of funds, ω:

$$0 \leq e(a) \leq \omega, \tag{5}$$

for any a. The optimal penalty schedule minimizes (4), subject to constraints that the schedule satisfies (5) and that it implements the negligence schedule $a(\cdot)$.[28]

4.2. **Characterization of Optimal Enforcement.** We make the following assumptions on the facility's baseline compliance cost function, $b(\cdot)$, and the regulator's preference on water quality, $h(\cdot)$.

Assumption 1. *$b(\cdot)$ and $h(\cdot)$ are strictly increasing.*

Let $\overline{b}$ denote $b(\overline{a})$, and notice that, by Assumption 1, $b(\cdot)$ is bounded above by $\overline{b}$ in $[0, \overline{a}]$. Under Assumption 1, it can be shown that a schedule of negligence choices, $a(\cdot)$, is implemented if and only if $a(\cdot)$ is nondecreasing and satisfies

$$\omega \geq \overline{\theta}\overline{b} - \int_0^{\overline{\theta}} b[a(\theta)]d\theta, \tag{6}$$

and the requisite expected penalty schedule is

$$e(a) = \theta(a)b(a) - \int_0^{\theta(a)} b[a(v)]dv, \tag{7}$$

where $\theta(a)$ denotes the highest type θ selecting an $a(\theta) \leq a$. For a proof, see the Lemma in Mookherjee and Png (1994). By this argument, the regulator chooses a schedule of negligence, $a(\cdot)$, to minimize

$$\int_0^{\overline{\theta}} \left\{ h[a(\theta)] + \psi\left(\theta b[a(\theta)] - \int_0^{\theta} b[a(v)]dv\right) - \theta b[a(\theta)]\right\} f(\theta)d\theta, \tag{8}$$

subject to $a(\cdot)$ being nondecreasing and (6). For simplicity we assume that (6) is not binding at the optimum. By using integration by parts, we rewrite (8) as

$$\int_0^{\overline{\theta}} \left\{ h[a(\theta)] - \left((1-\psi)\theta + \frac{\psi[1-F(\theta)]}{f(\theta)}\right) b[a(\theta)]\right\} f(\theta)d\theta.$$

presented in Section 5, the enforcement cost borne by the regulator may vary by facility attributes, such as the location of a facility.

[28]An individual rationality condition is not considered here. At optimum, $\lim_{\theta\to 0} e(\theta) = 0$, so the indirect (maximized) utility for any $\theta \in (0, \overline{\theta})$ is nonnegative.

We then consider point-wise optimization for each θ, and thus either $a(\theta) = 0$ or $a(\theta)$ satisfies the first order condition:

$$h'[a(\theta)] - b'[a(\theta)] \left((1-\psi)\theta + \frac{\psi[1-F(\theta)]}{f(\theta)} \right) = 0. \tag{9}$$

By totally differentiating (9), one can see that the following assumption, along with Assumption 1, is sufficient to guarantee that the negligence schedule characterized above, denoted by $a^*(\cdot)$, is optimal and strictly increasing in θ for any θ such that $a^*(\theta) > 0$.

Assumption 2. *(i)* $(1-\psi)\theta + \frac{\psi[1-F(\theta)]}{f(\theta)}$ *is strictly increasing in* θ*. (ii) The second order conditions for (3) and (9) are satisfied for all* $\theta \in (0, \overline{\theta})$*.*

The following proposition summarizes the characterization of the optimal negligence schedule.

Proposition 1. *Under Assumptions 1–2, the optimal negligence schedule,* $a^*(\cdot)$*, is continuous and nondecreasing in* θ*. For* θ *such that* $a^*(\theta) > 0$*,* $a^*(\cdot)$ *is characterized by (9) and strictly increasing in* θ*.*

5. Structural model

5.1. **Data generating process.** There are many facilities, which we index by i, and one regulator. Periods are indexed by t. Assume that Θ is i.i.d. across facilities and periods.[29] To reflect the institutional changes discussed in Section 2.3, we allow the primitives characterizing the regulator to vary across periods. The regulator sets the optimal penalty schedule, as described in Section 4. Because of the potential changes in the primitives, the solution to the regulator's problem can also change over time. We denote by $e_t(\cdot)$ the penalty schedule in period t. Given $e_t(\cdot)$ and a realization of Θ, each facility i sets its optimal negligence level. As Θ is a random variable, the equilibrium negligence set by facility i in period t is also a random variable, which we denote by $A_{i,t}$. Let $G_t(\cdot)$ be the distribution of negligence levels across the population of facilities in period t.

The primitives of the model are: $F(\cdot)$, the distribution of facilities' types; $b(\cdot)$, the baseline compliance cost function; the regulator's perceived social cost of violations

[29]By this assumption, each facility independently draws its type every period. An alternative assumption is that the facilities' types are constant over time and the regulator commits not to exploit the information on the facility type obtained in the previous periods. Our identification argument holds under either of these two assumptions, which are both consistent with the static penalty schedules in the data (Table 2 in Section 3.4; and Tables A2 and A3 in Appendix A).

(or negligence), $h_t(\cdot)$; and the marginal enforcement cost, ψ_t. The observables are: $K_{i,t}$, the number of violations in period t for each facility i; and the penalty assessed due to facility i's violations in period t. We also observe facility-period characteristics, denoted by $\mathbf{x}_{i,t}$.

We allow all model primitives and equilibrium objects to vary with $\mathbf{x}_{i,t}$. The vector $\mathbf{x}_{i,t}$ includes (i) the facility's size, age, treatment technology, capacity utilization, and threat to water as categorized by the water board; (ii) the dissolved oxygen saturation level in the watershed (as a measure of the existing water pollution level) and the precipitation amounts; and (iii) the fraction of fresh water use for irrigation, the average household income, the population density, and the vote share for the 2006 Proposition 84 in the county where the facility is located (see Table 5 in Section 6.3 or Table A5 in Appendix E.1 for a complete list). Each of these variables may affect all model primitives: for example, the population density of the facility's county is related to the size of population impacted by water pollution from the facility (and thus the social costs of violations); the nature of the incoming wastewater (which influences the compliance costs); and the administrative support for enforcement actions (which affects enforcement costs). Regional water board dummies may help account for heterogeneity of enforcement resources across the boards (see Table A4 in Appendix A.4), as well as other time-invariant unobserved local attributes.

Our key identifying assumption is that the primitives regarding facilities' compliance costs, $F(\cdot|\mathbf{x}_{i,t})$ and $b(\cdot|\mathbf{x}_{i,t})$, are time-invariant; in particular, we assume that they are unaffected by the 2006 institutional changes.[30] We do, however, allow that the regulator's preferences, $h_t(\cdot|\mathbf{x}_{i,t})$ and $\psi_t(\mathbf{x}_{i,t})$, may vary over time. For ease of notation, we do not explicitly condition the model primitives on $\mathbf{x}_{i,t}$ in the discussion of identification below.

5.2. **Identification.** For the identification of the model, we follow three steps. First we recover the distribution of negligence levels set by the facilities in each period, based on the observed violations. The second step, following the strategy proposed

[30]Our analysis controls for time-varying variables associated with the technology and cost structure of the facilities, such as the capacity utilization rate and the treatment level, and environmental factors including precipitation and water pollution. We argue that a systematic change in the compliance cost function beyond these observed attributes may not have occurred during the period of our study for two reasons. First, most facilities were operating well before and after 2006: 95 percent of the facilities in our sample started their operation before 1988; and the permit records show that the newest facility in our dataset started its operation in 2004, and 13 facilities retired during 2000–2006. Second, based on the Census of Government Finance and Employment, there has been a steady flow of capital investment for sewerage services by local governments in 1997–2012, with an average of \$1.87 billion (in 2010 dollars) per year in total.

by d´Haultfoeuille and Février (forthcoming), employs the exogenous change in the penalty schedule associated with the 2006 institutional changes to partially identify the facility type distribution and the marginal compliance cost function. This step does not rely on any assumption about the regulator's behavior, other than testable assumptions on the observed penalty schedule $e_t(\cdot)$.

The third step, which builds upon the approach by Luo, Perrigne and Vuong (2018), explores the restrictions imposed by the first-order conditions of the regulator to recover the marginal social cost of negligence and the marginal enforcement cost, as well as to achieve exact identification of the type distribution and the marginal compliance cost function. By exploiting the exogenous variations in the penalty schedule, we are able to consider a more flexible form for the regulator's objective function than would be possible using their approach alone. In particular, they assume that $h_t(\cdot)$ (the monopolist's cost function in their setting) is linear, whereas we can accommodate a polynomial specification of arbitrary degree.

We restrict our attention to the case in which it is optimal for all facilities to choose a nonzero rate of violations, or $a_t(\theta) > 0$, for any period t and $\theta \in (0, \overline{\theta})$.[31] Then, given any period t, the distribution of the number of violations by any facility is a mixture Poisson. Indeed, a facility chosen at random sets a negligence level according to the distribution $G_t(\cdot)$, and, given the negligence level, the number of violations for that facility follows a Poisson distribution. The following lemma establishes the identification of $G_t(\cdot)$ from the observed number of violations across facilities. To prove this lemma, we exploit the moment generating function of the Poisson distribution, which was also used in Aryal, Perrigne and Vuong (2019). See Appendix B for the proofs of the lemmas and the propositions in this section.

Lemma 1. *For every t, $G_t(\cdot)$ is identified.*

Having identified the distribution of negligence levels in each period, our strategy to partially identify $b'(\cdot)$ and $F(\cdot)$ closely follows that proposed by d´Haultfoeuille and Février (forthcoming). We consider two enforcement regimes, before and after the 2006 institutional changes, and assume that, within each regime, the penalty schedule does not change. Formally, we make the following assumption on $e_t(\cdot)$, the expected penalty in period t, as a function of the negligence level set by the facilities:

[31]This assumption is consistent with our data—where 10 percent of the facilities that were active during all the 60 quarters in 2000–2014 were always in compliance—in the sense that a very small, but positive value of a can generate no violations for a long period of time. For example, a facility that sets $a = 0.001$ will have no violations during 60 periods with probability $e^{-0.001\times 60} \approx 0.94$.

Assumption 3. *$e_t(\cdot) = e_{pre}(\cdot)$ for all $t < 2006$. Similarly $e_t(\cdot) = e_{post}(\cdot)$ for all $t > 2008$. Moreover, $e'_{post}(a) > e'_{pre}(a)$ for all $a > 0$.*

We can directly identify the penalty schedule, $\epsilon_t(\cdot)$ as a function of the number of violations, in each period. From (1), therefore, we readily identify the functions $e_{pre}(\cdot)$ and $e_{post}(\cdot)$, so Assumption 3 is testable.[32] The latter part of the assumption implies that the enforcement regime becomes stricter after the institutional changes. We exclude the period of 2006-2008 as a transition period, although such an exclusion is not necessary and the length of the transition period can be adjusted. In the definition of the model primitives, we assumed that $F(\cdot)$ and $b(\cdot)$ do not change over the entire time period covered by our sample, which is analogous to an exclusion restriction.

Under Assumption 3, any facility of a given type θ sets at most two different negligence levels—one for each of the two enforcement regimes. Accordingly, we denote by $G_j(\cdot)$ the distribution of negligence levels holding in period $j \in \{pre, post\}$, where, as above, *pre* refers to $t < 2006$ and *post* to $t > 2008$. Also, we denote by $\tilde{a}(\cdot, j)$ the equilibrium negligence function in period $j \in \{pre, post\}$. From equation (3), it is clear that $\tilde{a}(\theta, pre) > \tilde{a}(\theta, post)$ for all θ. Let the supports of the negligence level distributions before and after the regime change be given by $\mathcal{A}_{pre}$ and $\mathcal{A}_{post}$, respectively. We assume that $\mathcal{A}_{pre} \cap \mathcal{A}_{post} \neq \emptyset$.

The strategy described below, and formalized in Proposition 2, allows us to partially recover $b'(\cdot)$ and $F(\cdot)$ without making any assumptions about the behavior of the regulator. Define the function $\tilde{\theta}(a, j)$ as the inverse of $\tilde{a}(\cdot, j)$ for any $a \in \mathcal{A}_j$. Define also the following two functions:

$$T^H(a) \equiv G_{pre}^{-1}\left[G_{post}(a)\right], \tag{10}$$

$$T^V(\theta, a) \equiv \frac{e'_{post}(a)}{e'_{pre}(a)}\theta. \tag{11}$$

The function $T^H(\cdot)$ is defined for any $a \in \mathcal{A}_{pre} \cap \mathcal{A}_{post}$, while $T^V(\cdot, \cdot)$ is identified over the entire domain of a and θ. The following lemma plays a key role in the identification of $b'(\cdot)$ and $F(\cdot)$:

[32]Given that we assume that $F(\cdot)$ and $b(\cdot)$ remain the same for the whole sample period, Assumption 3 can be related to the changes in $h(\cdot)$ and ψ due to the institutional changes. Specifically, a sufficient condition for this assumption to hold is that $h'_{post} > h'_{pre}(\cdot)$ and $\psi_{post} < \psi_{pre}$. Appendix B.2 provides comparative statics of the model, and Corollary A2 states that the equilibrium stringency of enforcement, $e'(a)$, is increasing in γ (the slope of a linear $h(\cdot)$) and is decreasing in ψ.

Lemma 2. *Under Assumptions 1–3, we have that* $T^H(a) = \tilde{a}\left[\tilde{\theta}\left(a, post\right), pre\right]$ *for* $a \in \mathcal{A}_{pre} \cap \mathcal{A}_{post}$*, and* $T^V\left[\tilde{\theta}(a, pre), a\right] = \tilde{\theta}(a, post)$ *for any* $a \in \mathcal{A}_{pre}$*.*

This lemma establishes that $T^H(a)$ returns the negligence exerted in the *pre* regime by a facility type that, while in the *post* regime, exerted negligence level a; and $T^V\left[\tilde{\theta}(a, pre), a\right]$ returns the type that exerts negligence level a in the *post* regime.

To partially identify $F(\cdot)$ and $b'(\cdot)$, we normalize $\tilde{\theta}(a_0, post) = \theta_0 = 1$ for some $a_0 \in \mathcal{A}_{post}$.[33] We then define recursively:

$$\begin{aligned} a_l &= T^H(a_{l-1}), \\ \text{and} \quad \theta_l &= T^V\left(\theta_{l-1}, a_l\right). \end{aligned}$$

The transform $T^H(\cdot)$ connects points in the negligence distribution supports in both regimes. For any $a \in \mathcal{A}_{post}$, $T^H(a) \in \mathcal{A}_{pre}$. However, under Assumption 3, we have that $T^V\left[\tilde{\theta}(a, pre), a\right] > \bar{\theta}$ for $a > \max(\mathcal{A}_{post})$; i.e., there are relatively high negligence levels that, in equilibrium, are only set in the *pre* regime. Let $\bar{L}$ be largest integer such that $T^H(a_{\bar{L}}) \in \mathcal{A}_{post}$. We are now ready to state the following result.

Proposition 2. *Suppose Assumptions 1–3 hold. Then, for any* $l \in \{0, 1, \ldots, \bar{L}\}$ *and* $j \in \{pre, post\}$*, the following objects are identified up to the normalization* $\tilde{\theta}(a_0, post) = \theta_0 = 1$ *for some* $a_0 \in \mathcal{A}_{post}$*: (i) the equilibrium negligence level,* $\tilde{a}(\theta_l, j)$*; (ii) the distribution of cost types,* $F\left(\theta_l\right)$*; and (iii) the marginal baseline compliance cost function,* $b'\left[\tilde{a}(\theta_l, j)\right]$*.*

The proof, which we show in Appendix B, is based on d´Haultfoeuille and Février (forthcoming). Here, we just outline it. Starting from the normalization $\tilde{\theta}(a_0, post) = 1$, we apply the transforms $T^H(\cdot)$ and $T^V(\cdot)$ in an iterative fashion to recover a sequence of types $\{\theta_l\}_{l \in \{0,\ldots,\bar{L}\}}$, together with the corresponding negligence levels $\tilde{a}(\theta_l, pre)$ and $\tilde{a}(\theta_l, post)$ set by θ_l in equilibrium in the pre- and post-2006 periods, respectively. For every identified pair θ_l and $\tilde{a}(\theta_l, j)$, we use (3), the first order condition of the facility's problem, to obtain $b'\left[\tilde{a}(\theta_l, j)\right] = \frac{e_j'\left[\tilde{a}(\theta_l, j)\right]}{\theta_l}$. Finally, because of the one-to-one mapping between types and equilibrium negligence levels (Proposition 1), we can recover $F(\theta_l) = G_j\left[\tilde{a}(\theta_l, j)\right]$.

[33] This location normalization is necessary, as only the product of the cost type and the baseline function enter the facility's objective function. Thus, multiplying the type by a constant and dividing the baseline function by the same constant results in an observationally equivalent model structure. In our empirical application, we set $a_0 = 1$.

Under the assumptions of Proposition 2, $F(\cdot)$ and $b'(\cdot)$ are only identified over a finite set of values. The set is finite due to the boundedness of the type space, and the exact number of values at which the functions are identified depends on the shape of the functions $\tilde{a}(\cdot, pre)$ and $\tilde{a}(\cdot, post)$.

To complete the identification of the model, we must explicitly consider the regulator's problem. We begin by making the following simplifying assumption:

ASSUMPTION 4. *(i) $h_t(\cdot) = h_{pre}(\cdot)$ and $\psi_t = \psi_{pre}$ for all $t < 2006$, and $h_t(\cdot) = h_{post}(\cdot)$, $\psi_t = \psi_{post}$ for all $t > 2008$. (ii) For $j \in \{pre, post\}$, the function $h_j(a)$ is a polynomial function of a finite degree R with $h_j(0) = 0$; i.e., $h_j(a) = \sum_{r=1}^{R} \gamma_{j,r} a^r$ for any R.*

Assumption 4 (i) implies that all model primitives are constant within each of the two regimes, and 4 (ii) imposes a flexible parametric structure to the external costs of violations as perceived by the regulator. We also make the following technical assumption on the equilibrium penalty schedule, which guarantees that we can employ the fist-order conditions from the regulator's problem to recover ψ_j and $\gamma_{j,r}$, for $j \in \{pre, post\}$ and $r \in \{1, \ldots, R\}$:

ASSUMPTION 5. *There is an interval $U \in \mathbb{R}_+$ such that the functions $\tilde{E}_0(a) \equiv \frac{e'_{post}(a)}{e'_{pre}(a)}$ and $\tilde{E}_{j,r}(a) \equiv \frac{a^r}{e'_j(a)}$ for all $r \in \{1, \cdots, R\}$ are strictly monotone in $a \in U$.*

We can now state the following proposition.

