REGULATORY DISCRETION AND COMPLIANCE

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Abstract. This paper provides an empirical framework to evaluate regulatory discretion and apply it to California water quality regulation. We identify and estimate an adverse selection model of the regulator-discharger interaction to measure the extent to which the regulator's environmental preferences and administrative or political costs affect penalties and compliance. We find that if the regulator preferences were homogeneous across dischargers, both violation frequencies and penalties would decrease. However, our estimates show that regulators reflect environmental preferences of local constituents. Moreover, the estimated compliance cost heterogeneity across dischargers is large enough that the regulator expertise to allocate penalties is valuable.

1. Introduction

The enforcement of government regulation is in practice as important as its content. When enforcement is run on a case-by-case basis, the discretion of bureaucrats becomes a significant factor determining regulatory success. Heterogeneous standards for enforcement could, for example, partially explain why environmental outcomes differ substantially across regions in the United States, despite common regulatory frameworks such as the Clean Air Act and the Clean Water Act.

There are two main drivers of disparities in enforcement stringency across violators. First, the regulator's preferences on violations and enforcement costs may vary with the identity of the violator for political considerations that differ from the social objectives (Stigler, 1971; Peltzman, 1976). The incentives to relax law enforcement for votes or rents have been empirically documented in the context of deforestation in Indonesia (Burgess, Olken and Sieber, 2012), coal mining safety regulations in the U.S. (Gordon and Hafer, 2014) and China (Jia and Nie, 2017), and street vending

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and squatting in Latin American cities (Holland, 2016). The regulators may also respond to local preferences or economic conditions (Deily and Gray, 1991; Agarwal, Lucca, Seru and Trebbi, 2014), their own personal reputation (Leaver, 2009), budgetary concerns (Helland, 1998), and special interest groups (Cropper, Evans, Berardi, Ducla-Soares and Portney, 1992).

Second, the regulators may take into account the heterogeneity in the compliance costs paid by potential violators. In a seminal paper, Becker (1968) shows that the optimal amount of enforcement depends on the cost of catching and convicting violators and their responses to changes in enforcement. Recent empirical studies provide evidence of the regulator discretion to reduce enforcement costs and increase compliance by targeting motor vehicle searches in the U.S. (Knowles, Persico and Todd, 2001) and inspections of industrial plants in India (Duflo, Greenstone, Pande and Ryan, 2016).

In this paper, we empirically investigate these two drivers of bureaucratic discretion in California water quality regulations. In California, nine semi-autonomous regional water boards are in charge of enforcing the regulations. The regions vary considerably in socio-economic status, which, in principle, may affect both the dischargers' compliance costs and the regulators' objectives in enforcement. In our analysis, we focus on the domestic wastewater treatment facilities, most of which are publicly owned and operated. They are responsible for the vast majority (73%) of effluent violations statewide during the period of study. By studying public entities, we rule out the regulatory incentives to compete in a "race to the bottom" (Wilson, 1986) for local industry.

We exploit a set of institutional changes in the mid-2000s, which reduced the enforcement cost of the regional water boards. We document that the rate and the average amount of penalty increased after these changes, and that the dischargers also reduced violations. This institutional feature provides a unique opportunity to estimate the elasticity of violations to penalty, because we find little evidence that the institutional changes were associated with a change in compliance costs. Without such variation, it is difficult to demonstrate the effects of enforcement on compliance due to simultaneity bias (Gray and Shimshack, 2011).

Using the institutional changes as an instrument, we find that the penalty elasticity varies considerably across discharger locations, suggesting that there exists heterogeneity in the dischargers' compliance cost. To further investigate the extent to which the heterogeneity in compliance costs, as opposed to regulator preferences and costs, explains the regulator behaviors and compliance, we build, identify, and estimate a principal-agent model of regulation. The structural approach allows us to estimate regulator preferences and costs, none of which are observed, and to conduct two counterfactual exercises: first, the regulator preferences and costs are identical across dischargers; and second, the regulators are forced to set a uniform penalty schedule.

Our model of regulation enforcement is a variant of Maskin and Riley (1984) and Mookherjee and Png (1994), where a regulator sets a penalty schedule and given that schedule, dischargers choose the extent to which they comply to regulations. The regulator does not observe the dischargers' compliance costs nor their actions, and thus the penalty schedule depends on the violations only. In determining the penalty schedule, the regulator minimizes a weighted sum of the discharger compliance cost, the costs associated with expected violations, and the enforcement cost in assessing and imposing penalties.

We then provide conditions under which the model is non-parametrically identified. Specifically, two recent papers, d´Haultfoeuille and Février (2016) and Luo, Perrigne and Vuong (forthcoming), address the identification and estimation of screening models. The former study focuses on the informed party, and employs exogenous variation in the observed contracts to identify that party's distribution of types (which, in our application, would consist of the distribution of dischargers' compliance costs). 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. We show that, by combining both approaches, we are able to identify a more general model than the ones originally considered by these two papers. Closely following the identification strategy, we estimate the model semi-parametrically. In this regard, we contribute to the literature of the structural estimation of regulation models (Wolak, 1994; Gagnepain and Ivaldi, 2002; Timmins, 2002; Lim and Yurukoglu, forthcoming; Abito, 2017).