PROPOSITION 3. *Suppose Assumptions 1–5 hold. Then, if $\bar{L} \geq 1$, the following objects are identified up to the normalization $\tilde{\theta}(a_0, post) = 1$ for some $a_0 \in \mathcal{A}_{post}$: (i) the distribution of facilities' types, $F(\cdot)$; (ii) the derivative of the baseline compliance cost function, $b'(a)$ for any $a \in \mathcal{A}_{pre} \cup \mathcal{A}_{post}$; and (iii) the parameters of the regulator's objective function, $\{\gamma_{j,r}\}_{r=1}^{R}$ and ψ_j, for $j \in \{pre, post\}$.*

In a nutshell, we first identify the parameters of $h_j(\cdot)$ and ψ_j based on (9), the first order condition of the regulator, evaluated at the vector $\{\theta_l\}_{l=0}^{\bar{L}}$ for which $\tilde{a}(\theta_l, pre)$ and $\tilde{a}(\theta_l, post)$ are known from Proposition 2. The main challenge in the process is that $f(\theta_l)$ is not yet identified. To address the challenge, we exploit the relationship between a density and its quantile function, a technique that has been employed by Luo, Perrigne and Vuong (2018). Equation (9) holds for every θ in the support—not only those in $\{\theta_l\}_{l=0}^{\bar{L}}$. Thus, once $h_j(\cdot)$ and ψ_j are identified, we can use (9) to identify $\tilde{a}(\theta, j)$ for all θ. Knowing the whole mapping $\tilde{a}(\cdot, j)$, we employ the same techniques explained in the discussion of Proposition 2 to recover $F(\cdot)$ and $b'(\cdot)$.

5.3. **Estimation.** The estimation procedure consists of four steps. In the first step, we use flexible parametric functional forms to estimate the penalty schedules and the distribution of negligence levels before and after the 2006 institutional changes. Although these objects can be nonparametrically estimated in principle, our sample size and our intent to condition the estimates on $\mathbf{x}_{i,t}$ render such an approach infeasible. Steps two to four, which closely follow our identification strategy, give us estimates of the model primitives. We discuss details of each step below and in Appendix C.

5.3.1. *Estimation of the penalty schedules.* We assume that the penalties, denoted by $\epsilon_{i,t}$, take a Type 2 Tobit form. Recall that $k_{i,t}$ denotes the number of violations by facility i in period (quarter in our estimation) t, and define

$$\begin{aligned} \epsilon^*_{1i,t} &= \mathbf{x}_{i,t}\phi_{1,x} + 1\{t > 2006\}\phi_{1,post} + \phi_{1,k}k_{i,t} + u_{1i,t}, \qquad (12) \\ \log \epsilon^*_{2i,t} &= \log\left[\exp\left(\mathbf{x}_{i,t}\phi_{2,x}\right)k_{i,t} + \phi_{2,k^2}k^2_{i,t}\right] + u_{2i,t}, \\ \text{and } \epsilon_{i,t} &= \begin{cases} \epsilon^*_{2i,t} & \text{if } \epsilon^*_{1i,t} \geq 0, \\ 0 & \text{otherwise,} \end{cases} \end{aligned}$$

where $(u_{1i,t}, u_{2i,t})$'s are i.i.d. draws from a bivariate normal distribution with zero mean, variances 1 and σ_2^2, and covariance σ_{12}. We assume that $(u_{1i,t}, u_{2i,t})$ are independent of $(k_{i,t}, \mathbf{x}_{i,t})$, and that these error terms represent features of the facility and the occurred violations that might affect the regulator's willingness or ability to impose a penalty.[34]

This econometric specification of the observed penalties closely reflects the institutional features as described in Section 2. First, not all MMP violations are penalized, and both the event of nonzero penalty and the penalty amount depend on violations and facility attributes. Second, the penalty amount can be nonlinear in the number of violations. Third, to account for the institutional changes in 2006, we allow the probability of a nonzero penalty to depend on a dummy variable indicating the post-2006 period.

Denote $\phi \equiv \{\phi_{1,x}, \phi_{1,post}, \phi_{1,k}, \phi_{2,x}, \phi_{2,k^2}, \sigma_2, \sigma_{1,2}\}$. We estimate ϕ using the facility-quarter observations during 2000-2001 and 2009-2010 with at least one MMP violation, while truncating observations with an extreme number of violations, more than

[34]One important dimension that $(u_{1i,t}, u_{2i,t})$ might capture is violation severity. One could expect the number and severity of occurred violations to be related in reality, making our assumption of independence between $(u_{1i,t}, u_{2i,t})$ and $(x_{i,t}, k_{i,t})$ implausible. In Appendix F.1, we consider an extension of the model that explicitly incorporates violation severity as an endogenous variable. The results obtained from the extended model are very similar to those presented in the main text.

25 (the 95th percentile conditional on at least one MMP violation).[35] Let $\epsilon_{pre}(k|\mathbf{x};\phi)$ and $\epsilon_{post}(k|\mathbf{x};\phi)$ denote the expected penalties for a facility with characteristics $\mathbf{x}$ and k violations in a quarter before and after the 2006 institutional changes, respectively. Given our Tobit model, these expected penalties can be written as:

$$\epsilon_{pre}(k|\mathbf{x};\phi) = \Pr(\epsilon^*_{1i,t} \geq 0|k,\mathbf{x},\phi)\mathbb{E}\left[\epsilon^*_{2i,t}|\epsilon^*_{1i,t} \geq 0, k, \mathbf{x}, \phi\right].$$

We obtain an estimate $\hat{\phi}$ by MLE—and, by substituting $\hat{\phi}$ for ϕ in the above equation, we estimate the expected penalties. Then, using (1), we estimate $e_{pre}(a|\mathbf{x})$ and $e_{post}(a|\mathbf{x})$—the penalty schedules for a facility with characteristics $\mathbf{x}$, as functions of its negligence level a. With this objective, we approximate the infinite sum in (1) by a finite sum up to a large number. Specifically,

$$\hat{e}_j(a|\mathbf{x}) = \exp(-a)\sum_{k=0}^{k=150}\frac{\epsilon_j(k|\mathbf{x};\hat{\phi})}{k!}a^k, \tag{13}$$

for $j \in \{pre, post\}$.

5.3.2. *Estimation of the negligence distribution.* To estimate the negligence level distributions, $G_{pre}(\cdot|\mathbf{x}_{i,t})$ and $G_{post}(\cdot|\mathbf{x}_{i,t})$, we assume that the number of emission violations follows a Poisson-Gamma mixture distribution. Formally, let $\nu_{i,t}$ follow a gamma distribution with density

$$\frac{\Delta(\mathbf{z}_{i,t})^{\Delta(\mathbf{z}_{i,t})}}{\Gamma\left[\Delta(\mathbf{z}_{i,t})\right]}\nu_{it}^{\Delta(\mathbf{z}_{i,t})-1}\exp\left[-\nu_{it}\Delta(\mathbf{z}_{i,t})\right],$$

where $\Delta(\mathbf{z}_{i,t}) = \exp(\mathbf{z}_{i,t}\delta)$, the vector $\mathbf{z}_{i,t}$ is a subset of $\mathbf{x}_{i,t}$, and δ is a vector of parameters. In our estimation, we include in $\mathbf{z}_{i,t}$ a constant and region-specific dummies.[36] Assume that ν_{it} is i.i.d. across facilities and over periods, conditional on $\mathbf{z}_{i,t}$. Assume also that the distribution of violations by facility i in period t, conditional on $\nu_{i,t}$ and $\mathbf{x}_{i,t}$, follows a Poisson distribution with mean

$$\nu_{i,t}\exp\left(\beta_{0,j} + \beta_1\mathbf{x}_{i,t}\right), \tag{14}$$

where $j \in \{pre, post\}$. This distribution of violations is equivalent to a generalization of the negative binomial distribution with mean $\exp\left(\beta_{0,j} + \beta_1\mathbf{x}_{i,t}\right)$ and variance $\exp\left(\beta_{0,j} + \beta_1\mathbf{x}_{i,t}\right)\left[1 + \Delta(\mathbf{z}_{i,t})^{-1}\exp\left(\beta_{0,j} + \beta_1\mathbf{x}_{i,t}\right)\right]$, where we allow the overdispersion coefficient $\Delta(\mathbf{z}_{i,t})$ to vary with observed characteristics. Let $\beta_j \equiv (\beta_{0,j}, \beta_1)$, for

[35]Our findings are robust to reasonable perturbations of the truncation criterion. See the results for alternative specifications 4 and 5 in Tables A9 –A12, in Appendix F.2.

[36]Our results are robust to controlling for more variables in the specification for $\Delta(\mathbf{z}_{i,t})$. See the results for alternative specification 6 in Tables A9-A12, in Appendix F.2.

$j \in \{pre, post\}$. Then the estimation of the distribution of negligence levels amounts to estimating the parameter vectors δ, β_{pre}, and β_{post}. We estimate these parameters by MLE. See Cameron and Trivedi (2013) for details about this estimator.

5.3.3. *Estimation of the model primitives.* The remaining steps of the estimation procedure closely follow the identification strategy in Section 5.2. We employ the estimates in the first step and Proposition 2 to compute estimates of $\tilde{a}(\theta, pre)$ and $\tilde{a}(\theta, post)$ for a finite set of types θ. Then, we estimate the parameters of the regulator's objective function, using the regulator's first order condition (9) evaluated at the estimates from steps one and two. In our empirical analysis, we constrain the social costs of negligence as perceived by the regulator to be linear. This constraint facilitates the interpretation of our empirical results, as it keeps the social costs of negligence for each facility one-dimensional—making the comparison of costs across different facilities convenient. At the same time, as discussed in Section 6, it still allows for a good fit of the model to the data. Finally, employing the estimates from all previous steps, we estimate the distribution of cost types and the baseline compliance cost function without any extra parametric assumptions, following Proposition 3.

In sum, for any vector of observable attributes $\mathbf{x}_{i,t}$, we obtain estimates of the following model primitives: the functions $F(\cdot|\mathbf{x}_{i,t})$ and $b'(a|\mathbf{x})$, which characterize the distribution of facility compliance costs; and the scalars $\gamma_{pre}(\mathbf{x}_{i,t})$, $\gamma_{post}(\mathbf{x}_{i,t})$, $\psi_{pre}(\mathbf{x}_{i,t})$ and $\psi_{post}(\mathbf{x}_{i,t})$, which characterize the regulator preferences before and after the 2006 institutional changes.

6. Results

Given that the estimated model primitives are functions of observed attributes ($\mathbf{x}_{i,t}$), we obtain each i^{th} facility's primitives based on $\mathbf{x}_{i,t}$ in the first quarter of 2005 separately, for all 221 facilities that were active during that quarter, and build our results. We provide the summary statistics of the results across the facilities and bootstrap standard errors for the model fit and counterfactual results.

6.1. **Model Fit.** We find that the estimated model fits the data well. Table 3 compares the distributions of the number of quarterly violations and average quarterly penalty, as predicted by the estimated model, with the counterpart distributions observed in the data. The estimated model is able to reproduce both the high probability of no violations at the facility-quarter level and the shift in the distribution of violations and penalties that took place following the 2006 changes. In addition, Figure 2 shows the model fit for the point-wise average (per-violation) penalty for each number

Table 3. Model Fit

	Before		After	
	Data	Model	Data	Model
Number of violations				
0	0.771	0.789	0.843	0.805
		[0.783, 0.800]		[0.792, 0.808]
1	0.073	0.063	0.045	0.062
		[0.061, 0.068]		[0.060, 0.068]
2	0.038	0.031	0.027	0.030
		[0.030, 0.033]		[0.029, 0.033]
3	0.029	0.020	0.019	0.019
		[0.019, 0.021]		[0.018, 0.020]
4	0.017	0.014	0.013	0.013
		[0.013, 0.015]		[0.013, 0.014]
5 and more	0.072	0.082	0.053	0.071
		[0.078, 0.082]		[0.071, 0.074]
Penalties				
Average penalty (in $)	2,381	2,318	2,215	2,119
		[1860, 2511]		[2068, 2587]

Notes: This table provides the estimated distributions of the number of violations and penalty amounts across all facilities, as observed in the data and predicted by the fitted model. For the distribution of the number of violations, the data consist of facility-quarter observations in the periods 2002-2005 and 2011-2014. For the penalty statistics, we use facility-quarter observations in the periods of 2000-2001 and 2009-2010. Bootstrap 95% confidence intervals for the fitted values are between brackets.

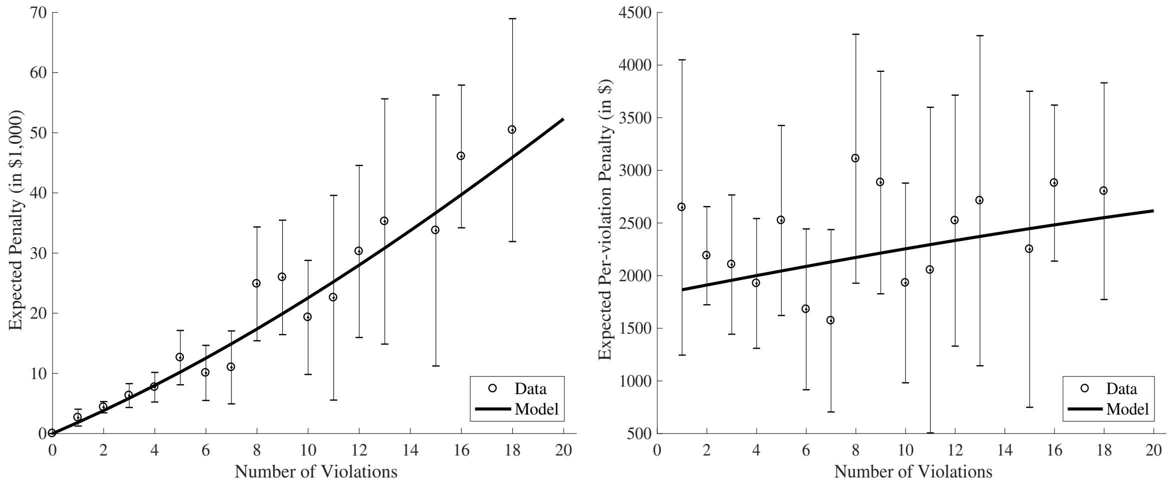
of violations across facilities. Both in the data and in the model, the penalty schedule exhibits strict convexity: the average per-violation penalty is strictly increasing in the number of violations (Panel (B)). This is consistent with our violation-level descriptive findings (Table 2 in Section 3.4; Table A3 in Appendix A.3).

In Appendix E.2, we show that the estimated model satisfies the assumptions in Sections 4 and 5. Recall that Assumptions 1 and 2 are sufficient for the equilibrium characterization; and Assumptions 3-5 are for the identification of the model.

6.2. **Estimated Model Primitives.** Table 4 presents the summary statistics of our estimates of the primitives of the model: the facilities' marginal compliance costs and regulator preferences (γ and ψ) for the periods before and after the 2006 institutional changes.[37] Noting that our model primitives include the marginal compliance

[37]Table A5 in Appendix E.1 provides the penalty schedule estimates, ϕ's in (12), and the estimates of the negligence distributions, δ and β's in (14).

Figure 2. Model Fit: Penalty as a Function of Violations



(A) Total Penalty Function (B) Per-violation Penalty Function

Notes: Panel (A) shows the average amount of total penalties conditional on each number of violations during a quarterly period in the data and as predicted by the model, respectively, before the 2006 institutional changes. The 95% confidence intervals for the average penalties in the data are indicated by the error bars. Panel (B) presents the average amount of *per-violation* penalties, as opposed to total penalties.

cost function and the cost type distribution, we report the median marginal compliance costs evaluated at the facility's median value of θ and the median value of the negligence level before the 2006 institutional changes, averaged across all facilities.[38]

Our estimates in Table 4 imply that the increase in enforcement stringency after the 2006 institutional changes, as documented in Table 1 and Figure 1, is rationalized by a decrease of the marginal enforcement costs (ψ) . The median value of the enforcement cost per extra dollar of penalty is 86 cents prior to the 2006 changes, and then falls by 66 cents. This decrease is both economically and statistically significant; however, the changes in the marginal external cost of violation as perceived by the regulator (γ) are statistically insignificant. These findings seem to be consistent with the nature of the institutional changes that aimed to reduce the administrative burden of imposing penalties borne by each regulator in the regional water boards, by providing the computerized information system and the support from the Office of Enforcement.

6.3. **Regulator vs. Local Resident Preferences.** We find suggestive evidence that the estimated regulator preferences on compliance at least partially represent

[38]We calculate the marginal compliance cost of a given facility with $\mathbf{x}$, $\theta\hat{b}'(a|\mathbf{x})$, evaluated at $\theta = \hat{F}^{-1}(0.5|\mathbf{x})$ and $a = \frac{1}{n}\sum_i \hat{a}^*_{pre}[\hat{F}^{-1}(0.5|\mathbf{x}), \mathbf{x}] = 0.01$, for the summary statistics in Table 4.

Table 4. Model Primitive Estimates: Summary Statistics

	Median	Interquartile Range
Facility Primitives		
Marginal compliance cost	1,431.0	1,090.3
	[1025.3, 1668.5]	[906.8, 1654.0]
Regulator Primitives		
Marginal external/social cost of violation (γ)		
Before the 2006 changes	3,589.4	1,633.0
	[2785.2, 4515.4]	[889.4, 2969.9]
After the 2006 changes	3,157.1	916.5
	[2810.8, 4127.2]	[740.5, 1727.5]
Difference before & after the 2006 changes	-114.5	1022.3
	[-483.9, 140.3]	[234.5, 1685.4]
Marginal enforcement cost (ψ)		
Before the 2006 changes	0.865	0.483
	[0.323, 0.999]	[0.026, 0.755]
After the 2006 changes	0.204	0.220
	[0.076, 0.475]	[0.104, 0.387]
Difference before & after the 2006 changes	-0.551	0.330
	[-0.660, -0.207]	[0.201, 0.545]

Notes: This table provides the summary statistics of the marginal benefit of violation (see footnote 38) and the regulator preference parameters (γ, ψ), before and after the 2006 institutional changes. Bootstrap 95% confidence intervals are between brackets.

those of the population at the facility location. Columns (2) and (3) of Table 5 provide the results of regressing the logarithm of the regulator preference parameters for the periods prior to the 2006 institutional changes, $\gamma_{pre}(\mathbf{x}_{i,t})$, and $\psi_{post}(\mathbf{x}_{i,t})$, respectively, on all facility and local attributes used in the estimation.[39] First, the regulator's perceived external cost of violation, $\gamma_{pre}(\mathbf{x}_{i,t})$, is 46.9 percent higher for a facility located in a county with a high average household income (over \$57K in 2010) than a facility located in a poorer county (Column (2) of Table 5); and the enforcement costs per extra dollar of penalty, $\psi_{post}(\mathbf{x}_{i,t})$, are 29.1 percent lower (Column (3) of the same table). Given that environmental goods or amenities are in general considered a normal good, we view this finding as a supporting piece of evidence that regulators reflect local preferences on water quality in their enforcement decisions. Second, we also find that the marginal enforcement costs are 13.4 percent lower for the facilities in counties where over half of voters supported the 2006 Proposition 84.

[39]The regression results on the estimated regulator preferences for the periods after the 2006 changes are presented in Table A6 in Appendix E.3, and are qualitatively similar to those presented here.

Table 5. Explaining Compliance Costs and Regulators' Preferences

Dependent variables:	Facility	Regulator: Before the 2006 Changes	
	log(Compliance Cost)	$\log\gamma$	$\log\psi$
	(1)	(2)	(3)
Facility attributes			
Major facility	0.452***(0.100)[0.358]	0.149***(0.038)[0.112]	-0.110(0.068)[0.114]
Started in 1982-7	-0.309***(0.108)[0.514]	0.025(0.032)[0.084]	0.031(0.065)[0.124]
Started in 1988-	-2.65***(0.486)[4.698]	-0.099*(0.051)[0.256]	-0.311*(0.168)[0.430]
Advanced/tertiary	0.057(0.089)[0.321]	-0.076***(0.029)[0.081]	-0.135**(0.055)[0.095]
Utilization$>$ 87%	0.110(0.089)[0.402]	-0.055*(0.029)[0.097]	0.097(0.055)[0.092]
Service pop.$<$ 10K	0.125(0.094)[0.269]	0.048(0.042)[0.088]	-0.109* (0.056)[0.114]
Special district	-0.404***(0.074)[0.355]	-0.292***(0.026)[0.097]	0.030(0.046)[0.137]
High threat	0.208**(0.088)[0.425]	-0.001(0.035)[0.076]	-0.189***(0.054)[0.117]
Weather & pollution			
Precip.$>$ 75th pct.	-0.223(0.177)[0.493]	-0.069**(0.034)[0.080]	0.048(0.056)[0.106]
Precip.$<$ 25th pct.	0.440**(0.192)[0.702]	0.072(0.094)[0.182]	0.003(0.170)[0.348]
Swimmable	-0.127*(0.066)[0.259]	-0.249***(0.055)[0.092]	-0.159* (0.087)[0.131]
County attributes			
Irrigation$>$ 67%	-0.274**(0.132)[0.408]	-0.004(0.036)[0.108]	0.012(0.079)[0.128]
Income$>$ \$57K	0.776***(0.118)[0.517]	0.469***(0.043)[0.163]	-0.291***(0.077)[0.194]
Density$>$ 722/mi^2	-0.631***(0.182)[0.739]	-0.267***(0.037)[0.176]	0.039(0.080)[0.255]
Density$<$ 80/mi^2	0.172*(0.099)[0.474]	0.083*(0.043)[0.184]	0.019(0.080)[0.302]
Proposition$>$ 50%	0.183 (0.127)[0.329]	-0.009(0.037)[0.164]	-0.134*(0.078)[0.210]
Regional water board FE†			
San Francisco Bay	-0.408*(0.216)[0.978]	0.033(0.061)[0.244]	-0.037(0.148)[0.317]
Central Coast	-0.539***(0.191)[1.217]	0.040(0.036)[0.255]	-0.462***(0.122)[0.240]
Los Angeles	-2.27***(0.191)[1.726]	0.053(0.105)[0.272]	0.055(0.150)[0.397]
Central Valley	-0.015(0.252)[1.288]	0.659***(0.058)[0.225]	-0.378***(0.075)[0.205]
Colorado River	0.276(0.317)[1.388]	0.843***(0.098)[0.263]	-0.719***(0.160)[0.391]
Santa Ana	0.154(0.132)[0.317]	0.347***(0.073)[0.635]	-0.125(0.140)[1.711]
San Diego	-5.54***(0.848)[7.769]	-0.050(0.105)[0.318]	-0.985***(0.302)[0.640]
Constant	7.38*** (0.434)[1.577]	7.88***(0.121)[0.443]	0.454***(0.160)[0.480]
Adjusted R^2	0.826	0.829	0.508

Notes: This table reports the OLS regression results of the logarithm of the estimated marginal compliance cost and the logarithm of the estimated regulator preferences for each of the 221 facilities active in the first quarter of 2005 on all facility attributes used in the estimation. Robust standard errors under the assumption that the estimated parameters are measured without error are in parenthesis, and the bootstrap standard errors without such an assumption are in brackets. Asterisk marks are based on the former standard errors; $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. † We omit Region 1 (North Coast) in the regressions.

These findings may be driven by the state government's political considerations, which partially determine the allocation of enforcement resources, and the regional board members' ability and willingness to tailor the enforcement standards to local preferences and needs. Because regional board members are paid by the hour at a relatively low rate while their job requires significant expertise, we speculate that they are likely to serve the boards out of civic duty or personal political aspirations, which may help align their actions with the local constituents' preferences.

6.4. **Regulator Preferences and Penalty Disparities.** Panel (A) of Figure 3 provides the scatter plot of (i) the expected penalties for each facility, evaluated at the average negligence level before the 2006 changes ($\overline{a} = 1.08$); and (ii) the marginal benefit of compliance, as perceived by regulators for each facility, at the same negligence level, which we define as:

$$\gamma_{pre}(\mathbf{x}_{i,t}) + \psi_{pre}(\mathbf{x}_{i,t})e'(\overline{a}|\mathbf{x}_{i,t}).$$

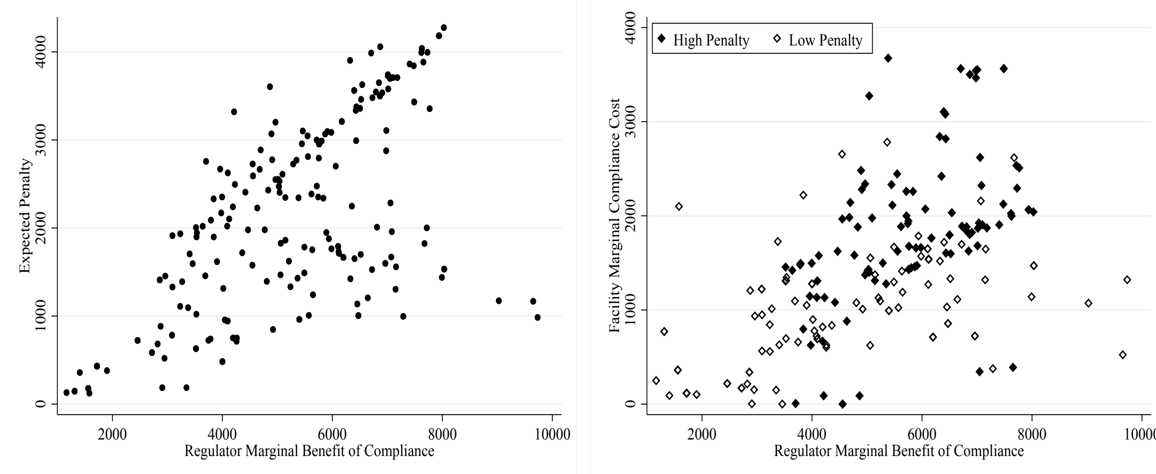
We find that there is a positive correlation between (i) and (ii), but the variation in the expected penalties across facilities is not fully explained by the variation in the regulator preferences. This is partially because there are facilities with high (low) marginal compliance costs and low (high) marginal benefits of compliance, as can be seen in Panel (B) of Figure 3. We show in Corollary A2 in Appendix B.2 that it is optimal for the regulator to set a higher penalty for facilities with higher marginal compliance costs and/or higher marginal benefits of compliance. Therefore, a facility with a low (high) benefit of compliance, as perceived by the regulator, may still face a stringent (lenient) penalty if its marginal compliance costs are high (low)—explaining the *remaining* variation in the expected penalties across facilities in Figure 3(A).

Now, to quantitatively assess the extent to which the heterogeneity in regulator preferences explains the disparities in penalties associated with facility and local attributes, as documented in Section 3, we consider a counterfactual scenario where all facilities are subject to the regulator with the median values of γ and ψ (whom we refer to as the *median regulator*).[40] Column (1) of Table 6 presents the counterfactual outcomes under the median regulator scenario compared to the baseline scenario outcomes, prior to the 2006 changes.[41] Considering the expected penalties

[40]Another source of penalty dispersion for an observationally identical violation is nonlinearity in penalty schedule. However, in explaining the dispersion of the expected penalties for *a given negligence level*, which is our focus in this exercise, nonlinearity is not a factor.

[41]See Table A7 in Appendix E.3 for the corresponding results based on the estimated regulator preferences for the periods after the 2006 changes.

FIGURE 3. Disparities in Penalties and Regulator Preferences



(A) Vs. Expected Penalty (B) Vs. Facility Marginal Compliance Costs

Notes: Panel (A) shows the scatter plot of the estimated marginal benefit of compliance as perceived by the regulator for each facility at the average negligence level before the 2006 institutional changes ($\overline{a} = 1.08$) and the expected penalty at the same negligence level. Panel (B) shows the scatter plot of the estimated marginal benefit of compliance (the same as in Panel (A)) and the estimated marginal cost of compliance for each facility. In Panel (B), we indicate whether the expected penalty at $\overline{a}$ for each facility is below or above the median, \$1,945.5.

for each facility at the average negligence level before the 2006 institutional changes ($\overline{a} = 1.08$), we find that the standard deviation in the expected penalties across the facilities would, relative to the baseline scenario, decrease under the median regulator by a relatively small extent, 11 percent—and this decrease is not statistically significant.[42] In addition, Figure A2 in Appendix E.4 provides evidence that this pattern is not limited to the penalties associated with a particular negligence level. These results suggest that the heterogeneity in the regulator preferences across facilities are not the main driver of the observed disparities in penalties.

[42]The 95% confidence interval of the change in the standard deviation of penalty stringency, $[-0.546, 0.059]$, includes positive values. Our model accommodates the possibility that the dispersion in penalties across facilities under the median regulator scenario is larger than that under the baseline scenario. To see this, consider a facility that faces a relatively low penalty for a given violation, but is perceived by its regulator as having high benefits of compliance (such as the facilities in the lower right corner in Panel (B) in Figure 3). The median regulator would impose to this facility an even lower penalty for the same violation than in the baseline scenario, intensifying the extent of the penalty dispersion.

Table 6. Counterfactual Analyses: The Effects of Regulatory Discretion

	Median Regulator (1)	Uniform Penalty (2)	Linear Penalty (3)	Green Regulator (4)
Violation frequency				
Mean	0.055	-0.061	-0.059	-0.511
	[-0.096, 0.177]	[-0.119, -0.015]	[-0.066, -0.014]	[-0.793, -0.448]
Standard deviation	0.278	-0.189	-0.050	-0.408
	[0.022, 0.516]	[-0.299, -0.104]	[-0.049, 0.038]	[-0.716, -0.346]
Penalty stringency (at the mean negligence)				
Mean	-0.063	-0.071	0.487	3.085
	[-0.135, 0.058]	[-0.147, 0.083]	[0.248, 0.802]	[1.682, 8.545]
Standard deviation	-0.109	-1.000	0.222	-0.807
	[-0.546, 0.059]	-	[-0.061, 1.081]	[-0.918, 0.252]
Equilibrium penalty				
Total	-0.119	0.013	0.158	0.766
	[-0.171, 0.033]	[-0.022, 0.093]	[0.092, 0.345]	[0.200, 1.161]

Notes: This table presents the results of four counterfactual scenarios. All outcomes are proportional changes, relative to the baseline scenario. Means and standard deviations are taken across facilities. In Column (1), every facility is under a regulator with preferences set at the median across all facilities active in the first quarter of 2005. In Column (2), each facility is subject to the same penalty schedule. In Column (3), the regulator is constrained to impose a penalty schedule linear in the number of violations. The scenario in Column (4) is similar to that of Column (1), except that, from the perspective of the common regulator, damages from violation are high and enforcement costs are low (see the text for details). The table reports the results based on the estimates for the period prior to the 2006 institutional changes.

6.5. **Limiting Regulatory Discretion.** In our estimated model, we assume that the regulator knows the distribution of compliance costs faced by each facility. Moreover, we let her set the optimal enforcement schedule, as characterized in Proposition 1, individually for each facility. That is, our model assumes that the regulator possesses *expertise* on the distribution of facilities' compliance costs, and is able to fully employ this expertise in the determination of the enforcement schedules. We now conduct counterfactual policy experiments in which we limit the regulator's discretion to use her expertise. We evaluate the extent to which reducing regulatory discretion affects the equilibrium compliance behavior by the facilities, the penalties, and the enforcement costs borne by the regulator. With this goal, we consider two counterfactual scenarios. In the first one, the regulator must determine the same (potentially non-linear) enforcement schedule to all facilities. This case is closely related to policies aimed at reducing the autonomy of the regional water boards, as discussed in Section 2.1. In the second case, the regulator can still vary the enforcement schedules across the facilities, but these schedules are constrained to be linear in the number of violations. For technical details on the implementation of these counterfactual policies, see Appendices D.1 and D.2.

6.5.1. *One-size-fits-all Policy.* Suppose the regulator sets a one-size-fits-all penalty schedule to minimize the sum of the total expected costs, as defined by (4), across all facilities. We refer to such a scenario as the *uniform policy.* Relative to the penalties in the baseline scenario, the uniform policy would be harsher to some facilities and more lenient to others. Hence, in transitioning from the baseline to the uniform scenarios, some facilities would violate more, and others less—so the aggregate impact of the uniform policy on violations would depend on the relative importance of these two effects. Column (2) of Table 6 shows that, under the uniform policy, the average violation frequency across the facilities would fall by six percent. Despite this reduction, the total amount of penalties assigned would increase by one percent.

To evaluate in a more transparent manner how the constraint to an uniform policy affects enforcement costs, we consider penalty schedules that (i) can be tailored to facility and local attributes, and (ii) would achieve the same reduction of six percent in the average violation frequency across the facilities. In Appendix D.1, we provide the details of one such schedule that would lower the total penalties by 2.5 percent, relative to the uniform policy.[43] This result illustrates that not being able to individually consider the attributes of each facility increases the total amount of penalties—and, accordingly, raises the enforcement costs—without improving compliance. From this perspective, our findings are consistent with the ones by Duflo et al. (2018), who find evidence favorable to providing regulators with discretion in targeting inspections.

Another disadvantage of adopting the one-size-fits-all policy is that it limits the extent to which the preferences of local residents are represented in law enforcement. To see this, we regress whether a facility increases its negligence level in the transition from the baseline to the uniform policy on all control variables employed in the estimation of the structural model. Table 7 shows the regression results.[44] We find that switching to the uniform policy would lead to more violations by facilities that are major, pose a high threat to water quality, or are located in a county with a high average household income or a high approval rate for the 2006 proposition for water projects. These facilities tend to be perceived as having high benefits of compliance by the regulator (Table 5) and, arguably, also by the local residents.

[43]This particular set of penalty schedules is not very sophisticated, suggesting that a regulator with full discretion might be able to reduce total penalties even more, given a target violation rate.

[44]Table A8 in Appendix E.3 provides the counterpart results based on the model primitive estimates for the periods after the 2006 changes.

Table 7. Heterogenous Effects of Regulatory Discretion

Dependent Variable:	*Any increase in the negligence level due to a change to the one-size-fits-all policy?*		
Facility attributes		*County attributes*	
Major	0.404*** (0.061) [0.100]	Irrigation use	-0.042 (0.066) [0.109]
Started in 1982-87	-0.118** (0.054) [0.079]	High income	0.317*** (0.059) [0.138]
Started after 1987	-0.214* (0.109) [0.234]	High density	-0.082 (0.053) [0.091]
Advanced/tertiary	0.153*** (0.046) [0.071]	Low density	0.390*** (0.070) [0.129]
Cap. util.$>$ 87%	0.148*** (0.046) [0.064]	High approval	0.456*** (0.071) [0.165]
Service pop.$< 10K$	-0.007 (0.063) [0.097]	*Regional board FE*†	
Special district	-0.027 (0.039) [0.055]	San Francisco	0.556*** (0.121) [0.184]
High threat to water	0.077*(0.042) [0.073]	Central Coast	0.296*** (0.110) [0.229]
Weather & pollution		Los Angeles	-0.514*** (0.121) [0.199]
Precip.$> 75^{th}$ pct.	0.040 (0.052) [0.070]	Central Valley	0.385*** (0.085) [0.144]
Precip.$< 25^{th}$ pct.	-0.092 (0.116) [0.243]	Colorado River	0.642*** (0.131) [0.266]
Swimmable	0.033 (0.053) [0.085]	Santa Ana	0.611*** (0.124) [0.310]
Constant	-0.607*** (0.169) [0.235]	San Diego	0.244 (0.180) [0.374]
Adjusted R^2	0.729		

Notes: This table reports the OLS regression results where the dependent variable indicates if the facility would increase its negligence level (and hence increase the frequency of violations) under the uniform penalty scenario, compared to the baseline scenario, prior to the 2006 institutional changes. The unit of observation is each of the 221 facilities active in the first quarter of 2005. Robust standard errors under the assumption that the estimated parameters are measured without error are in parenthesis, and the bootstrap standard errors without such an assumption are in brackets. Asterisk marks are based on the former standard errors; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. † We omit Region 1 (North Coast) in the regressions.