Our estimates indicate that the regulator's environmental preferences and enforcement costs vary considerably across dischargers. For example, the environmental costs per emission violation, as perceived by the regulator, for a large wastewater treatment facility in the coastal regions are on average twice as much as those for its counterpart in the inland regions. We find that these perceived environmental costs are positively correlated with local constituency preferences for water quality, as measured by the vote shares for statewide ballot propositions authorizing the issuing of bonds to fund water projects. Additionally, the correlation between our estimated enforcement costs and the measure of constituency water quality preferences is negative. Our results thus suggest that regulators reflect local preferences for water quality—a finding that complements those of List and Sturm (2006) based on state environmental expenditures.

We also find that the regulators tend to discount the harm from violations from a high-cost wastewater treatment facility and they find it more expensive to penalize a high-cost one than a low-cost one. These patterns may arise because a high-cost facility is more likely to be located in inland regions, where the local preference for water quality is not as strong as that in coastal regions on average. These patterns partially explain the results of one of our counterfactual exercises where the regulator preferences and costs are homogeneous across dischargers. Under this scenario, we find that both violation frequencies and penalties would decrease and the heterogeneity in compliance across dischargers would also decrease. This is because the new penalty scheme is more stringent for a high-cost facility and less stringent for a low-cost one than the current scheme.

However, mandating a uniform penalty schedule would increase violation frequencies and the heterogeneity in compliance across dischargers. One explanation of this result is that the estimated compliance cost heterogeneity across dischargers is large, which is consistent with our aforementioned reduced-form evidence, and the uniform enforcement policy does not take advantage of the regulator expertise to allocate penalties. The result also indicates that differences in compliance costs, as opposed to regulators' objectives, are the main drivers of the observed heterogeneity in compliance across dischargers. Considering also that regulator preferences and costs are in part aligned with local constituency preference for water quality, our results provide supports for allowing regulators to exercise discretion can be beneficial.

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 mid-2000s. 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. **Federal Water Pollution Regulation.** The Clean Water Act of 1972 created the National Pollutant Discharge Elimination System (NPDES) permit program. The

program regulates facilities that discharge pollutants from any point source, such as a pipe or a ditch, into surface waters in the US, including lakes, rivers and the ocean. Although the program is federal, many of its permitting, administrative, and enforcement aspects are implemented by state governments.[1] 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. It sets limits on the concentration of the pollutants based on both the availability of pollution control technologies and the water quality standards of the receiving water body.

A permit also requires that dischargers periodically submit self-monitoring reports. Enforcement actions are mostly based on these reports as well as findings from inspections conducted by the regulatory agencies in charge of the program. The reports are in general considered reliable by the regulatory community because intentional misreporting can be punished by criminal sanctions to the responsible employees.[2]

2.2. **California Water Pollution Regulation.** The California Water Boards, consisting of the State Water Resources Control Board and nine Regional Water Quality Control Boards (the *state water board* and the *regional water boards* hereafter) are in charge of enforcing the federal Clean Water Act and the state's Poter-Colone Water Quality Control Act of 1969, and the regional water boards have primary jurisdiction.[3] Although the state board has oversight authority over the regional boards, its intervention is limited.[4]

The nine semi-autonomous regional water boards develop basin plans, issue permits, monitor water quality and take enforcement actions against violating facilities. They were created in 1949 by the Dickey Water Pollution Act, recognizing that water

[1]Authorization for states to implement the program follows a process defined by Clean Water Act Section 402 (b) and 40 CFR Part 123. Currently 46 states, including California, and one territory are authorized to implement the NPDES program.

[2]According to 40 CFR 122.22(d), any person signing reports required by the permits must make the following certification that the person is aware that there are significant penalties for submitting false information, including the possibility of fine and imprisonment for knowing violations. Self-reported data have been used in the existing literature to assess compliance to environmental regulation in the literature (Magat and Viscusi, 1990; Earnhart, 2004; Shimshack and Ward, 2005).

[3]The state water board consists of five full-time salaried members and each of the regional boards has seven part-time members. These board members are appointed to a four-year term by the governor and confirmed by the state senate.

[4]The state water quality enforcement policy specifies the circumstances under which the state water board may take enforcement action in lieu of the regional water boards. Examples of such circumstances are as follows: (i) in response to petitions alleging inaction or ineffective enforcement action by a regional board; (ii) to enforce statewide or multi-regional general permits; and (iii) to address violations by the same discharger in more than one region.