6.5.2. *Linear vs. Nonlinear Penalties.* According to our estimates, the enforcement schedule assigned to each facility is a strictly convex function of the negligence level (Figure 2). We now consider the scenario in which this schedule must be linear. Specifically, suppose that, for a facility with attributes vector $\mathbf{x}$, the regulator is constrained to set the penalty schedule $e(a|\mathbf{x}) = p(\mathbf{x})a$. Column (3) of Table 6 shows how the outcomes under linear penalties would compare to those in the baseline scenario. The convex penalties in the latter scenario allow the regulator to impose, to a given facility, large penalties per violation if the facility commits many violations (likely due to its draw of a high cost type, θ), while keeping the penalties relatively low in case the facility has a small number of violations (probably associated with a low θ). That is, *holding* $\mathbf{x}$ *constant*, convex penalties imply larger penalties per violation to facilities with relatively high compliance costs. If forced to assign linear penalties, the regulator would decrease (increase) the per-violation penalties for high (low) θ draws. Our findings indicate that the resulting decrease in violations by low θ facilities would more than compensate the increase by high θ ones, leading the expected violations to fall by roughly six percent, overall. The equilibrium penalties would increase, on average, by 15 percent, raising enforcement costs. At the mean negligence level, expected penalties would go up by almost 50 percent. All these effects are statistically significant.

The relatively mild reduction in violation frequencies under linear penalties contrasts with the large increases in penalty stringency—suggesting that, from the point of view of a regulator facing enforcement costs, linear penalties would be substantially less efficient than non-linear ones. One way of assessing the magnitude of the excessive enforcement costs associated with linear penalties is through the following exercise: for every facility, we compute the linear penalty that would lead to the same expected number of violations as in the baseline scenario. Averaging across the facilities in the pre-2006 period, we find that penalties would increase by 12 percent. These results stress the role played by non-linear penalties in reducing the regulator's enforcement costs. They are related to the findings by Blundell et al. (2019), who, in the context of air quality regulation, argue that allowing the regulator to use relatively sophisticated dynamic penalty schemes leads to reductions in average fines.

6.5.3. *Discussion.* Insofar as regulator preferences reflect the preferences of local residents (Section 6.3) and that the spillovers of water pollution to nearby areas are limited (to a distance of 20-25 miles; see Keiser and Shapiro (2018)), policies that restrict regulatory discretion, such as the aforementioned counterfactual policies, are sub-optimal for two reasons. First, the regulator cannot utilize her expertise on facilities' compliance costs to efficiently allocate enforcement resources. Second, the extent to which law enforcement represents the preferences of local residents gets limited. We discuss these effects in detail in the previous sections (Sections 6.5.1 and 6.5.2).

However, the regulator preferences might also reflect her private interests, possibly due to corruption or lack of dedication. These interests could lead the regulator to have inappropriately low perceptions of the benefits of compliance. Although our analysis cannot identify whether the heterogeneity in the estimated regulator preferences reflects differences in private or social concerns, we compute a reasonable *upper* bound for the *excess* expected number of violations associated with private interests, if any.[45]

[45] Alternatively, we could obtain the social costs of a violation by combining estimates of (i) the social cost of water pollution and (ii) the effects of a wastewater treatment facility's violation on water

With this intent, we consider a counterfactual scenario where, as in the baseline case, a regulator sets a different penalty schedule to each facility. But, instead of using our estimated regulator preferences, we consider a *green* regulator, who highly appreciates the benefits of compliance for *all* facilities. Specifically, the green regulator has $\gamma = \max\{\hat{\gamma}_{pre}(\mathbf{x}_{i,t})\} = 8,020$ and $\psi = 0.015$, which is the observed average staff costs per one dollar of penalty.[46] The difference in violations frequencies between the baseline and the green regulator scenarios would be equal to the number of violations due to private interests, under the assumption that these interests are responsible for the entirety of the differences between the estimated regulator preferences and those of the green regulator. The comparison of these frequencies thus provides an upper bound for the share of violations associated with private concerns in the baseline scenario. Column (4) of Table 6 shows that this upper bound is equivalent to 51 percent of the violations. These numbers are based on extreme assumptions about the green regulator preferences, and should thus be interpreted cautiously.

7. Conclusion

We provide an empirical framework to evaluate regulatory discretion by identifying and estimating a model of strategic interactions between a regulator and a privately-informed discharger. Applying our framework to data on the regulation of wastewater treatment facilities in California, we estimate the environmental preferences and enforcement costs of regulators and the distribution of facilities' compliance costs. The estimates provide empirical support for regulatory discretion in our setting by showing that (i) regulator preferences reflect environmental preferences of local constituents; (ii) the heterogeneity of regulator preferences is not the main driver of observed disparities in penalties; and (iii) limiting regulatory discretion, by mandating a one-size-fits-all policy or a linear penalty schedule, would increase enforcement

pollution in a nearby area. To measure (i), we could employ existing estimates on the willingness-to-pay for water quality, but these estimates are likely to be exceeded by the social cost of water pollution, due to issues like non-use or existence values and the possibility that individuals may not be fully informed about the (health-related and otherwise) implications of local water quality changes (Keiser and Shapiro, 2018). Estimating (ii) would require data on various sources of water pollution other than the violations by wastewater treatment facilities, including discharges by other point sources (e.g., industrial plants) as well as those from non-point sources that are not regulated by the Clean Water Act.

[46] We observe staff costs for 28 percent of the penalty actions during the period of study in the data. The average ratio of staff costs to penalty amounts among these actions is 0.015.

costs overall and increase violations by facilities with high marginal benefits of compliance as perceived by the regulator. We also provide an upper bound on the excess amount of violations associated with the regulator's private interests.

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Appendix A. Revisiting Modeling Assumptions

A.1. **The 2006 Institutional Changes and Confounding Factors.** Our research design relies on the changes in compliance and enforcement before and after the 2006 institutional changes, conditional on (time-varying) observed attributes. Section 3.3 documents unconditional time trends in compliance and enforcement (Figure 1), and the present section shows that these trends persist even after controlling for all observed facility and local attributes.

Column (1) of Table A1 provides the regression results of the following equation:

$$compliance_{i,q,y} = \beta \mathbf{x}_{i,q,y} + \mu_i + \delta_q + \phi_y + \xi_{i,q,y},$$

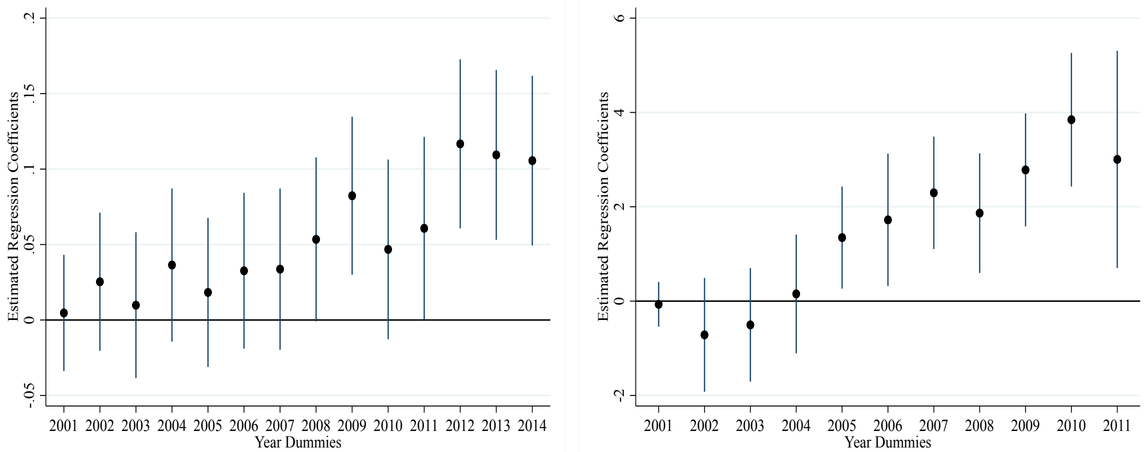
where $compliance_{i,q,y}$ is a dummy indicating that no effluent MMP violations occurred in facility i during the q^{th} quarter of year y, and $\mathbf{x}_{i,q,y}$ is a vector of all facility and local attributes delineated in Table 1. Panel (A) in Figure A1 shows the regression coefficient estimates of year dummies (ϕ_y) with the year of 2000 being the base year, and it can be seen that the estimated year dummy coefficients are not statistically different from zero for the years of 2001–2007, while those after 2007 are statistically significant and are greater than zero. If we interpret these year dummy coefficients after 2006 as the effects of the 2006 institutional changes on compliance, then we conclude that there is a two-year lag.

Column (2) of Table A1 provides the regression results of the following equation, and Panel (B) in Figure A1 shows the regression coefficient estimates of year dummies ($\tilde{\phi}_y$):

$$\log(penalty_{v,i,q,y} + 1) = \alpha \mathbf{z}_{v,i,q,y} + \tilde{\beta} \mathbf{x}_{i,q,y} + \tilde{\mu}_i + \tilde{\delta}_q + \tilde{\phi}_y + \tilde{\epsilon}_{v,i,q,y},$$

where $penalty_{v,i,q,y}$ is the amount of penalty imposed within four years of the occurrence date of violation v by facility i during the q^{th} quarter of year y, and $\mathbf{z}_{v,i,q,y}$ denotes the violation-specific attributes used in Table 2. Panel (B) in the figure shows that the estimated year dummy coefficients are not statistically different from zero for the years of 2001–2004, while those after 2004 are statistically significant and are greater than zero. Given the retroactive nature of the institutional changes and the four-year penalty window that we use in this specification, it is not a surprise that there is an upward slopping trend among the estimated year dummy coefficients between 2002 and 2006. These results show that both compliance rates and penalties increased after the 2006 institutional changes, even after controlling for an extensive set of (time-varying) facility and local attributes, including treatment technology, capacity, pollution, and weather conditions.

Figure A1. Compliance and Enforcement



(A) Probability of Being in Compliance (B) Average Penalty per MMP Violation

Notes: Panels (A) and (B) show the regression coefficient estimates and the 95% confidence intervals for year dummies, where year 2000 is the base year. The dependent variable in the regression for Panel (A) is the fraction of the domestic wastewater treatment facilities without an effluent MMP violation, and the unit of observations is a facility×year×quarter. The dependent variable in the regression for Panel (B) is the average penalty per effluent MMP violation assessed within 4 years of the occurrence of the violation, and the unit of observation is a violation. We control for a variety of facility attributes; see the text for the specifications.

A.2. **Static vs. Dynamic Enforcement.** We assume that the penalty schedule is static in our analysis, motivated by our findings in Section 3.4. The present section provides additional empirical evidence to support the assumption. Table A2 presents the estimates of a regression model where we assess the extent to which the total amount of penalties for the violations during the quarter is associated with the number of total effluent MMP violations, the number of past effluent MMP violations up to one year, and all facility and local attributes that are described in Table 1. In Specifications (1) and (2) in Table A2, we control for the weighted sum of the number of violations during the past four quarters, where the weights reflect "depreciation" with a rate of 10 percent per quarter, following Blundell et al. (2019). In Specification (3), we control for the number of violations of each of the past four quarters separately. In all three specifications, we do not find that past violations are associated with a higher penalty for a current violation, conditional on the number of violations during the current period and (time-varying) facility and local attributes.

Table A1. Compliance and Enforcement Over Time

Dependent Variable:	In Compliance (1)	Log (Penalty Amount + 1) (2)
Year FE		
2001	0.005 (0.020)	0.042 (0.241)
2002	0.025 (0.023)	-0.616 (0.603)
2003	0.010 (0.025)	-0.348 (0.608)
2004	0.036 (0.026)	0.262 (0.645)
2005	0.018 (0.025)	1.556*** (0.559)
2006	0.033 (0.026)	1.895*** (0.700)
2007	0.037 (0.027)	2.426*** (0.615)
2008	0.053* (0.028)	2.100*** (0.636)
2009	0.082*** (0.027)	2.957*** (0.597)
2010	0.047 (0.030)	4.048*** (0.732)
2011	0.061** (0.031)	3.257*** (1.170)
2012	0.117*** (0.028)	-
2013	0.109*** (0.029)	-
2014	0.106*** (0.029)	-
Quarter FE		
2^{nd} quarter (April-June)	0.027*** (0.008)	-0.254 (0.166)
3^{rd} quarter (July-September)	0.053*** (0.012)	0.087 (0.121)
4^{th} quarter (October-December)	0.025*** (0.008)	-0.135 (0.834)
Weather & pollution		
Precipitation$>75^{th}$ percentile	-0.034*** (0.009)	-0.119 (0.175)
Precipitation$<25^{th}$ percentile	-0.015** (0.008)	0.019 (0.196)
Swimmable	0.019 (0.014)	0.523 (0.396)
Facility attributes†	Yes	Yes
Violation attributes††	No	Yes
Facility FE	Yes	Yes
Number of observations	12,779	15,827
Adjusted R^2	0.223	0.615

Notes: This table reports the OLS regression results where the dependent variables are a dummy variable indicating if the facility was in compliance during the quarterly period (Column (1)) and the logarithm of the sum of one and the amount of penalty imposed within four years of the occurrence date of the violation (Column (2)). Standard errors are adjusted for clustering at the facility level, and are provided in parentheses; $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$. † All facility attributes used in the main structural estimation of the model (see Table 5). †† All violation attributes used in Table 2.

We argue that the potential efficiency loss associated with the static enforcement scheme as observed in the data, compared to a history-dependent enforcement mechanism, is not likely to be large in our setting. Once initial compliance has been achieved, violations are mainly affected by maintenance and operation of pollution

Table A2. Does Past Compliance Behavior Matter for Enforcement?

Dependent variable: Log (Penalty Amount + 1)	(1)	(2)	(3)
Current violations			
Number of MMP violations	0.0341***	0.0358***	0.0347**
	(0.0122)	(0.0130)	(0.0128)
Past violations			
Accumulated number of MMP violations†	-0.0000330	-0.000264	
	(0.00503)	(0.00578)	
1st lagged number of MMP violations			0.00515
			(0.00676)
2nd lagged number of MMP violations			-0.00708
			(0.00995)
3rd lagged number of MMP violations			0.00448
			(0.00515)
4th lagged number of MMP violations			-0.00392
			(0.0124)
Technology/cost/county, weather, pollution attributes	No	Yes	Yes
Regional water board, year, quarter FE's	Yes	Yes	Yes
Adjusted R^2	0.143	0.190	0.190

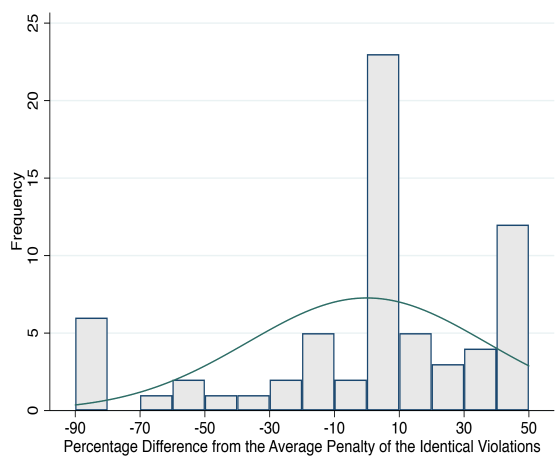
Notes: This table reports OLS estimates. The unit of observation is a facility-quarter; 2,617 observations. Standard errors are adjusted for clustering at the facility level, and are provided in parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. † The weighted sum of the number of MMP violations in the past four quarters, where the weight for t^{th} lagged number of violations is 0.9^{t-1}.

abatement equipment (Harrington, 1988), which is the case for the wastewater treatment facilities. In the engineering literature, for example, Weirich et al. (2015) find that past violations of a wastewater treatment facility increase the likelihood of subsequent violations, but such effect only lasts from 2 to 5 months, depending on capacity and capacity utilization. This contrasts to the other regulatory settings studied by Duflo et al. (2018) and Blundell et al. (2019) where the compliance is mainly achieved by (discrete) investment.

A.3. **Discretion in Enforcement.**

A.3.1. *Identical Violations.* In Section 3.4, we show that the variation in penalties, conditional on violation priority rank and pollutant category, is explained by the facility and local attributes as well as other violations during the same quarter. This finding does not necessarily mean that regulator's discretion matters, because violation attributes that are not controlled for in the analysis could be driving the conditional variation in penalties observed in the data. To address this concern, we look at MMP violations that are identical in terms of the pollutant and its permitted

Figure A2. Heterogeneous Penalties for Identical Violations



Notes: This figure shows a histogram of the percentage difference of the assigned penalty for a given violation from the average penalty for its identical violations in terms of the pollutant and the permitted and actual amounts of discharge, overlaid with a fitted Normal density function. The histogram and the density function are based on 67 violation records with nonzero penalties, grouped into 17 unique cases of identical violations by at least three distinct domestic wastewater treatment facilities during 2009–2014.

and actual amounts of discharge for a given period (e.g. 30-day median, weekly average, etc.). Focusing on the domestic wastewater treatment facilities' violations from 2009–2014 that resulted in a nonzero penalty, we identify 17 unique groups of identical violations by at least three distinct facilities, with a total of 67 violation records. Figure A2 presents a histogram of the percentage difference of the assigned penalty for a violation from the average penalty for its identical violations in the group. The percentage differences range from -84 to 49, and 48 percent of the 67 violations led to penalties that differ by more than 20 percent from the average penalty of their group.

Table A3 shows that this observed dispersion in penalties, conditional on the detailed nature and severity of violation, is explained by the number of concurrent violations during the same quarter of the violation and some of the facility and local attributes. This finding is consistent with our finding from Table 2 in Section 3.4. The specifications of Columns (1) and (2) in Table A3 are similar to Columns (3) and (6) in Table 2—except that, in the latter, we control for violation attributes, while, in the former, we control for violation fixed effects. These fixed effects are based on pollutant, emission limit and result, and measurement unit and period.[1] By controlling for violation fixed effects, we look at how the remaining variation in penalties, as represented in Figure A2, can be explained by the factors considered in Section 3.4. We find that facilities run by a special district, built after 1982, or located in a county with high average household income or a high population density tend to get higher penalties in expectation.

A.3.2. *Penalty Assessment: Staff vs. Board.* As described in Section 2.2, the penalty assessed by the enforcement staff at the regional water board can then be adjusted by the board. For a large fraction (86 percent) of the penalty actions of 2009 –2015, we have data on the penalty amount assessed by staff as well as the final penalty amount.[2] Among the 263 penalty actions with the staff assessment information, we find that the final penalty amount by the board differs from the initial amount assessed by the staff for 63 penalty actions (24 percent), and is on average 16 percent higher than the initial amount, with the 5^{th} percentile being a decrease of 44 percent and the 95^{th} percentile being an increase of 130 percent.

To investigate the sources of the variation in the adjustment made by the board, we regress the logarithm of the final penalty amount on the logarithm of the initial amount and (time-varying) facility and local attributes. Column (3) of Table A3 provides the regression results. By controlling for the initial penalty amount by the staff, we control for all violation attributes as assessed by the staff, and thus the remaining variation represents the discretion of the regional water board, including any efforts to obtain and evaluate extra, relevant information on violations after the staff decisions. We find that facilities located in a county where more than 2/3 of the fresh water is used for irrigation tend to get a "discount" in penalties, while those located in a county with high average household income tend to receive an upward adjustment to the initial amount assessed by the staff. These results further support the idea that regulatory discretion is important in understanding the penalty disparities in the data, consistent with our findings in Section 3.4.

[1]For Columns (1) and (2) in Table A3, we use all effluent MMP violations by the wastewater treatment facilities in our dataset during 2009–2014. However, the final sample size, 770, is much smaller than that for Table 2 because we control for violation fixed effects, and most violations are unique in terms of pollutant, emission limit and result, and measurement unit and period.

[2]Staring in 2007, it is required to report the staff assessment amount in the data system, but the system may not have been set up to encourage the reporting in the beginning. As a result, we have the staff assessment amount for 11 percent of the penalty actions from 2000-2006, 57 percent for the 2007 penalty actions, and 79 percent for the 2008 penalty actions.

Table A3. Further Evidence on Regulatory Discretion

Dependent variable:	Penalized (1)	Log (Penalty+ 1) (2)	Log(Penalty) (3)
Number of current MMP violations	0.00208**	0.0186**	-
	(0.000992)	(0.00779)	
Any violations in the past semester	0.0733	0.505	-
	(0.0541)	(0.426)	
Facility attributes			
Major facility	0.148	1.491	-0.158
	(0.201)	(1.555)	(0.109)
First operated in 1982-87	0.298*	2.470*	-0.0814
	(0.174)	(1.337)	(0.0508)
First operated after 1987	0.326	2.769*	-0.122
	(0.198)	(1.507)	(0.128)
Advanced or tertiary treatment level	0.114	0.352	-0.0693
	(0.0953)	(0.720)	(0.0622)
Capacity utilization > 87%	0.0627	0.496	0.0232
	(0.106)	(0.832)	(0.0657)
Service population < 10,000	-0.119	-0.974	-0.165*
	(0.204)	(1.577)	(0.0843)
Run by a special district	0.299***	2.060**	-0.0422
	(0.0961)	(0.792)	(0.0592)
High threat to water quality (by the board)	-0.136	-1.229	0.0337
	(0.113)	(0.910)	(0.0654)
County attributes			
Large irrigation water use (> 67%, 2010)	0.200	1.198	-0.186***
	(0.166)	(1.322)	(0.0620)
High income (>$57K, 2010)	0.296*	2.578*	0.124*
	(0.162)	(1.303)	(0.0707)
High population density (> 722/mi^2, 2010)	0.201	1.656	-0.0130
	(0.206)	(1.662)	(0.0812)
Low population density (< 80/mi^2, 2010)	-0.527***	-3.404***	0.000421
	(0.134)	(1.030)	(0.106)
High approval for the 2006 prop. (> 50%)	-0.141	-0.642	-0.0645
	(0.167)	(1.336)	(0.0600)
Log (Staff penalty assessment)	-	-	0.995***
			(0.0164)
Violation FE†	Yes	Yes	-
Weather and pollution††	Yes	Yes	Yes
Regional water board/year/quarter FEs††	Yes	Yes	Yes
Number of observations	770	770	373
Adjusted R^2	0.748	0.742	0.929

Notes: This table reports OLS estimates. Standard errors are adjusted for clustering at the facility level, and are provided in parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. The unit of observation is a violation (Columns (1) and (2)) or a penalty action (Column (3)).† : Each fixed effect parameter is associated with a group of violations that share identical pollutant, emission limit and result, and measurement unit and period. ††: All weather and pollution attributes in Table 1. Violation year/quarter fixed effects for (1)–(2); penalty action year fixed effects for (3).

Table A4. Number of Permits and Staff Size in FY 2006–2007

Regional Boards	Permits	Compliance Staff	Enforcement Staff	Permits Per Staff
North Coast	1,789	2	3	368
San Francisco Bay	5,116	11	20	165
Central Coast	2,465	11	6	145
Los Angeles	8,078	10	5	539
Central Valley	15,778	21	22	367
Lahontan	2,305	4	6	231
Colorado River	1,636	12	3	109
Santa Ana	7,757	13	8	369
San Diego	5,365	10	4	383

Source: California Water Boards Baseline Enforcement Report, FY 2006–2007. All permits for the 5 core regulatory programs, NPDES, Stormwater, WDRs, Land Disposal, and 401 Certification, are considered in this table. The total regional board staff size is much larger than the sum of compliance and enforcement staff size. For example, there were 113 staff members at the San Francisco Bay Regional Water Quality Control Board during the period.

A.4. **Heterogenous Enforcement Resources.** The regional water boards differ by their resources to enforce the regulations. Table A4 shows the number of permits and staff size by the regional boards. We observe a large heterogeneity in the average number of permits per staff, from 109 permits per staff in the Colorado River board to 539 in the Los Angeles board.

Appendix B. More on Theory and Identification

B.1. Proofs for Sections 4 and 5.

B.1.1. *Proof of Lemma A1.*

Lemma A1. *Consider any continuous function $e(\cdot)$ with domain $a \in [0, \overline{a}]$, where $\overline{a} < \infty$. Then, for any $\delta > 0$, there exists $\epsilon(\cdot) : \mathbb{N} \to \mathbb{R}$ such that*

$$\sup_{a \in [0,\overline{a}]} \left| e(a) - \exp(-a) \sum_{k=0}^{\infty} \frac{\epsilon(k)}{k!} a^k \right| < \delta.$$

Proof. For any continuous $e(\cdot)$ and $\delta > 0$, by the Weierstrass approximation theorem, the regulator can select a polynomial $\sum_{k=0}^{K_\delta} \beta_k a^k$ such that

$$\sup_{a \in [0,\overline{a}]} \left| e(a) \exp(a) - \sum_{k=0}^{K_\delta} \beta_k a^k \right| < \delta,$$

where we make explicit the dependency between the polynomial degree K_δ and δ (Royden and Fitzpatrick, 1988). Thus, for every $a \in [0, \overline{a}]$, we have that

$$exp(-a)\left|e(a)exp(a) - \sum_{k=0}^{K_\delta}\beta_k a^k\right| = \left|e(a) - \exp(-a)\sum_{k=0}^{K_\delta}\beta_k a^k\right| < exp(-a)\delta \leq \delta.$$

By setting $\epsilon(k) = \beta_k k!$ for $k \leq K_\delta$ and $\epsilon(k) = 0$ for $k > K_\delta$, we obtain

$$\sum_{k=0}^{\infty}\frac{\epsilon(k)}{k!}a^k = \sum_{k=0}^{K_\delta}\beta_k a^k.$$

□

B.1.2. *Proof of Lemma 1.*

Proof. Fix any time period t. The moment generating function of the number of violations K_t, $M_{K_t}(\cdot)$, is:

$$\begin{aligned} M_{K_t}(s) &= \mathbb{E}[\exp(ks)] = \mathbb{E}_{A_t}[\mathbb{E}_K[\exp(ks)|a]] \\ &= \mathbb{E}_{A_t}[\exp(a[\exp(s) - 1])] = M_{A_t}[\exp(s) - 1], \end{aligned}$$

where the third equality follows from the moment generating function of the Poisson distribution with parameter a. Because A_t has a bounded support, $[0, a_t(\overline{\theta})]$, $M_{K_t}(s)$ exists for any $s \in \mathbb{R}$. Letting $u = \exp(s) - 1$ shows that

$$M_{A_t}(u) = M_{K_t}[\log(1 + u)],$$

for $u \in (-1, \infty)$. Therefore, $M_{A_t}(\cdot)$ is identified on a neighborhood of 0, thereby identifying $G_t(\cdot)$. □

B.1.3. *Proof of Lemma 2.*

Proof. The first equation follows from $F(\cdot)$ and $b(\cdot)$ not changing over time and from the strict monotonicity $\tilde{a}(\cdot, j)$ in its first argument. Concerning the second equation, from (3), we have that $\tilde{\theta}(a, j)b'(a) = e'_j(a)$ for $j \in \{pre, post\}$, which implies that $\tilde{\theta}(a, post) = \frac{e'_{post}(a)}{e'_{pre}(a)}\tilde{\theta}(a, pre)$. □

B.1.4. *Proof of Proposition 2.*

Proof. We first show by induction that $\theta_l = \tilde{\theta}(a_l, post) = \tilde{\theta}(a_{l+1}, pre)$. From the normalization, $\theta_0 = \tilde{\theta}(a_0, post)$. For any l, let $\theta_l = \tilde{\theta}(a_l, post)$. Then, $a_{l+1} = T^H(a_l) = \tilde{a}\left[\tilde{\theta}(a_l, post), pre\right] = \tilde{a}(\theta_l, pre)$, where the first and second equalities are due to the definition of a_{t+1} and Lemma 2, respectively. Thus, $\theta_l = \tilde{\theta}(a_{l+1}, pre)$. Moreover,

$\theta_{l+1} = T^V(\theta_l, a_{l+1}) = T^V\left[\tilde{\theta}(a_{l+1}, pre), a_{l+1}\right]$, where the second equality is due to the definition of θ_{l+1}. Therefore, from Lemma 2, we have that $\theta_{l+1} = \tilde{\theta}(a_{l+1}, post)$. We can then use (3) to write $b'(a_l) = \frac{e'_{pre}(a_l)}{\theta_{l-1}} = \frac{e'_{post}(a_l)}{\theta_l}$. Moreover, $F(\theta_l)$ is identified by

$$F\left(\theta_l\right) = G_{post}\left(a_l\right) = G_{pre}\left(a_{l+1}\right).$$

□

B.1.5. *Proof of Proposition 3.*

Proof. Let $Q(\alpha)$ denote α-quantile of $F(\cdot)$. We can rewrite equation (9) as

$$b'\left[G_j^{-1}(\alpha)\right]\left[(1-\psi_j)Q(\alpha) + \frac{\psi_j(1-\alpha)}{f\left[Q(\alpha)\right]}\right] = \sum_{r=1}^{R} \gamma_{j,r}\left[G_j^{-1}(\alpha)\right]^{r-1}. \tag{A.1}$$

We may also rewrite equation (3) as:

$$e'_j\left[G_j^{-1}(\alpha)\right] = Q(\alpha) b'\left[G_j^{-1}(\alpha)\right]. \tag{A.2}$$

Using equation (A.2) and the relationship between the density and its quantile function, i.e.,$f\left[Q(\alpha)\right] = 1/Q'(\alpha)$, we rewrite equation (A.1) as

$$\frac{e'_j\left[G_j^{-1}(\alpha)\right]}{Q(\alpha)}\left[(1-\psi_j)Q(\alpha) + Q'(\alpha)\psi_j(1-\alpha)\right] = \sum_{r=1}^{R} \gamma_{j,r}\left[G_j^{-1}(\alpha)\right]^{r-1},$$

which implies

$$\frac{Q'(\alpha)}{Q(\alpha)} = \frac{\sum_{r=1}^{R} \gamma_{j,r}\left[G_j^{-1}(\alpha)\right]^{r-1} - e'_j\left[G_j^{-1}(\alpha)\right](1-\psi_j)}{e'_j\left[G_j^{-1}(\alpha)\right]\psi_j\left(1-\alpha\right)}, \tag{A.3}$$

for $j \in \{pre, post\}$. Define $\Gamma_{j,r} \equiv \frac{\gamma_{j,r}}{\psi_j}$ and $\Psi_j = \frac{1-\psi_j}{\psi_j}$, and notice that there is a one-to-one relationship between $\left(\{\Gamma_{j,r}\}_{r=1}^{R}, \Psi_j\right)$ and $\left(\{\gamma_{j,r}\}_{r=1}^{R}, \psi_j\right)$. Integrating the above equation from some α_0 to α gives

$$\log\frac{Q(\alpha)}{Q(\alpha_0)} = \int_{\alpha_0}^{\alpha}\left(\sum_{r=1}^{R}\Gamma_{j,r}\frac{\left[G_j^{-1}(u)\right]^{r-1}}{e'_j\left[G_j^{-1}(u)\right]} - \Psi_j\right)\frac{1}{(1-u)}du. \tag{A.4}$$

Remember that $F\left(\theta_l\right) = G_j\left[\tilde{a}(\theta_l, j)\right]$. From Proposition 2, there is a vector $\{\theta_l\}_{l=0}^{\bar{L}}$ such that $\tilde{a}(\theta_l, j)$ is known for $j \in \{pre, post\}$. Since equation (A.4) holds for arbitrary α and α_0, the following holds for for any $l \in \{1, \ldots, \bar{L}\}$ and $j \in \{pre, post\}$:

$$\log\frac{\theta_l}{\theta_0} = \sum_{r=1}^{R}\Gamma_{j,r}\int_{G_j[\tilde{a}(\theta_0,j)]}^{G_j[\tilde{a}(\theta_l,j)]}\frac{\left[G_j^{-1}(u)\right]^{r-1}}{e'_j[G_j^{-1}(u)]\,(1-u)}du - \Psi_j\int_{G_j[\tilde{a}(\theta_0,j)]}^{G_j[\tilde{a}(\theta_l,j)]}\frac{1}{(1-u)}du. \tag{A.5}$$

Furthermore, we obtain the following equations for any α by observing that equation (A.3) holds for both regimes:

$$\frac{\sum_{r=1}^{R}\Gamma_{post,r}\left[G_{post}^{-1}(\alpha)\right]^{r-1}}{e'_{post}\left[G_{post}^{-1}(\alpha)\right]}-\frac{\sum_{r=1}^{R}\Gamma_{pre,r}\left[G_{pre}^{-1}(\alpha)\right]^{r-1}}{e'_{pre}\left[G_{pre}^{-1}(\alpha)\right]}+\Psi_{pre}-\Psi_{post}=0. \quad \text{(A.6)}$$

For each regime, equation (A.5) specifies a system of $\bar{L}$ linear equations and $R+1$ unknowns $\left(\{\Gamma_{j,r}\}_{r=1}^{R}\,\text{and}\Psi_j\right)$, and equation (A.6) specifies an infinite number of equations. Assumption 5 suffices for a system consisting of equations (A.5) and (A.6) to have an unique solution for $\{\gamma_{pre,r}\}_{r=1}^{R}, \{\gamma_{post,r}\}_{r=1}^{R}, \psi_{pre}$ and ψ_{post}. Now, setting $\alpha_0 = G_j(a_0)$ in equation (A.4), we identify $Q(\cdot)$ and, accordingly, $F(\cdot)$ and $f(\cdot)$. Lastly, using equation (A.1), we identify $b'(a)$ for $a \in \mathcal{A}_{pre} \cup \mathcal{A}_{post}$.

Our model is over-identified because we can evaluate (A.6) at an arbitrarily large number of quantiles. Moreover, for each regime, there is at least one more equation that we could use for the identification of the model primitives, which we obtain by evaluating equation (9) at the upper bounds of $\mathcal{A}_j$'s. □

B.2. **Comparative Statics.** We study how the equilibrium violations (or the negligence levels) and the stringency in enforcement vary with the regulator preferences (γ, ψ) and the compliance costs. To simply capture the heterogeneity of costs for this comparative statics, we introduce a parameter, β, which enters in $b'(a, \beta)$. We assume that $\partial b'(a, \beta)/\partial\beta > 0$.

Corollary A1. *Suppose the assumptions for Proposition 1 are satisfied. Then, for any $\theta \in (0, \overline{\theta})$, (i) the optimal negligence level for θ, $a(\theta)$, is decreasing in γ; (ii) if $-\theta + \frac{1-F(\theta)}{f(\theta)} > 0$, then $a(\theta)$ is increasing in ψ; and (iii) if $b(\cdot)$ is concave, then $a(\theta)$ is increasing in β.*

Proof. The comparative statics on violations are based on the regulator's first order condition:

$$\gamma - b'[a(\theta)]\left((1-\psi)\theta + \frac{\psi\{1-F(\theta)\}}{f(\theta)}\right) = 0. \quad \text{(A.7)}$$

First, taking a derivative of (A.7) with respect to γ:

$$1 - b''[a(\theta)]\left((1-\psi)\theta + \frac{\psi\{1-F(\theta)\}}{f(\theta)}\right)\frac{\partial a(\theta)}{\partial\gamma} = 0.$$

Rearranging the above equation:

$$\frac{\partial a(\theta)}{\partial\gamma} = \left[b''[a(\theta)]\left((1-\psi)\theta + \frac{\psi\{1-F(\theta)\}}{f(\theta)}\right)\right]^{-1}.$$

Because we assume that the second order condition for the regulator holds, $a(\theta)$ is decreasing in γ for any θ.

Second, taking a derivative of (A.7) with respect to ψ:

$$-b''[a(\theta)]\left((1-\psi)\theta+\frac{\psi\{1-F(\theta)\}}{f(\theta)}\right)\frac{\partial a(\theta)}{\partial\psi}-b'[a(\theta)]\left(-\theta+\frac{1-F(\theta)}{f(\theta)}\right)=0.$$

Rearranging the above equation:

$$\frac{\partial a(\theta)}{\partial\psi}=-b'[a(\theta)]\left(-\theta+\frac{1-F(\theta)}{f(\theta)}\right)\left[b''[a(\theta)]\left((1-\psi)\theta+\frac{\psi\{1-F(\theta)\}}{f(\theta)}\right)\right]^{-1}.$$

Under the assumptions that the second order condition for the regulator holds and $b'>0$, $a(\theta)$ is increasing in ψ if $\left(-\theta+\frac{1-F(\theta)}{f(\theta)}\right)$ is positive for any given θ.

Lastly, taking a derivative of (A.7) with respect to β:

$$-\left((1-\psi)\theta+\frac{\psi\{1-F(\theta)\}}{f(\theta)}\right)\left(\frac{\partial b'[a(\theta)]}{\partial a}\frac{\partial a(\theta)}{\partial\beta}+\frac{\partial b'[a(\theta)]}{\partial\beta}\right)=0.$$

Rearranging the above equation:

$$\frac{\partial a(\theta)}{\partial\beta}=-\frac{1}{b''[a(\theta)]}\left(\frac{\partial b'[a(\theta)]}{\partial\beta}\right).$$

Thus, as $b(\cdot)$ is concave, $a(\theta)$ is increasing in β for any θ. □

We consider the stringency of enforcement as $e'[a(\theta)]$. The following proposition shows our comparative statics results on $e'[a(\theta)]$.