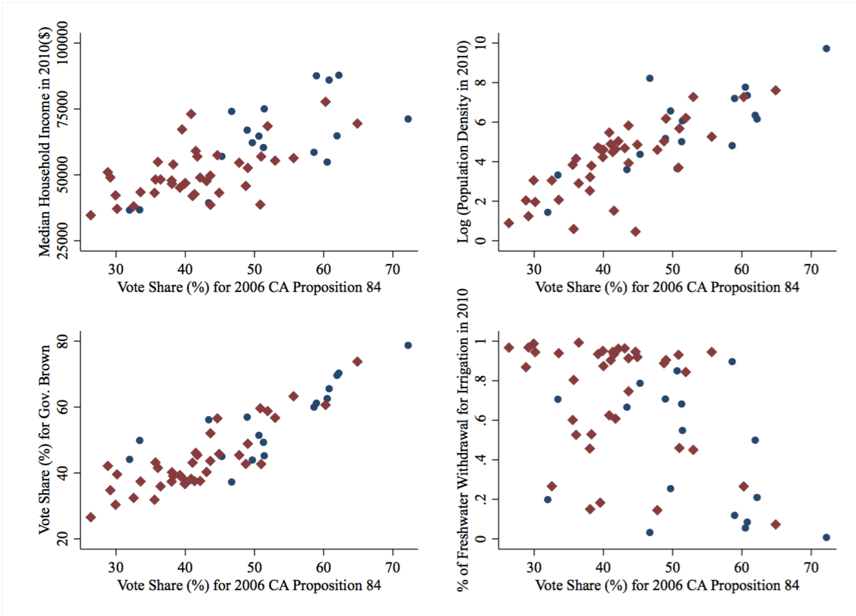
Figure 1. California Regional Water Quality Control Boards

Source: California State Water Resources Control Board

pollution problems are regional in the sense that they are affected by rain and snowfall, the configuration of the land, and population density, as well as recreational, agricultural, urban and industrial development. The regional boards' boundaries follow natural mountain chains and ridges that define watersheds rather than political boundaries. Figure 1 shows the map with the division of the state into regional board areas.

The areas managed by each regional board are heterogeneous in the residents' preferences for water quality. One measure of these preferences is the vote share for California ballot propositions to authorize billions of dollars in general obligation bonds to fund a variety of water projects. During the period covered by our study, there were three such propositions: the 2002 proposition 50, the 2006 proposition 84, and the 2014 proposition 1. The average county-level vote share greatly varies; for the 2006 proposition, for example, it varies from 26% to 72%. The voting patterns for these propositions are associated with local demographic and political characteristics, such as income, population density, political affiliation, and water use. Figure 2 presents four scatter plots that show that the residents in a county with a high vote share for the 2006 proposition tended to have high income, live in densely populated areas, vote for the Democratic party in the 2010 gubernatorial election, and use water for purposes other than irrigation.

Figure 2. Vote Shares for Water Quality Proposition in 2006



Notes: Each red diamond corresponds to a county which is regulated at least partially by the inland regional water boards, i.e., Central Valley, Lahontan, and Colorado River Basin; and each blue circle corresponds to the remaining counties. Each of the four scatter plots shows the relationship between the vote share for the 2006 California Proposition 84, which authorizes $5.4 billion in bonds to fund various water projects, and the median household income, the logarithm of the population density per squared miles, the vote share for Governor Brown from the Democratic party during the 2010 general gubernatorial election, and the ratio of freshwater withdrawal for irrigation in 2010, respectively.

2.3. **Wastewater Treatment Facilities.** We focus on the facilities that treat domestic wastewater and discharge the treated water, and based on our data, there are in total 288 such facilities that had an active NPDES permit during 2000–2014.[5] They are responsible for the vast majority (73%) of effluent 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. It is notable that most (95%) of them are publicly owned and operated by cities, counties, or special districts.

[5]There are 12 treatment facilities that treat non-domestic wastewater, all of which are excluded from the analyses to maintain homogeneity of our sample.

The wastewater treatment facilities reduce oxygen-demanding substances, such as organic matter and ammonia, disinfect and chlorinate wastewater to decrease 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, an advanced or tertiary stage is used for disinfection and the treatment of nitrogen and phosphorus, as well as other pollutants. Even after all three stages, pollutants may remain in the water. The Clean Water Act requires that municipal wastewater treatment plant discharges meet a minimum of secondary treatment.

2.4. **Institutional Changes on Water Regulation Enforcement.** In 1999, the California legislature enacted the Clean Water Enforcement and Pollution Prevention Act, requiring serious or multiple non-serious permit violations under the California Water Code to be 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 pollutant by 40 percent or more or a Group II pollutant by 20 percent or more.[6] As for non-serious violations, the minimum penalty applies when such violations occur four or more times in any period of six consecutive months.

This act triggered various state-level regulatory policy changes aimed at increasing the overall stringency of water pollution regulation and ensuring greater consistency in enforcement actions taken across the regional water boards. Two of the major changes were the launching of the California Integrated Water Quality System (CIWQS) in July 2005 and the establishment of the Office of Enforcement under the state water board in July 2006.

The new data system introduced electronic self-monitoring whereby dischargers submit data electronically and the data is automatically screened and reviewed. Previously, data had been manually entered to the system and reviewed by the boards' staff. This electronic system dramatically increased efficiency and enabled more resources to be devoted to compliance.[7]

The Office of Enforcement, comprised of legal and investigative staff, was established to provide statewide enforcement and support to the regional water boards regarding their enforcement programs. The staff of the office regularly meet with

[6]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.