Corollary A2. *Suppose the assumptions for Proposition 1 are satisfied. Then, for any $\theta\in(0,\overline{\theta})$, (i) $e'[a(\theta)]$, is increasing in γ; (ii) if $-\theta+\frac{1-F(\theta)}{f(\theta)}>0$, then $e'[a(\theta)]$ is decreasing in ψ; and (iii) if $b(\cdot)$ is concave, then $e'[a(\theta)]$ is decreasing in β.*

Proof. To study the comparative statics on penalty, we rely on the facility's first order condition:

$$\theta b'[a(\theta)]=e'[a(\theta)], \tag{A.8}$$

First, taking a derivative of (A.8) with respect to γ:

$$\theta b''[a(\theta)]\frac{\partial a(\theta)}{\partial\gamma}=\frac{\partial e'[a(\theta)]}{\partial\gamma}+e''[a(\theta)]\frac{\partial a(\theta)}{\partial\gamma}.$$

We have shown that $a(\theta)$ is decreasing in γ and we assume that the second order condition for the facility holds. Hence, $e'[a(\theta)]$ is increasing in γ for any θ.

Second, taking a derivative of (A.8) with respect to ψ:

$$\theta b''[a(\theta)]\frac{\partial a(\theta)}{\partial\psi}=\frac{\partial e'[a(\theta)]}{\partial\psi}+e''[a(\theta)]\frac{\partial a(\theta)}{\partial\psi}.$$

Assuming that the second order condition for the facility holds, $e'[a(\theta)]$ is decreasing in ψ for any given θ if $a(\theta)$ is increasing in ψ.

Lastly, taking a derivative of (A.8) with respect to β:

$$\theta b''[a(\theta)]\frac{\partial a(\theta)}{\partial \beta}+\theta\frac{\partial b'[a(\theta)]}{\partial \beta}=\frac{\partial e'[a(\theta)]}{\partial \beta}+e''[a(\theta)]\frac{\partial a(\theta)}{\partial \beta}.$$

Under the assumption that the second order condition for the facility holds, $e'[a(\theta)]$ is increasing in β for any given θ if $a(\theta)$ is increasing in θ. □

Appendix C. Estimation Procedure

Step 1. We parametrically estimate the expected penalties as specified in (12) by MLE. Given the estimates, we estimate the marginal expected penalty, $\hat{e}'_j\,(a|\mathbf{x})$ using equation (1) for $j=\{pre, post\}$. To estimate $G_j(\cdot|\mathbf{x})$, we use the parametric specification of (14) and estimate δ and β_j's by MLE. The parameter estimates are provided in Table A5.

Step 2. We denote by $\hat{\theta}(a,j|\mathbf{x})$ an estimator of the facility type that sets negligence level a under regime j, given $\mathbf{x}$. We normalize $\hat{\theta}(1,post)=1$, and employ the empirical counterparts of the transforms T^H and T^V, defined in (10) and (11), to obtain $\hat{\theta}(a,j|\mathbf{x})$ for a sequence of values of a. Normalizing $\hat{a}_0(\mathbf{x})=1$ and $\hat{\theta}_0(\mathbf{x})=1$, we define recursively:

$$\begin{aligned}
&\hat{a}_l(\mathbf{x})\equiv\hat{G}_{pre}^{-1}\left[\hat{G}_{post}\left[\hat{a}_{l-1}(\mathbf{x})|\mathbf{x}\right]|\mathbf{x}\right],\\
\text{and}\qquad &\hat{\theta}_l(\mathbf{x})\equiv\frac{\hat{e}'_{post}\left[\hat{a}_l(\mathbf{x})|\mathbf{x}\right]}{\hat{e}'_{pre}\left[\hat{a}_l(\mathbf{x})|\mathbf{x}\right]}\hat{\theta}_{l-1}(\mathbf{x}).
\end{aligned}$$

Let us define $\hat{\theta}_l^{post}(\mathbf{x})\equiv\hat{\theta}_l(\mathbf{x})$, $\hat{\theta}_l^{pre}(\mathbf{x})\equiv\hat{\theta}_{l-1}(\mathbf{x})$, $\hat{a}_l^{post}(\mathbf{x})\equiv\hat{a}_l(\mathbf{x})$ and $\hat{a}_l^{pre}(\mathbf{x})\equiv\hat{a}_l(\mathbf{x})$, for every l. We employ $\hat{\theta}_l^j(\mathbf{x})$ as an estimator of $\tilde{\theta}\left(\hat{a}_l^j(\mathbf{x}),j|\mathbf{x}\right)$, for $j\in\{pre,post\}$ and any l.

Step 3. Equation (A.5) implies that

$$\sum_l\left\{\log\frac{\theta_l}{\theta_0}-\sum_{r=1}^R\Gamma_{j,r}\int_{\alpha_0}^{\alpha_l}\frac{\left[G_j^{-1}(u)\right]^{r-1}}{e'_j\left[G_j^{-1}(u)\right](1-u)}du+\Psi_j\int_{\alpha_0}^{\alpha_l}\frac{1}{(1-u)}du\right\}^2=0,$$

for $j\in\{pre,post\}$. Also, from (A.6), we have

$$\sum_{\alpha\in\mathbf{U}}\left\{\frac{\sum_{r=1}^R\Gamma_{post,r}\left[G_{post}^{-1}(\alpha)\right]^{r-1}}{e'_{post}\left[G_{post}^{-1}(\alpha)\right]}+\Psi_{pre}-\frac{\sum_{r=1}^R\Gamma_{pre,r}\left[G_{pre}^{-1}(\alpha)\right]^{r-1}}{e'_{pre}\left[G_{pre}^{-1}(\alpha)\right]}-\Psi_{post}\right\}^2=0,$$

where $U = \{\alpha_1, \ldots, \alpha_{N_U}\}$ is a grid in the $(0,1)$ interval such that $G^{-1}_{post}(\alpha) > 0$ for all $\alpha \in U$. We estimate $\{\Gamma_{pre,r}(\mathbf{x})\}_{r=1}^{R}$, $\Psi_{pre}(\mathbf{x})$, $\{\Gamma_{post,r}(\mathbf{x})\}_{r=1}^{R}$ and $\Psi_{post}(\mathbf{x})$ using a sample analogue of the above two equations for any given $\mathbf{x}$. In our application, the system comprised by these equations is over-identified, so we employ the least-squares solution. We then estimate $\{\gamma_{j,r}(\mathbf{x})\}_{r=1}^{R}$ and $\psi_j(\mathbf{x})$ as

$$\hat{\psi}_j(\mathbf{x}) \equiv \frac{1}{1-\hat{\Psi}_j(\mathbf{x})} \quad \text{and} \quad \hat{\gamma}_{j,r}(\mathbf{x}) \equiv \hat{\Gamma}_{j,r}(\mathbf{x})\hat{\psi}_j(\mathbf{x}),$$

for $j \in \{pre, post\}$ and $r = \{1, \ldots, R\}$. In solving the system of equations, we constrain the least-squares solution to ensure that all regulator parameter estimates are positive.

Step 4. From the empirical analogue to (A.4) with $\alpha_0 = 0$, we estimate the quantile function associated with the distribution of types, conditional on $\mathbf{x}$, as

$$\hat{Q}_j\left(\alpha|\mathbf{x}\right) \equiv \hat{\theta}^j_0(\mathbf{x}) \exp\left(\int_{\hat{G}_j\left[\hat{a}^j_0(\mathbf{x})|\mathbf{x}\right]}^{\alpha} \left[\sum_{r=1}^{R} \Gamma_{j,r}(\mathbf{x}) \frac{\left[\hat{G}^{-1}_j(u|\mathbf{x})\right]^{r-1}}{e'_j\left[\hat{G}^{-1}_j(u|\mathbf{x})|\mathbf{x}\right]} - \Psi_j(\mathbf{x})\right] \frac{1}{(1-u)} du\right),$$

for $j \in \{pre, post\}$. An estimator for $F(\cdot|\mathbf{x})$, or $\hat{F}_j(\cdot|\mathbf{x})$, is the inverse of $\hat{Q}_j\left(\cdot|\mathbf{x}\right)$—which, under Assumption 2, is guaranteed to exist. Finally, we define

$$\hat{b}'_j\left(a|\mathbf{x}\right) \equiv \hat{e}'_j\left(a|\mathbf{x}\right)/\hat{Q}_j[\hat{G}_j\left(a|\mathbf{x}\right)|\mathbf{x}],$$

and numerically integrate the above expression over a to obtain $\hat{b}_j\left(a|\mathbf{x}\right)$. For any finite sample, we might have $\hat{F}_{pre}(\cdot|\mathbf{x}) \neq \hat{F}_{post}(\cdot|\mathbf{x})$ and $\hat{b}'_{pre}\left(\cdot|\mathbf{x}\right) \neq \hat{b}'_{post}\left(\cdot|\mathbf{x}\right)$, even though our estimator is consistent. In our counterfactual analyses, we employ $\hat{F}_{pre}(\cdot|\mathbf{x})$ and $\hat{b}'_{pre}\left(\cdot|\mathbf{x}\right)$ for scenarios referring to the pre-2006 period, and $\hat{F}_{post}(\cdot|\mathbf{x})$ and $\hat{b}'_{post}\left(\cdot|\mathbf{x}\right)$ for post-2006 scenarios.

Appendix D. Counterfactual Analyses Details

We now provide details on the implementation of the counterfactual analyses described in Section 6.5. As in our empirical application, we assume that the social costs of negligence are linear—that is, $R = 1$.

D.1. **Uniform Penalties.** We start by considering the case in which the regulator chooses a single nonlinear penalty schedule to be applied to all facilities. For computational convenience, we restrict our attention to polynomial schedules of degree three. Specifically we assume that the regulator sets $\tilde{\epsilon} \equiv \{\epsilon_1, \epsilon_2, \epsilon_3\}$, and the penalty for a facility with k violations in a quarter is

$$\epsilon(k;\tilde{\epsilon}) = \begin{cases} \epsilon_1 k + \epsilon_2 k^2 + \epsilon_3 k^3 & \text{if } k \geq 1, \\ 0 & \text{otherwise.} \end{cases}$$

Given our assumption that the number of violations follows a Poisson distribution with mean a, we can then write the expected penalty as

$$e(a;\tilde{\epsilon}) = \mathbb{E}[\epsilon(k;\tilde{\epsilon})|a] = \epsilon_1 a + \epsilon_2(a + a^2) + \epsilon_3(a + 3a^2 + a^3),$$

for a facility that sets the negligence level $a \geq 0$.[3] From the facility's FOC (3), and given a choice of $\tilde{\epsilon}$ by the regulator, we compute the negligence level set by a facility with type θ and observed attributes $\mathbf{x}$ as the solution to

$$\theta \hat{b}'(a|\mathbf{x}) = \epsilon_1 + \epsilon_2(1 + 2a) + \epsilon_3(1 + 6a + 3a^2).$$

Let $a(\theta, \mathbf{x}, \tilde{\epsilon})$ denote this solution. We can then take the expectation of (4) over the facility attributes $\mathbf{X}$ to write the objective function of the regulator as

$$\mathbb{E}_{\mathbf{X}}\left[\mathbb{E}_{\Theta|\mathbf{X}}\left[-\theta\hat{b}\left(a(\theta,\mathbf{x},\tilde{\epsilon})|\mathbf{x}\right) + \hat{\gamma}_j(\mathbf{x})a(\theta,\mathbf{x},\tilde{\epsilon}) + \hat{\psi}_j(\mathbf{x})e\left(a(\theta,\mathbf{x},\tilde{\epsilon});\tilde{\epsilon}\right)|\mathbf{x}\right]\right],$$

$j \in \{pre, post\}$. We minimize this objective function numerically to obtain $\epsilon_1 = 1,764.10$, $\epsilon_2 = 0.00$ and $\epsilon_3 = 2.47$ for $j = pre$; and $\epsilon_1 = 2360.98$, $\epsilon_2 = 45.94$ and $\epsilon_3 = -0.48$ for $j = post$.

In the main text we report that the uniform schedule above leads to a reduction in negligence levels of six percent, but it also increases the total amount of penalties, relative to the baseline enforcement schedule. To obtain a flexible schedule that achieves the same reduction in negligence levels without increasing the assigned penalties, we proceed as follows: first we classify each facility as having either high or low compliance costs, based on whether their median marginal cost, defined in footnote 38, is above or below the median marginal cost across all facilities. Then, given an arbitrary number ξ_H, and for every facility with high compliance cost, we use the FOC (3) to determine the penalty schedule that would induce an increase of ξ_H percent in the negligence level set by every possible realization of that facility's type Θ, relative to the baseline scenario. Similarly, given an arbitrary ξ_L, and for every facility with low compliance cost, we determine the penalty schedule that would lead to a decrease of ξ_L percent in the negligence level set by every possible realization of that

[3]This equation is based on the known closed form solution for the following power series: (i) $\sum_{k=0}^{\infty} \frac{a^k}{k!} = e^a$; (ii) $\sum_{k=0}^{\infty} k\frac{a^k}{k!} = ae^a$; (iii) $\sum_{k=0}^{\infty} k^2\frac{a^k}{k!} = (a + a^2)e^a$; and (iv) $\sum_{k=0}^{\infty} k^3\frac{a^k}{k!} = (a + 3a^2 + a^3)e^a$.

facility's type. In other words, starting from the baseline scenario, we manipulate the penalty schedules so that high compliance cost facilities are expected to violate more, whereas low cost facilities are expected to violate less. By setting $\xi_H = 20$ and $\xi_L = 30.5$, we obtain a reduction of six percent in the average violation frequency across all facilities—exactly the same reduction that would arise under the uniform policy. Moreover, the total amount of penalties under this targeted manipulation of the schedules would be 2.5 percent below that in the uniform scenario. We would like to stress that the manipulation defined above is just one example, and a particularly simple one. It is likely that another choice of the values ξ_H and ξ_L or a partition of the facilities into more than two compliance cost groups would achieve even larger reductions in the total penalties, relative to the uniform scenario, while maintaining the same average violation frequency.

D.2. **Linear Penalties.** Now we address the computation of the optimal linear penalties, from the regulator's perspective. Consider a facility with observed attributes $\mathbf{x}$, and let $\hat{b}'^{-1}(\cdot|\mathbf{x})$ denote the inverse of $\hat{b}'(\cdot|\mathbf{x})$. From the FOC of the facility (3), given per-violation penalty p, the facility chooses its negligence level according to $a = \hat{b}'^{-1}(p/\theta|\mathbf{x})$. Thus we may rewrite (4), the regulator's objective function, as

$$\mathbb{E}_{\Theta|\mathbf{X}}\left[-\theta\hat{b}\left(\hat{b}'^{-1}\left(p/\theta|\mathbf{x}\right)|\mathbf{x}\right)+\hat{b}'^{-1}\left(p/\theta|\mathbf{x}\right)\left(\hat{\gamma}_j(\mathbf{x})+\hat{\psi}_j(\mathbf{x})p\right)|\mathbf{x}\right],$$

subject to $p > 0$, for $j \in \{pre, post\}$. We minimize this function numerically.

Finally we consider the computation of the linear penalty that leads to the same expected number of violations as in the baseline scenario. Let $\hat{a}_j(\mathbf{x})$ denote the mean baseline negligence level set by a facility with observed attributes $\mathbf{x}$ in period $j \in \{pre, post\}$. We numerically solve for p the equation

$$\mathbb{E}_{\Theta|\mathbf{X}}\left[\hat{b}'^{-1}\left(p/\theta|\mathbf{x}\right)|\mathbf{x}\right]-\hat{a}_j(\mathbf{x})=0,$$

using the optimal linear schedule calculated above as a starting point.

Appendix E. Further Discussions on the Estimation Results

This section presents empirical results that, due to space considerations, we do not show in the main text. First, we present the results from the first step in the estimation procedure. Second, we argue that the estimated model satisfies the assumptions in Sections 4 and 5, which are sufficient for equilibrium characterization and the identification of model primitives. Third, we report our results based on the estimated regulator preferences in the post-2006 period. Lastly, we provide further results on the extent to which the heterogeneity in regulator preferences explain penalty disparities across facilities.

E.1. **Penalty Schedule and Negligence Distribution Estimates.** In Table A5, we present the penalty schedule estimates, ϕ's in (12), and the estimates of the negligence distributions, δ and β's in (14). Consistent with the preliminary results discussed in Section 3, we find that $\hat{\phi}_{1,post} > 0$. That is, given the same number of violations, a facility expects to pay a higher penalty in the period following the changes, relative to the prior periods. Furthermore, $\hat{\beta}_{0,pre} - \hat{\beta}_{0,post} < 0$; the facilities decrease negligence levels after the changes.

E.2. **Model Primitives and the Assumptions.** Assumptions 1 and 2 in Section 4 are used in Proposition 1 to characterize the equilibrium negligence schedule. For every facility, the estimated γ_{pre} and γ_{post} are positive, and the estimated $b'(\cdot)$ is positive all over its domain. Thus, Assumption 1 is satisfied.

As for Assumption 2, our estimated distribution of types for each facility satisfies the strict monotonicity of $(1-\psi_j)\theta + \frac{\psi_j[1-F(\theta)]}{f(\theta)}$ on θ, for $j \in \{pre, post\}$. Furthermore, our estimated function $b'(\cdot)$ is decreasing for all facilities; and both the evidence presented in Section 3.4 and the positive estimate of the parameter ϕ_{2,k^2} from (12), shown in Table A5, suggest that the enforcement schedule is strictly increasing in the negligence levels. Therefore, our results indicate that the second order conditions for (3) holds. That the second order condition for (9) also holds is implied by $h(\cdot)$ being a linear function and by the aforementioned strict concavity of $b(\cdot)$.

Assumption 3 is used in Proposition 2 for the partial identification of the distribution of compliance costs. In our estimation of the enforcement function specified in (12), the parameter $\phi_{1,post}$ is positive, implying that the marginal enforcement function in the post-2006 period is always above that in the pre-2006 period.

We employ Assumptions 4 and 5 in Proposition 3 to achieve the identification of the regulator preferences and the exact identification of the facilities' compliance cost distribution. Since we do not directly observe the function $h(\cdot)$, Assumption 4 is non-testable. That we are able to solve the system of equations implied by (A.5) and (A.6) indicates that our estimates satisfy Assumption 5.

E.3. **Results based on the Regulator Preferences after the 2006 Changes.** Most results presented in Section 6 are based on the model primitive estimates for the periods prior to the 2006 institutional changes. Here we provide the results

Table A5. Penalty Schedule and Negligence Distribution Estimates

	Penalties		Negligence	
$\phi_{1,post}$	$0.76^{***}(0.15)$		-	
$\phi_{1,k}$	$0.05^{***}(0.01)$		-	
ϕ_{2,k^2}	4.94 (9.18)		-	
σ_2	$0.50^{***}(0.06)$		-	
$\sigma_{1,2}$	$0.27^{*}(0.16)$		-	
$\beta_{0,post} - \beta_{0,pre}$	-		$-0.26^{***}(0.10)$	
	$\phi_{1,x}$	$\phi_{2,x}$	β_1	δ
Facility attributes				
Major facility	$0.49^{***}(0.21)$	0.12 (0.10)	-0.20 (0.14)	-
First operated in 1982-87	-0.04 (0.18)	-0.01 (0.08)	-0.06 (0.15)	-
First operated after 1987	$-1.28^{***}(0.56)$	-0.01 (0.17)	-0.35 (0.27)	-
Advanced or tertiary	0.06 (0.15)	0.05 (0.07)	$-0.22^{*}(0.12)$	-
Capacity utilization$>$ 87%	0.19 (0.16)	-0.01 (0.09)	$-0.24^{**}(0.11)$	-
Service pop.$< 10K$	0.20 (0.21)	-0.07 (0.07)	0.12 (0.15)	-
Run by a special district	-0.13 (0.15)	$-0.14^{**}(0.07)$	$-0.38^{***}(0.12)$	-
High threat to water	0.24 (0.16)	0.08 (0.06)	-0.28 (0.13)	-
Weather & pollution				
Precipitation$> 75^{th}$ pct.	0.04 (0.17)	0.00 (0.06)	-0.03 (0.12)	-
Precipitation$< 25^{th}$ pct.	0.29 (0.23)	0.04 (0.11)	-0.06 (0.13)	-
Swimmable	-0.13 (0.14)	0.00 (0.06)	-0.14 (0.11)	-
County attributes				
Irrigation use$>$ 67%	-0.15 (0.18)	-0.05 (0.10)	$0.34^{**}(0.15)$	-
Household income$> \$57K$	$0.50^{**}(0.24)$	0.25 (0.16)	0.40 (0.17)	-
Pop. density$> 722/mi^2$	-0.36 (0.27)	-0.05 (0.13)	$-0.51^{**}(0.19)$	-
Pop. density$< 80/mi^2$	-0.12 (0.21)	$0.30^{***}(0.12)$	-0.29 (0.19)	-
Prop. approval$>$ 50%	0.28 (0.25)	0.16 (0.11)	$-0.43^{**}(0.19)$	-
Regional water board FE†				
Region 2: San Francisco Bay	$1.62^{***}(0.37)$	0.09 (0.18)	$-1.31^{***}(0.25)$	$-0.84^{***}(0.18)$
Region 3: Central Coast	0.82 (0.38)	-0.05 (0.19)	$-0.83^{***}(0.28)$	$-0.41^{*}(0.21)$
Region 4: Los Angeles	-0.08 (0.37)	$-0.40^{**}(0.16)$	0.78 (0.26)	-0.73 (0.16)
Region 5: Central Valley	0.99 (0.26)	0.19 (0.18)	0.21 (0.18)	$-0.43^{***}(0.12)$
Region 7: Colorado River	$1.17^{***}(0.34)$	0.33 (0.20)	0.42 (0.21)	-0.34 (0.17)
Region 8: Santa Ana	$2.32^{*}(1.19)$	-0.09 (0.30)	0.29 (0.27)	$-0.95^{***}(0.17)$
Region 9: San Diego	1.79 (5.24)	0.08 (0.24)	-0.09 (0.98)	$-2.93^{***}(0.41)$
Constant	$-1.63^{***}(0.48)$	$7.51^{***}(0.27)$	$0.94^{***}(0.36)$	$-1.89^{***}(0.10)$
Number of observations	729		8,429	

Notes: Bootstrap standard errors are in parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. We estimate the parameters of the penalty schedules in (14) by MLE, employing facility-quarter observations of 2000-2001 and 2009-2010. The parameters of the negligence distributions are estimated by MLE, based on facility-quarter observations in the periods 2002-2005 and 2011-2014. See Section 3.1 and Table 1 for the description of the control variables. † Region 1 (North Coast) is omitted.

Table A6. Explaining Regulators' Preferences: After the 2006 Changes

Dependent variables:	$\log \gamma$	$\log \psi$
Facility attributes		
Major facility	0.143*** (0.019)	-0.078 (0.092)
First operated in 1982-7	-0.005 (0.009)	0.046 (0.076)
First operated after 1987	-0.018 (0.018)	-0.468* (0.261)
Advanced or tertiary	0.008 (0.011)	-0.005 (0.069)
Capacity utilization$>$ 87%	-0.033*** (0.012)	0.243*** (0.090)
Service pop.$< 10K$	-0.007 (0.021)	-0.092 (0.078)
Run by a special district	-0.192*** (0.010)	0.161*** (0.060)
High threat to water	0.061*** (0.011)	-0.012 (0.063)
Weather & pollution		
Precipitation$> 75^{th}$ pct.	-0.016 (0.013)	0.105 (0.085)
Precipitation$< 25^{th}$ pct.	0.021 (0.029)	-0.013 (0.199)
Swimmable	-0.059*** (0.018)	-0.058 (0.069)
County attributes		
Irrigation use$>$ 67%	-0.048*** (0.014)	-0.075 (0.102)
Average household income$> \$57K$	0.306*** (0.013)	-0.477*** (0.101)
Population density$> 722/mi^2$	-0.100*** (0.011)	0.265** (0.109)
Population density$< 80/mi^2$	0.246*** (0.017)	0.184* (0.109)
Proposition 84 approval$>$ 50%	0.116*** (0.012)	0.020 (0.105)
Regional water board FE†		
Region 2: San Francisco Bay	0.135*** (0.035)	0.380** (0.162)
Region 3: Central Coast	0.034 (0.031)	-0.295** (0.122)
Region 4: Los Angeles	-0.242*** (0.036)	-0.330*** (0.164)
Region 5: Central Valley	0.356*** (0.031)	-0.593*** (0.096)
Region 7: Colorado River	0.518*** (0.039)	-1.036*** (0.202)
Region 8: Santa Ana	0.098***(0.034)	0.068 (0.207)
Region 9: San Diego	0.147*** (0.039)	-0.232 (0.345)
Constant	7.648***(0.051)	-1.157***(0.199)
Adjusted R^2	0.942	0.585

Notes: This table reports the OLS regression results of the logarithm of the estimated marginal compliance cost and the logarithm of the estimated regulator preferences for each of the 221 facilities active in the first quarter of 2005 on all facility attributes used in the estimation. Robust standard errors under the assumption that the estimated parameters are measured without error are in parenthesis; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

based on the estimates for the periods after the 2006 changes. Given that these results are qualitatively similar to those presented in Section 6, we omit the bootstrap confidence intervals. Table A6 documents the results of regressing the logarithm of the regulator preference estimates for the periods after the 2006 changes on the facility and local attributes. Tables A7 and A8 present the counterfactual analyses results, the counterparts of Tables 6 and 7 in Section 6.

Table A7. The Effects of Regulatory Discretion: Further Results

	Baseline Policy (1)	Median Regulator (2)	Uniform Penalty (3)	Linear Penalty (4)	Green Regulator (5)
Prior to the 2006 institutional changes					
Violation frequency					
Mean	1.082	1.141	1.016	1.018	0.529
SD	0.785	1.000	0.636	0.745	0.465
Penalty stringency (at the mean negligence)					
Mean	2,069.9	1,940.5	1,923.5	3,077.9	8,455.3
SD	1,121.9	999.5	-	1,370.5	216.9
Total amount of penalty					
Mean	2,380.8	2,096.3	2,411.8	2,757.6	4,205.6
After the 2006 institutional changes					
Violation frequency					
Mean	0.838	0.801	0.810	0.820	0.605
SD	0.603	0.600	0.558	0.594	0.456
Proportional change in Mean	-	-0.044	-0.033	-0.022	-0.279
Proportional change in SD	-	-0.006	-0.074	-0.015	-0.244
Penalty stringency (at the mean negligence)					
Mean	2,660.1	2,607.2	2,655.6	3,107.0	5,248.3
SD	1,035.8	513.7	-	988.2	125.9
Proportional change in Mean	-	-0.020	-0.002	0.168	0.973
Proportional change in SD	-	-0.504	-1.000	-0.046	-0.878
Total amount of penalty					
Mean	2,151.4	2,070.1	2,288.1	2,324.2	2,986.8
Proportional change in Mean	-	-0.038	0.064	0.080	0.388

Notes: This table presents the summary statistics on compliance and enforcement under the baseline and the four counterfactual scenarios that reduce the regulator's discretion in Section 6.5. See Table 6 for the proportional changes compared to the baseline outcomes, based on the estimates for the period prior to the 2006 institutional changes, and the short descriptions of each scenario.

E.4. **Revisiting Disparities in Penalties and Regulator Preferences.** Figure A2 shows the point-wise differences between the 5th and 95th percentiles of penalty schedules across the 221 facilities active in the first quarter of 2005 under the baseline scenario and the median regulator scenario (top lines), the 10th and 90th percentiles (middle lines) and the 25th and 75th percentiles (bottom lines), before and after the 2006 institutional changes, respectively.

There are three notable patterns in Figure A2. First, the differences between the 5th and 95th percentiles under the median regulator scenario are smaller than those under the baseline scenario, both before and after the 2006 changes. These findings are not specific to the choice of percentiles: the 10th-90th ranges and the interquartile

TABLE A8. Heterogenous Effects of Discretion: After the 2006 Changes

Dependent Variable:	*Any increase in the negligence level due to a change to the one-size-fits-all policy?*		
Facility attributes		*County attributes*	
Major facility	0.255*** (0.059)	Irrigation use> 67%	-0.290*** (0.069)
Started in 1982-87	-0.074 (0.052)	High income> \$57K	0.304*** (0.062)
Started after 1987	-0.0719 (0.088)	High density> $722/mi^2$	-0.132** (0.057)
Advanced/tertiary	0.124*** (0.043)	Low density< $80/mi^2$	0.387*** (0.078)
Cap. util.> 87%	0.017 (0.043)	High approval> 50%	0.374*** (0.071)
Service pop.< 10K	0.0002 (0.055)	*Regional water board FE*†	
Special district	-0.060 (0.039)	San Francisco Bay	0.437*** (0.126)
High threat to water	0.174*** (0.052)	Central Coast	0.062 (0.116)
Weather & pollution		Los Angeles	-0.581*** (0.134)
Precip.> 75^{th} pct.	-0.062 (0.056)	Central Valley	0.295*** (0.092)
Precip.< 25^{th} pct.	0.392* (0.199)	Colorado River	0.280 (0.196)
Swimmable	0.058 (0.073)	Santa Ana	-0.318** (0.133)
Constant	-0.222 (0.180)	San Diego	0.319* (0.193)
Adjusted R^2	0.727		

Notes: This table reports the OLS regression results where the dependent variable indicates if the facility would increase its negligence level (and hence increase the frequency of violations) under an alternative scenario compared to the baseline policy after the 2006 institutional changes. The unit of observation is each of the 221 facilities active in the first quarter of 2005. Robust standard errors under the assumption that the estimated parameters are measured without error are in parenthesis; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. † Region 1 (North Coast) is omitted.

ranges are all smaller under the median regulator than under the baseline scenario. This is because the facility-specific marginal benefits of compliance and the expected penalties are positively correlated, as shown in Panel (A) of Figure A3.

Second, the decreases in these point-wise ranges under the median regulator scenario are not very large, regardless of the negligence level, before the 2006 institutional changes. To be specific, the ratio of the 5th-95th range under the median regulator scenario to that under the baseline scenario varies from 0.72 to 0.84 depending on the negligence level.

Third, such decreases based on the regulator preference estimates after the 2006 institutional changes are relatively large. For example, the ratio of the 5th-95th range under the median regulator scenario to that under the baseline scenario varies from 0.38 to 0.45. This is rationalized by the fact that the correlation between the facility-level marginal benefits of compliance and the expected penalties is larger before the 2006 changes than after them, as can be seen in Panel (A) of Figure A3. In a similar vein, the correlation between the regulator marginal benefit estimates and the facility marginal cost estimates is also higher before the 2006 changes than after them (Panel (B) of the same figure).

Appendix F. Sensitivity Analyses

This Appendix assesses the sensitivity of our findings to some of the assumptions made in our main empirical analysis. First, we develop and estimate an extension of the model that explicitly incorporates information about violation severity. In this extension, the negligence level set by a facility affects not only the number but also the severity of violations, and the regulator perceives the social costs of severe and non-severe violations differently. In further sensitivity analyses, we consider alternative choices on the length of the panel, the sample selection, and the covariates used in our estimation.

F.1. **Alternative Specification 1: Endogenous Violation Severity.**

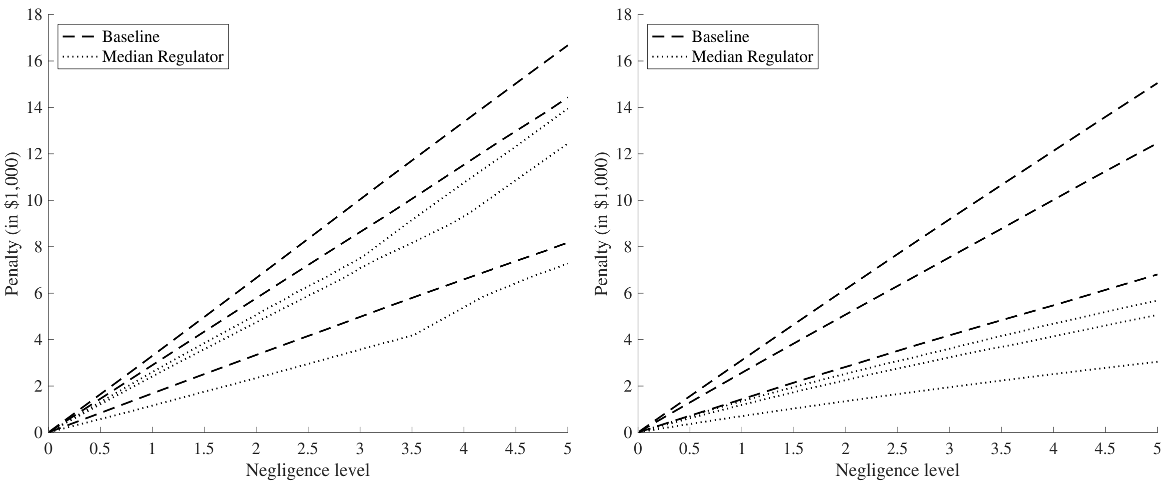
F.1.1. *Model.* As in the model presented in the main text, a facility has privately known type θ, drawn from a distribution $F(\cdot)$. The facility sets a negligence level a, which affects the frequency and the severity of violations. Differently from the model in the main text, each occurred violation may be *severe* or not. Denote by $k \in \mathbb{N}$ and $m \in \mathbb{N}$, respectively, the total number of violations and the number of severe violations by a facility in a period. Also, let $\iota \in \mathbb{R}$ be a random variable representing features of the occurred violations that are not captured by k and m. We make the following assumption concerning the relationship between negligence levels and violation outcomes:

Assumption A1. *$k \sim Poisson(a)$; $m|k \sim Binomial(k, s(a))$; and $\iota \perp a$.*

After the violations occur, (k, m, ι) are observed by both the regulator and the facility. Hence the penalty schedule is a function of (k, m, ι), which we denote by $\epsilon(\cdot, \cdot, \cdot)$. Let $e(a) \equiv \mathbb{E}[\epsilon(k, m, \iota)|a]$. Like in the main text, we assume that the regulator chooses $e(\cdot)$, since, for any continuous $e(\cdot)$, there exists an enforcement schedule $\epsilon(\cdot, \cdot, \cdot)$ that implements $e(\cdot)$. We revisit this assumption below, in our discussion of identification.

The facility derives private benefit $\theta b(a)$ from the negligence level a. The facility's objective function is thus given by (2). We allow the social costs of violations, as perceived by the regulator, to depend on (k, m, ι). Specifically, let us denote these

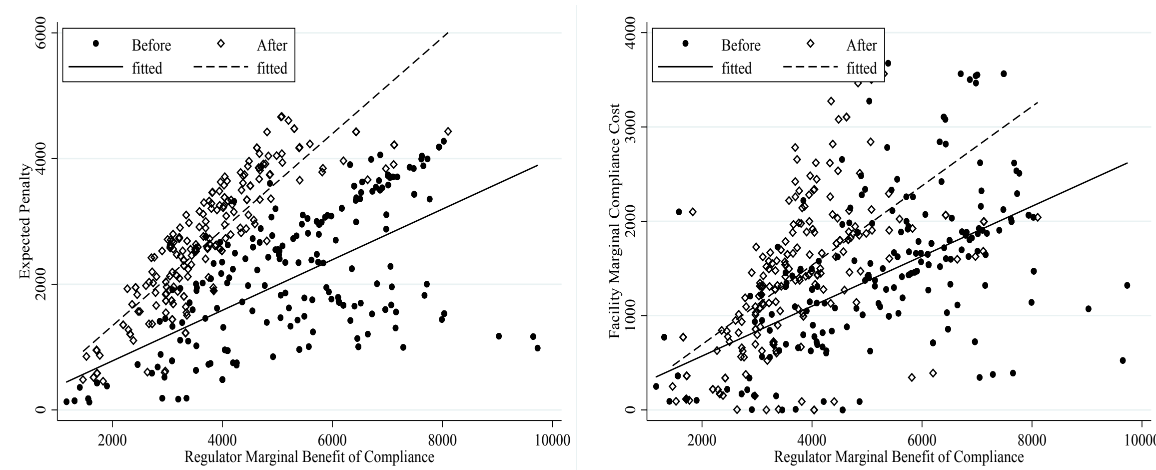
Figure A2. Dispersion of Penalty Schedules



(A) Before the 2006 Changes (B) After the 2006 Changes

Notes: Panel (A) shows the point-wise differences between the 5th and 95th percentiles of penalty schedules across the 221 facilities active in the first quarter of 2005 under the baseline scenario and the median regulator scenario (top lines), the 10th and 90th percentiles (middle lines), and the 25th and 75th percentiles (bottom lines), before the 2006 institutional changes. Panel (B) is for the periods after the 2006 changes.