[7]Data from prior to July 2005 was imputed retroactively into the CIWQS.

representatives from the regional water boards to discuss enforcement matters and get feedback on enforcement approaches.[8] Besides providing support to the regional water boards, it also has the authority to perform independent enforcement actions.

3. Descriptive Statistics

We draw data from the California Integrated Water Quality System (CIWQS) database for the NPDES violations and enforcement actions during 2000–2014. We also obtain county-level attributes from various sources: the California Secretary of State website for the vote shares for each ballot proposition, the American Community Survey for average household income, the Census for population and water use, Congressional Quarterly Press for gubernatorial election results, and the California Irrigation Management Information System for precipitation. The precipitation data is provided at the 253 weather station level, which we aggregate at the county level based on the stations' locations.

Table 1 provides the summary statistics of the variables for the wastewater treatment facilities in our sample by their location: those regulated by the inland regional water boards, i.e., Central Valley, Lahonton, and Colorado River Basin; and those by the rest, or the coastal water boards. On average, a domestic wastewater facility in the coastal area had 1.03 effluent MMP violations per three months, while a counterpart in the inland area had 1.59 violations. The violations during a three-month period accrued an average penalty of \$2,690 within five years to a coastal facility and \$4,473 to an inland one.[9] Note that 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.[10] The faction of the *major* facilities, which either discharge more than 1 million gallons per day on average or pose a high degree of threat to water quality is larger in the coastal regions than in the inland regions, but the age distribution is comparable between the two regions.

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[8] California Senate Bill 729, which was enacted in September 2006, requires that each regional board coordinate with the state board and other state agencies and report rates of compliance to the state legislature.

[9] Penalties may occur even after five 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 five-year window. The bulk of penalty actions occurs within this window and our results are robust to the length of the window.

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

Table 1. Summary Statistics

	Coastal		Inland	
	Mean	SD	Mean	SD
Quarterly compliance and enforcement per facility				
Number of MMP violations	1.03	6.61	1.59	8.30
Amount of penalty (in 2010 USD)[a]	2,690	23,382	4,473	27,675
Facility characteristics				
Major[b]	0.79	0.41	0.55	0.50
First NPDES permit during 1982-1987[c]	0.63	0.48	0.66	0.47
First NPDES permit after 1987	0.12	0.32	0.11	0.32
County characteristics				
% of votes for the 2006 CA proposition 84	57.20	10.46	44.95	9.75
% of votes for Governor Brown in 2010	46.67	6.72	43.43	10.29
% turnout in the 2010 gubernatorial election	54.36	7.38	43.42	7.42
Population density in 2010 (in squared miles)	1,188	2,405	213	332
Average household income in 2010 (in USD)	63,859	13,314	50,709	11,352
% of fresh water withdrawal for irrigation	39.55	29.10	73.94	24.06
Total precipitation during a quarter (in inches)	5.48	6.61	5.62	6.76

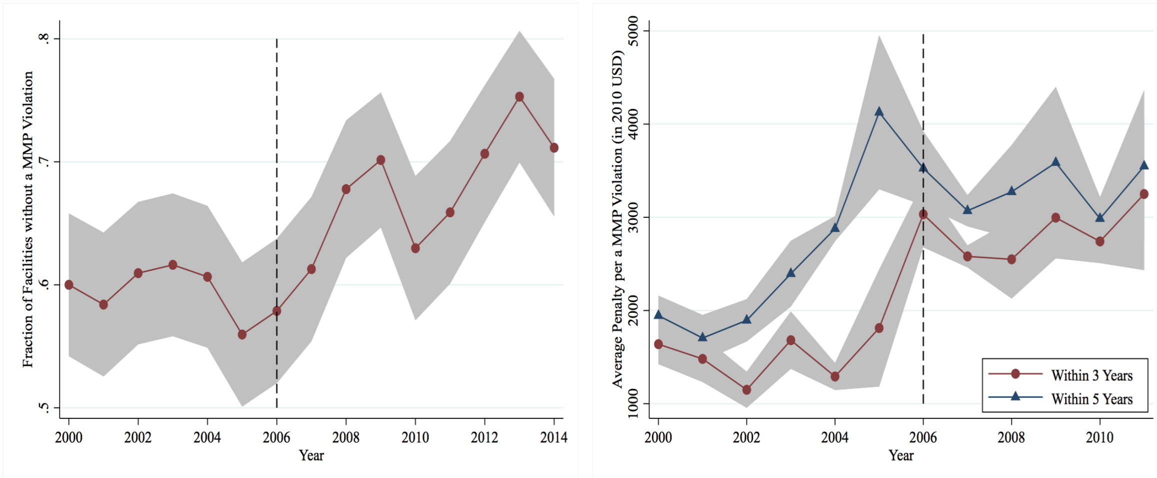
Notes: This table is based on the CWIQS database regarding all domestic wastewater treatment facilities that have an active NPDES permit under the Clean Water Act during 2000–2014. The unit of observation is facility-quarter, and there are 9,263 observations for the coastal area and 6,350 for the inland area. a. This variable indicates the total amount of penalty associated with all MMP effluent violations that occurred during three months. b. The Clean Water Act defines a *major* facility as one with an average daily discharge of greater than 1 million gallons per day or a high degree of threat to water quality. c. The NPDES permits are typically renewed every five years. By looking at the first permit record, we measure the age of the facility.

3.1. **Compliance and Enforcement Over Time.** The institutional changes in mid-2000's are associated with an increase in both compliance and enforcement stringency. Panel (A) in Figure 3 provides the fraction of the facilities without a effluent MMP violation during a given year. We focus on effluent violations, and hereafter a violation refers to an effluent violation unless indicated otherwise.[11] The graph in Panel (A) in Figure 3 shows that the annual fraction of the compliant facilities before 2006 is relatively stable, while after 2006, it increased over time.

In Panel (B) of Figure 3, we present the average penalty per effluent MMP violation within three and five years of the occurrence of the violation, respectively. A large fraction of penalty actions occurs in five years: for example, based on 1,457 effluent

[11]Note that non-effluent violations are mostly associated with the timing of self-reports. The regulations on the report schedule violations fluctuated over time. During 2004–2010, failure to file a self-report for each 30 days was considered as a serious violation.

FIGURE 3. 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 3 years and 5 years of the occurrence of the violation, respectively. Note that the 2006 institutional changes affected the within-3-year penalty for the violations that occurred in 2004 and after, and the within-5-year penalty for those of 2002 and after. The shaded areas represent the 95 percent confidence intervals.

MMP violations that occurred in 2005, the average lag before the first penalty record is 2.92 years, with the median 3.08 years, the 95 percentile 5.48, and the 99th percentile 7.43. Note that the 2006 institutional changes affected the within-3-year penalty for the violations that occurred in 2004 and after, and the within-5-year penalty for those of 2002 and after. Both graphs of Panel (B) of Figure 3 show that the average penalty started increasing since these two years, respectively.

These changes in both compliance and enforcement do not seem to have been driven by a change in the concurrent cost structure. Most facilities were present well before and after 2006: more than 85% of the facilities in our sample started their operation before 1988; and the permit records show that 15 wastewater treatment facilities (5%) in our data became inactive before 2006, and 8 facilities (3%) were newly registered after 2006. Based on the Census of government finance and employment in 1997–2012, there has been a steady flow of capital investment for sewerage services by local governments, and the total amount is \$1.87 billion (in 2010 dollars) per year on average.[12] The capital investment may lead to a decrease in the marginal cost of reducing effluent emissions. However, given that the investment size did not markedly increase after 2006 and the population that the facilities serve has been increasing, there is not enough evidence that the increase in compliance after 2006 was driven by changes in the cost structure.

3.2. **Heterogeneous Compliance and Enforcement.** Table 2 shows that both compliance and enforcement behaviors vary across facility location and size. First, the domestic wastewater treatment facilities in the coastal area and those designated as major tend to have a smaller number of effluent MMP violations and are more likely to be in compliance than their counterparts. Second, the average and the frequency of penalty are both larger for the inland or major facilities than the costal or minor ones. Third, all of the aforementioned patterns persist before and after the 2006 institutional changes.

In Table 2, we use the sample of 2002–2005 for the period before the 2006 institutional changes and 2011–2014 for the post-change period for the statistics on violations. We do not use the observations from 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 statistics on penalty, the penalty actions within five years of the violations in 2000–2001 are used for the pre-change period, and this is to ensure that the five-year window does not overlap the starting point of the mid-2000's institutional changes. The penalty actions after the institutional changes are measured by looking at those associated with the violations of 2009–2010, acknowledging that the changes may take time to be fully incorporated. The key patterns found in the table are robust to the choice of the periods.

3.3. **Effects of Enforcement Stringency on Compliance.** We employ the 2006 institutional changes to assess the effects of an increase in the stringency of enforcement on the compliance behavior of the facilities. Consider the following equation:

$$Violations_{i,t} = \beta Stringency_{i,t} + \gamma Stringency_{i,t} \times X_i + \delta Z_{i,t} + \rho_i + \epsilon_{i,t},$$

where X_i includes time-invariant facility attributes such as location, $Z_{i,t}$ is the amount of precipitation in the location of facility i at quarter t, ρ_i represents the facility fixed

[12]During the years when all governments were surveyed, the total capital expenditures for sewerage services by local governments in California are \$2.24 billion (1997), \$1.43 billion (2002), \$2.27 billion (2007), and \$1.16 billion (2012) in 2010 dollars.