Figure A3. Disparities in Penalties and Regulator Preferences: Revisited



(A) Vs. Expected Penalty (B) Vs. Facility Marginal Compliance Costs

Notes: Panel (A) shows the scatter plot of the estimated marginal benefit of compliance as perceived by the regulator for each facility at the average negligence level before the 2006 institutional changes ($\overline{a} = 1.08$) and the expected penalty at the same negligence level. Panel (B) shows the scatter plot of the estimated marginal benefit of compliance (the same as in Panel (A)) and the estimated marginal cost of compliance for each facility.

cost by $c(k, m, \iota)$. The total regulator's expected costs are

$$\int_{o}^{\overline{\theta}} \{-\theta b[a(\theta)] + \mathbb{E}\left[c(k, m, \iota)|a(\theta)\right] + \psi e\left[a(\theta)\right]\} f(\theta) d\theta.$$

By defining $h(a) \equiv \mathbb{E}[c(k, m, \iota)|a]$, we are able to write the regulator's objective function as (4). Under assumptions 1 and 2, the optimality conditions derived in the main text still hold in the extended model.

F.1.2. *Identification.* In addition to the observables described in the main text, we assume that the data report the severity of each occurred violation. In our estimation, we use an indicator of whether the violation is classified by the water boards as a *priority*, as explained in the notes in Table 2, to measure severity.

Like in the main text, we consider a vector $\mathbf{x}$ of observed facility attributes, and thus all primitives and the equilibrium objects of the model are allowed to vary with $\mathbf{x}$. The regulator may implement the expected enforcement function $e(\cdot; \mathbf{x})$ using a variety of schedules $\epsilon(\cdot, \cdot, \cdot; \mathbf{x})$. In the following lemma, we consider a particular schedule:

Lemma A2. *Let $e(a; \mathbf{x})$ be a continuous function with domain $a \in [0, \overline{a}]$, where $\overline{a} < \infty$, and fix any vector $\mathbf{x}$. Then, for any $\delta > 0$, there exists $\epsilon_1(\cdot, \cdot; \mathbf{x}) : \mathbb{N} \times \mathbb{N} \to \mathbb{R}$ and $\epsilon_2(\cdot) : \mathbb{R} \to \mathbb{R}$ such that*

$$\sup_{a \in [0, \overline{a}]} |e(a; \mathbf{x}) - \mathbb{E}[\epsilon_1(k, m; \mathbf{x}) + \epsilon_2(\iota)|a, \mathbf{x}]| < \delta,$$

and $\mathbb{E}[\epsilon_2(\iota)|k, m, \mathbf{x}] = 0$ for any (k, m).

Proof. Following the same argument as in Lemma A1, we can show that, for every continuous $e(\cdot; \mathbf{x})$, there is a function $\epsilon_1(\cdot, \cdot; \mathbf{x})$ such that $e(a) \approx \mathbb{E}[\epsilon_1(k, m; \mathbf{x})|a, \mathbf{x}]$ for any $a \in [0, \overline{a}]$. Given that, an alternative schedule, $\epsilon(k, m, \iota, \mathbf{x}) \equiv \epsilon_1(k, m, \mathbf{x}) + \epsilon_2(\iota)$ such that $\mathbb{E}[\epsilon_2(\iota)|a, \mathbf{x}] = 0$ implements $e(\cdot; \mathbf{x})$ as well. Under the assumption that $\iota \perp a$ (Assumption A1), $\mathbb{E}[\epsilon_2(\iota)|a, \mathbf{x}] = \mathbb{E}[\epsilon_2(\iota)|\mathbf{x}]$. Therefore, any $\epsilon_2(\cdot)$ that satisfies $\mathbb{E}[\epsilon_2(\iota)|k, m, \mathbf{x}] = 0$, along with $\epsilon_1(\cdot, \cdot, \mathbf{x})$, also implements $e(\cdot; \mathbf{x})$. □

Given the lemma, we make the following assumption:

Assumption A2. *The regulator, among the schedules that implement $e(a; \mathbf{x})$ for any $a \in [0, \bar{a}]$ and $\mathbf{x}$, employs a schedule of the following form, $\epsilon(k, m, \iota; \mathbf{x}) \equiv \epsilon_1(k, m; \mathbf{x}) + \epsilon_2(\iota)$, with $\mathbb{E}[\epsilon_2(\iota)|k, m, \mathbf{x}] = 0$ for any (k, m).*

Under this assumption, as k, m, $\mathbf{x}$, and the assigned penalties are observable, $\epsilon_1(k, m, \mathbf{x})$ is directly identified from the data—and so is $e(\cdot; \mathbf{x})$. Regarding the distribution of negligence, Lemma 1 still holds under Assumption A1, which allows us to apply the same strategy as in the main text for the identification of $G_{pre}(\cdot; \mathbf{x})$ and $G_{post}(\cdot; \mathbf{x})$.

The additional primitive to be recovered in the extended model is $s(\cdot)$, the probability that each occurred violation is severe, as a function of the negligence level a. We impose the following parametric assumption concerning this function:

ASSUMPTION A3. *The probability $s(a)$ that an occurred violation is severe, conditional on the facility setting a negligence equal to a, is $\Phi(p_0 + p_1 a)$, where $\Phi(\cdot)$ is the standard normal CDF.*

Under assumption A3, the identification of $s(\cdot)$ consists of identifying the parameters p_0 and p_1, which we achieve by exploiting the relationship between the proportion of severe violations and the negligence distribution in the pre- and post-2006 periods. Recall that the penalty schedules $\epsilon_{1,j}(k, m, \mathbf{x})$ for $j \in \{pre, post\}$ are directly identified from the data. Having identified p_0, p_1, we identify $e_j(\cdot; \mathbf{x})$, the expected penalty as a function of negligence, as

$$e_j(a; \mathbf{x}) \equiv \sum_{k=0}^{\infty} \sum_{m=0}^{k} \frac{\exp(-a)\Phi\left[p_0 + p_1 a\right]^m \left\{1 - \Phi\left[p_0 + p_1 a\right]\right\}^{k-m}}{\zeta!(k - \zeta!)} \epsilon_{1,j}(k, m, \mathbf{x}),$$

for $j \in \{pre, post\}$. The rest of the identification argument follows the steps from the main text. Under assumptions 1-3, Proposition 2 holds. Under assumptions 1-5, Proposition 3 is valid.

F.1.3. *Estimation.* We adopt the same parametric assumptions on the distribution of negligence as in the basic model: The number of violations by a facility with covariates $\mathbf{x}$ in period $j \in \{pre, post\}$ follows a negative binomial distribution with mean $\exp(\beta_{0,j} + \beta_1 \mathbf{x})$ and variance $\exp(\beta_{0,j} + \beta_1 \mathbf{x})\left[1 + \Delta(\mathbf{z})^{-1} \exp(\beta_{0,j} + \beta_1 \mathbf{x})\right]$, where the term $\Delta(\mathbf{z}) = \exp(\mathbf{z}\delta)$ and $\mathbf{z}$ is a subset of $\mathbf{x}$. Define $\beta_j \equiv (\beta_{0,j}, \beta_1)$, for $j \in \{pre, post\}$, and let $g(\cdot|\mathbf{x}; \delta, \beta_j)$ be the density function of negligence levels implied by the parameters δ, β_{pre} and β_{post}, conditional on $\mathbf{x}$.

We estimate the severity parameters p_0 and p_1 by maximum likelihood. Specifically, under assumptions A1 and A3, we can write the joint distribution of (k, m), conditional on the negligence level a, as

$$\Pr(k, m|a; p_0, p_1) = \frac{a^k \exp(-a)}{k!} \binom{k}{m} \Phi\left(p_0 + p_1 a\right)^m \left[1 - \Phi\left(p_0 + p_1 a\right)\right]^{k-m}.$$

We can then write the joint distribution of (k, m) for a facility, conditional on $\mathbf{x}$, as

$$\Pr(k, m; p_0, p_1, \delta, \beta_j, \mathbf{x}) = \int \Pr(k, m|a; p_0, p_1) g(a|\mathbf{x}; \delta, \beta_j) da,$$

for $j \in \{pre, post\}$. Denote by $\hat{\delta}$, $\hat{\beta}_{pre}$ and $\hat{\beta}_{post}$, respectively, the estimates of δ, β_{pre} and β_{post} presented in the main text. Under the assumptions above, these estimates are consistent. A maximum likelihood estimator of p_0 and p_1 is then

$$(\hat{p}_0, \hat{p}_1) = \arg\max_{p_0, p_1} \sum_t \sum_i \log \left[\int \Pr(k_{i,t}, m_{i,t}|a; p_0, p_1) g(a|\mathbf{x}_{i,t}; \hat{\delta}, \hat{\beta}_j) da \right],$$

where $m_{i,t}$ is the number of severe violations by facility i in period t. To estimate the enforcement functions, we extend specification (12) as follows:

$$\begin{aligned}
\eta^*_{1i,t} &= \mathbf{x}_{i,t}\phi_{1,x} + 1\{t > 2006\}\phi_{1,post} + \phi_{1,k} k_{i,t} + \phi_{1,m} m_{i,t} + u_{1i,t}, \\
\log \eta^*_{2i,t} &= \log \left[\exp\left(\mathbf{x}_{i,t}\phi_{2,x}\right) k_{i,t} + \phi_{2,k^2} k^2_{i,t} + \phi_{2,m} m_{i,t}\right] + u_{2i,t}, \\
\text{and } \epsilon_{i,t} &= \begin{cases} \eta^*_{2i,t} & \text{if } \eta^*_{1i,t} \geq 0, \\ 0 & \text{otherwise,} \end{cases}
\end{aligned} \tag{A.9}$$

where $(u_{1,i,t}, u_{2,i,t})$'s are i.i.d. draws from a bivariate normal distribution with mean zero, independent of $(k_{i,t}, m_{i,t}, \mathbf{x}_{i,t})$. By Assumption A2, we have that $\epsilon_{1,pre}(k, m, \mathbf{x}) = \mathbb{E}[\epsilon_{i,t}|k, m, \mathbf{x}, t < 2006]$ and $\epsilon_{1,post}(k, m, \mathbf{x}) = \mathbb{E}[\epsilon_{i,t}|k, m, \mathbf{x}, t > 2006]$. Therefore, the difference between the observed penalty amount and the predicted penalty amount—i.e.,$(\epsilon_{i,t} - \epsilon_{1,j}(k, m, \mathbf{x}))$, where $j = pre$ for $t < 2006$ and $j = post$ for $t > 2006$—is $\epsilon_2(\iota_{i,t})$, or the part of the enforcement schedule associated with the violation aspects that are not observed in the data. With the parameters in (A.9), denoted by ϕ, we compute $\epsilon_{1,j}(k, m, \mathbf{x}; \phi)$ for $j \in \{pre, post\}$. We obtain estimates $\hat{\phi}$ by maximum likelihood. We then estimate the expected penalty for a facility with covariates $\mathbf{x}$, as a function of the negligence level a, by

$$\hat{e}_j(a|\mathbf{x}) \equiv \exp(-a) \sum_{k=0}^{\infty} \sum_{m=0}^{k} \frac{\Phi\left(\hat{p}_0 + \hat{p}_1 a\right)^m \left[1 - \Phi\left(\hat{p}_0 + \hat{p}_1 a\right)\right]^{k-m}}{\zeta!(k - \zeta!)} \epsilon_{1,j}(k, m, \mathbf{x}; \hat{\phi}).$$

Having estimates for the enforcement function and the distribution of negligence, we can proceed with the estimation of the model primitives, exactly as explained in the main text.

F.2. **Other Sensitivity Analyses.** We consider four other alternative specifications of our model. In *alternative specification 2*, we estimate the penalty schedule by considering all penalties within three years of the occurrence of each violation, as opposed to the four years used in the original results. This change allows us to use a longer period of data for the penalty schedule estimation in the first step. Specifically, we employ the penalties for the violations of 2000–2002 (2009-2011) to estimate the penalty schedule before (after) the 2006 institutional changes, instead of 2000–2001 (2009–2010), as in the original results.

In *alternative specification 3*, we change the unit of observation from a facility-quarter to a facility-semester. For a given period, a facility draws its cost type and determines the level of negligence; and a regulator sets a penalty schedule over the violations during the period. A quarter reflects the distinct precipitation patterns across four seasons in California. A semester, however, may also be a suitable period to consider, because, among all 1,605 penalty actions imposed on domestic wastewater treatment facilities in 2000-2014, the median period of violations comprised by an unique penalty action (either an ACL or a settlement in court) is 7 months.

The results presented in the main text are based on estimates of the penalty schedule in which we truncate facility-quarter years with more than 25 violation. *Alternative specification 4* and *alternative specification 5* address the estimation of the model with truncations at 20 and 30 violations, respectively.

Finally, *alternative specification 6* considers a more flexible estimator of the negligence distribution. This specification incorporates into $\mathbf{z}$, the vector of covariates that determines the overdispersion coefficient $\Delta(\mathbf{z})$, all the elements of $\mathbf{x}$ used in the estimation of other parts of the model.

The results from alternative specification 1-6 are in Tables A9-A12. All the main results are similar to our original estimates. Specifically, the marginal compliance cost estimates and regulator preferences are very similar to those presented in the main text. Perhaps most importantly, the main results of our counterfactual analysis in Section 6.5 are robust to these six alternative specifications.

Table A9. Sensitivity Analyses: Model Primitive Estimates

	Sensitivity: Primitives				
	Marginal Compliance Cost	Environmental Cost per Violation (γ)		Enforcement Cost per Penalty (ψ)	
		Before	After	Before	After
Original specification					
Median	1431.0	3589.4	3157.1	0.865	0.204
Interquartile range	1090.3	1633.0	916.5	0.483	0.220
Alternative specification 1: Endogenous severity					
Median	1401.4	3517.1	3054.9	0.712	0.184
Interquartile range	1086.1	1525.5	959.6	0.545	0.215
Alternative specification 2: Penalty within 3 years					
Median	1324.5	3315.1	3042.2	0.922	0.237
Interquartile range	1160.5	1192.8	861.9	0.557	0.256
Alternative specification 3: Semester-long period					
Median	1252.8	3717.1	3215.7	0.636	0.130
Interquartile range	1261.2	1277.9	972.5	0.652	0.130
Alternative specification 4: Violations truncated at 20					
Median	1438.7	3856.5	3308.3	0.999	0.235
Interquartile range	1015.9	1927.6	850.9	0.367	0.229
Alternative specification 5: Violations truncated at 30					
Median	1454.5	3455.6	3114.6	0.696	0.174
Interquartile range	1094.3	1639.4	957.6	0.585	0.219
Alternative specification 6: Flexible overdispersion					
Median	1024.9	3608.5	3194.2	0.702	0.185
Interquartile range	1379.1	1480.4	954.3	0.551	0.214

Table A10. Sensitivity Analyses: Counterfactuals - Violation Frequency

	Median Regulator (1)	Uniform Penalty (2)	Linear Penalty (3)	Green Regulator (4)
Original specification				
Proportional change in Mean	0.055	-0.062	-0.064	-0.511
Proportional change in SD	0.274	-0.191	-0.048	-0.408
Alternative specification 1: Endogenous severity				
Proportional change in Mean	-0.015	-0.071	-0.053	-0.553
Proportional change in SD	0.192	-0.179	-0.037	-0.440
Alternative specification 2: Penalty within 3 years				
Proportional change in Mean	0.047	-0.062	-0.053	-0.491
Proportional change in SD	0.161	-0.240	-0.065	-0.463
Alternative specification 3: Six months-long period				
Proportional change in Mean	-0.010	-0.022	-0.035	-0.558
Proportional change in SD	0.088	-0.133	-0.040	-0.528
Alternative specification 4: Violations truncated at 20				
Proportional change in Mean	0.077	-0.062	-0.071	-0.510
Proportional change in SD	0.275	-0.203	-0.067	-0.426
Alternative specification 5: Violations truncated at 30				
Proportional change in Mean	-0.002	-0.075	-0.051	-0.508
Proportional change in SD	0.200	-0.194	-0.040	-0.398
Alternative specification 6: Flexible overdispersion				
Proportional change in Mean	0.051	-0.168	-0.043	-0.483
Proportional change in SD	0.173	-0.267	-0.013	-0.406

Table A11. Sensitivity Analyses: Counterfactuals - Penalty Stringency

	Median Regulator (1)	Uniform Penalty (2)	Linear Penalty (3)	Green Regulator (4)
Original specification				
Proportional change in Mean	-0.063	-0.072	0.527	3.081
Proportional change in SD	-0.110	-1.000	-0.070	-0.807
Alternative specification 1: Endogenous severity				
Proportional change in Mean	0.024	-0.048	0.450	2.460
Proportional change in SD	-0.170	-1.000	0.245	-0.917
Alternative specification 2: Penalty within 3 years				
Proportional change in Mean	-0.134	-0.037	0.507	2.624
Proportional change in SD	-0.228	-1.000	-0.059	-0.774
Alternative specification 3: Six months-long period				
Proportional change in Mean	-0.003	0.046	0.543	4.489
Proportional change in SD	-0.183	-1.000	-0.031	-0.604
Alternative specification 4: Violations truncated at 20				
Proportional change in Mean	-0.063	-0.051	0.569	3.203
Proportional change in SD	-0.021	-1.000	0.230	-0.747
Alternative specification 5: Violations truncated at 30				
Proportional change in Mean	-0.016	-0.070	0.393	2.964
Proportional change in SD	-0.179	-1.000	0.149	-0.846
Alternative specification 6: Flexible overdispersion				
Proportional change in Mean	-0.024	-0.039	0.433	2.880
Proportional change in SD	-0.133	-1.000	0.166	-0.774

Table A12. Sensitivity Analyses: Counterfactuals - Equilibrium Penalties

	Median Regulator (1)	Uniform Penalty (2)	Linear Penalty (3)	Green Regulator (4)
Original specification				
Total	-0.119	0.013	0.158	0.766
Alternative specification 1: Endogenous severity				
Total	-0.081	0.002	0.148	0.280
Alternative specification 2: Penalty within 3 years				
Total	-0.056	0.006	0.196	0.613
Alternative specification 3: Six months-long period				
Total	-0.022	0.023	0.194	0.930
Alternative specification 4: Violations truncated at 20				
Total	-0.114	0.000	0.188	0.709
Alternative specification 5: Violations truncated at 30				
Total	-0.091	0.020	0.158	0.801
Alternative specification 6: Flexible overdispersion				
Total	-0.019	0.039	0.156	0.838