Table 2. Compliance and Enforcement by Facility Location and Size

	Location			Size		
	Coastal	Inland	Diff.	Major	Minor	Diff.
Before the 2006 changes						
Num. of MMP violations[a]	35.6	40.1	-4.5	34.1	44.4	-10.3
	(1.2)	(1.1)	(1.6)	(1.0)	(1.5)	(1.7)
% of violating facilities[b]	58.7	68.9	-10.3	61.8	66.4	-4.6
	(0.7)	(0.7)	(1.0)	(0.6)	(0.8)	(1.1)
Penalty per violation (in $)[c]	1,582	2,387	-805	1,971	1,150	821
	(78.3)	(47.4)	(134.9)	(74.4)	(45.1)	(145.0)
% of being penalized[d]	46.3	65.4	-19.2	55.3	36.8	18.5
	(0.7)	(1.2)	(1.4)	(0.7)	(1.3)	(1.5)
After the 2006 changes						
Num. of MMP violations	7.5	16.5	-8.9	10.3	14.5	-4.2
	(0.3)	(0.5)	(0.5)	(0.3)	(0.5)	(0.6)
% of violating facilities	41.8	57.0	-15.2	45.4	55.8	-10.3
	(0.8)	(0.9)	(1.2)	(0.7)	(1.1)	(1.3)
Penalty per violation (in $)	3,381	3,450	-69	4,588	2,655	1,933
	(281.2)	(164.9)	(356.4)	(350.6)	(30.0)	(290.8)
% of being penalized	78.5	91.2	-12.7	96.1	83.5	12.6
	(1.3)	(0.4)	(0.01)	(0.4)	(0.7)	(0.9)

Notes: Standard errors are in parentheses. For the statistics on violations, the unit of observations is facility-quarter, and we use the sample of 2002–2005 for the period before the 2006 institutional changes and 2011–2014 for the post-change period. As for penalties, the unit of observations is a record of violation, and the effluent MMP violations of 2000–2001 and 2009–2010 and the follow-up penalty actions are employed. The statistics are (a) the quarterly average number of effluent MMP violations; (b) the fraction of the facilities with at least one effluent MMP violation per three months among the active facilities; (c) the average penalty assessed within five years of an effluent MMP violation, in 2010 dollars; and (d) the probability that an effluent MMP violation incurs nonzero penalty within five years.

effects, and $\epsilon_{i,t}$ represents the remaining factors that affect violations. $Violations_{i,t}$ is the number of effluent MMP violations by facility i during quarter t .

We measure the enforcement stringency faced by facility i during period t as the logarithm of the average penalty per effluent MMP violation at the regional board and the major/minor designation level. Here we assume that the average penalty assessed within five years of the 2000–2001 violations represents the enforcement schedule before the 2006 institutional changes and that of the 2009-2010 violations is the schedule after the changes.

An obvious problem in the OLS estimates of β and γ is a simultaneity bias. A facility that is more likely to violate than others expects to receive more stringent

Table 3. Effects of Enforcement Stringency on Violations

	Number of MMP Violations			
	(1)	(2)	(3)	(4)
	OLS	2SLS	OLS	2SLS
Enforcement stringency	-0.210***	-0.542***	-0.177***	-0.160
	(0.064)	(0.191)	(0.056)	(0.111)
Enforcement stringency × Inland			-1.585***	-2.510***
			(0.375)	(0.707)
Precipitation and facility FE	Yes	Yes	Yes	Yes
N	7,799	7,799	7,799	7,799
R^2	0.212	0.212	0.213	0.212

Notes: Standard errors are clustered at the region and quarter level, and are provided in parentheses. The unit of observation is facility-quarter and the violation records of 2002–2005 and 2011–2014 are employed in the regressions. *Enforcement stringency* is defined as the logarithm of the average penalty per effluent MMP violation at the regional board and the major/minor designation level. See the text for detailed definition. The instruments are a dummy variable that indicates that the 2006 institutional changes have already taken place, and an interaction of that dummy variable with the region type dummy (*Inland*).

sanctions in equilibrium, biasing β upwards. To deal with this problem, we employ a dummy variable indicating the post-change period as an instrument for enforcement stringency. This strategy relies on the assumption that the effect of the 2006 changes on the compliance behavior of the facilities was through the subsequent enforcement changes, as documented in Figure 3, only.

Table 3 shows the regression results. We find that an increase in the average penalty decreases the number of violations. As expected, the estimates of β under the 2SLS specifications are much larger in absolute values than those under the OLS specifications. Our estimate of a negative β implies that both penalties and the efforts to reduce emissions are costly to the wastewater treatment facilities.

Importantly, we do find evidence that the effects of the enforcement stringency on violations vary with the region type (coastal or inland). This suggests that the heterogeneity in the way the facilities respond to changes in the enforcement stringency across regions is substantial; i.e., the heterogeneity in the marginal cost of reducing emissions across regions may be large enough to justify the dispersion in the compliance rates. We further examine the sources of compliance heterogeneity across regions, explicitly building upon a model of regulation enforcement, in Section 6.

Note that our study assumes a static environment in the sense that past MMP violations do not affect the enforcement on the current MMP violations. As Harrington (1988) first discussed, dynamic deterrence can be effective especially when penalties

Table 4. Do the Penalty Schedules Depend on Past Violations?

	Penalty for Quarterly MMP Violations			
	(1)	(2)	(3)	(4)
Number of MMP violations[a]	1,445.3***	1446.5**	1,441.9***	1452.6**
	(501.2)	(598.2)	(502.7)	(611.3)
Num. of violations in the past year[b]		20.49		14.41
		(87.90)		(83.99)
Num. of violations × Repeat[c]			-3.0	-30.19
			(438.8)	(488.3)
Precipitation, facility FE, and quarter FE	Yes	Yes	Yes	Yes
N	2,922	2,922	2,922	2,922
R^2	0.352	0.352	0.352	0.352

Notes: Standard errors are clustered at the region and quarter level, and are provided in parentheses. All facility-quarter observations with at least one effluent MMP violation are included. The definition of each variable in this table is as follows: (a) the total number of effluent MMP violations per three months; (b) the total number of effluent MMP violations in the four quarters before the quarter in question; and (c) the interaction of (a) and an dummy variable that indicates that (b) is nonzero (*Repeat*).

are restricted, and it is widely used in practice for environmental regulations; for example, in the Clean Air Act, penalties are larger for the priority noncompliance facilities (Blundell, 2017). The MMP regulations also incorporate a dynamic feature in that the minimum mandatory penalty applies if the facility violates effluent limitations, regardless of the seriousness of the violations, four or more times in any period of six consecutive months. Table 4 shows, however, that there is not enough evidence to support the claim that the past MMP violations affect the penalty actions regarding the current MMP violations.

4. Theoretical model

4.1. **Setup.** We model regulation enforcement as an adverse selection problem, as analyzed by Maskin and Riley (1984) and Mookherjee and Png (1994). Consider a wastewater treatment facility that chooses the extent to which it complies to regulations given a penalty schedule. 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 which is distributed according to 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 $a \in \mathbb{R}_+$, which is not observed by the regulator, that influences its 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. By setting the negligence level a, the facility derives private benefit $\theta b(a)$, which reflects the operation cost savings associated with lower compliance. Note that 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. We assume that the facility benefits from avoiding both compliance costs and penalty, following our empirical findings in Table 3 that the facilities reduced the frequency of violations in response to an increase in penalty.

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. Given k violations, the facility has to pay a fine according to a random function $\epsilon(k)$.[13] Assuming that the facility is risk-neutral, we can restrict our attention to the expected fine, conditional on a, which we denote by

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

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 $\theta \in \Theta$. Notice that, 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

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

where $\psi > 0$ denotes the marginal cost of imposing penalty, and $h(\cdot)$ represents the regulator's preference on the water quality related to the facility emission violations.

[13]This is to reflect the feature in the data that the facilities with the same number of MMP effluent violations do not necessarily face the same amount of penalty, even after controlling for observed attributes.

The regulator's enforcement costs, given by $\psi e[a(\theta)]$, reflect both the administrative and political costs associated with taking formal actions against a facility. Notice that the term $\theta b[a(\theta)]$ already captures the environmental costs of emission violations, as perceived by the facility administrators. Thus, $h\,[a(\theta)]$ represents the environmental costs that, from the perspective of the regulator, are above and beyond those recognized by the facility.

When choosing a penalty schedule, the regulator faces a constraint that the expected penalty for any a must be nonnegative and not exceed ω:

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

for any a. Note that without the limit on punishments, any desired $a(\cdot)$ could be achieved by sufficiently steep penalties. The optimal penalty schedule minimizes (4), subject to constraints that the schedule satisfies (5) and that it implements the negligence schedule $a(\cdot)$.

4.2. **Characterization of equilibrium.** We make the following assumptions on the facility's private benefit function from negligence, $b(\cdot)$, and the regulator's preference on water quality, $h(\cdot)$.

Assumption 1. *(i) $b(\cdot)$ is strictly increasing and is bounded by $0 < \overline{b} < \infty$. (ii) $h(\cdot)$ is strictly increasing.*

Note that since the regulator cannot impose infinitely large punishments, we assume that $b(\cdot)$ is bounded above. 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 are able to rewrite (8) as

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

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 neglience 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 one regulator and many facilities, which we index by i. Periods are indexed by t. Assume that Θ is i.i.d. across facilities and periods.[14] To reflect the institutional changes discussed in Section 2.4, 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 $\bar{\epsilon}_t(\cdot)$ the expected penalty function in period t. Given $\bar{\epsilon}_t(\cdot)$ and a realization of Θ, each facility i sets its optimal negligence level. As Θ is

[14]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 4).

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 private benefit function from negligence; the regulator's perceived social cost of emissions, $h_t(\cdot)$; and the marginal enforcement cost, ψ_t. We allow all model primitives to vary with observable facility-period characteristics but, for ease of notation, we do not explicitly condition the model primitives on these characteristics in the present section. 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.

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 by d´Haultfoeuille and Février (2016), employs the exogenous change in the penalty schedule associated with the 2006 institutional changes to partially identify the facility type distribution and the marginal baseline private benefit function. Note that this step does not rely on any assumption about the regulator's behavior, other than testable assumptions on the observed penalty schedule $\bar{\epsilon}_t(\cdot)$.

The third step, which builds upon the approach by Luo, Perrigne and Vuong (forthcoming), explores the restrictions imposed by the first-order conditions of the regulator to recover the social cost of emissions and the marginal enforcement cost, as well as to achieve exact identification of the type distribution and the marginal baseline private benefit function. By exploiting the exogenous variations in the penalty schedule, we are able to identify a more general model than would be possible using their approach alone.[15]

In this section, we restrict our attention to the case where it is optimal for all facilities to choose a nonzero rate of violations, or $a_t(\theta) > 0$ for any period t and $\theta \in [0, \overline{\theta}]$.[16] Our identification argument can be extended to a case where a corner

[15]In particular, our approach enables us to consider a more flexible form for the regulator's objective function. For example, Luo, Perrigne and Vuong (forthcoming) assume that $h(\cdot)$ (the monopolist's cost function in their setting) is linear, while we can accommodate a polynomial specification of arbitrary degree.

[16]Even if we do not allow that $a = 0$, we can rationalize the data, where 10 percent of the facilities never violated during the 60 quarters (2000–2014). Note that if the number of violations follows a Poisson distribution, a facility with $a = 0.001$ will never violate during 60 periods with probability $exp(-0.001 \times 60) = 0.94$.

solution for the facility (or complete compliance, $a_t = 0$) is allowed. A sufficient condition to guarantee that $a(\theta) > 0$ for any θ is $b'(0)\psi - h'(0)f(0) > 0$.

We begin by noticing that, 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. The proof of this lemma exploits the moment generating function of the Poisson distribution, which was also used in Aryal, Perrigne and Vuong (2017).

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

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. Note that 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 $G_t(\cdot)$. □

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 (2016). We consider two enforcement regimes before and after the institutional changes of 2005–2006 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:

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* $a > 0$*.*

Because the functions $e_{pre}(\cdot)$ and $e_{post}(\cdot)$ are directly observed from the data, this assumption is testable. 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. Notice that, 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 further 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:

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

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

Notice that $T^H(\cdot)$ 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 $F(\cdot)$:

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* $a \in \mathcal{A}_{pre}$*.*

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 $\tilde{\theta}(a, post) = \frac{e'_{post}(a)}{e'_{pre}(a)}\tilde{\theta}(a, pre)$. □

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 $a_0 \in \mathcal{A}_{post}$, and then define recursively:

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

The transform $T^H(\cdot)$ connects points in the negligence distribution supports in both regimes. Notice that 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 $\theta_0 = 1$: (i) the equilibrium negligence level, $\tilde{a}(\theta_l, j)$; (ii) the distribution of cost types, $F(\theta_l)$; and (iii) the marginal baseline private benefit function, $b'\left(\tilde{a}(\theta_l, j)\right)$.*

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

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

□

Notice that, 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 the primitives of the model are constant within each of the two regimes. Assumption 4 (ii) imposes a flexible parametric structure to the regulator's costs of emissions. Notice that it implies $h_j(0) = 0$, for $j \in \{pre, post\}$. 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 private benefit 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 $j \in \{pre, post\}$.*

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

$$b'\left[G_j^{-1}(\alpha)\right]\left[(1-\psi_j)Q(\alpha) + \frac{\psi_j(1-\alpha)}{f\left[Q(\alpha)\right]}\right] = \sum_{r=1}^{R} \gamma_{j,r}\left[G_j^{-1}(\alpha)\right]^{r-1}. \tag{12}$$

We may also rewrite equation (3) as:

$$e'_j\left[G_j^{-1}(\alpha)\right] = Q(\alpha) b'\left[G_j^{-1}(\alpha)\right]. \tag{13}$$

Using equation (13) and the relationship between the density and its quantile function, i.e.,$f\left[Q(\alpha)\right] = 1/Q'(\alpha)$, we rewrite equation (12) 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

$$\frac{Q'(\alpha)}{Q(\alpha)} = \frac{\sum_{r=1}^{R} \gamma_{j,r}\left[G_j^{-1}(\alpha)\right]^{r-1} - e'_j\left[G_j^{-1}(\alpha)\right](1-\psi_j)}{e'_j\left[G_j^{-1}(\alpha)\right]\psi_j(1-\alpha)}, \tag{14}$$

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

$$\log \frac{Q(\alpha)}{Q(\alpha_0)} = \int_{\alpha_0}^{\alpha} \left(\sum_{r=1}^{R} \Gamma_{j,r} \frac{\left[G_j^{-1}(u)\right]^{r-1}}{e_j' \left[G_j^{-1}(u)\right]} - \Psi_j \right) \frac{1}{(1-u)} du. \tag{15}$$

From Proposition 2, there is a vector $\{\theta_l\}_{l=0}^{\bar{L}}$ such that $\tilde{a}(\theta_l, j)$ is known for $j \in \{pre, post\}$, and remember that $F(\theta_l) = G_j[\tilde{a}(\theta_l, j)]$. Since equation (15) holds for arbitrary α and α_0, the following holds for for any $l \in \{1, \ldots, \bar{L}\}$ and $j \in \{pre, post\}$:

$$\log \frac{\theta_l}{\theta_0} = \sum_{r=1}^{R} \Gamma_{j,r} \int_{G_j[\tilde{a}(\theta_0,j)]}^{G_j[\tilde{a}(\theta_l,j)]} \frac{\left[G_j^{-1}(u)\right]^{r-1}}{e_j'[G_j^{-1}(u)]\,(1-u)} du - \Psi_j \int_{G_j[\tilde{a}(\theta_0,j)]}^{G_j[\tilde{a}(\theta_l,j)]} \frac{1}{(1-u)} du. \tag{16}$$

Furthermore, we obtain the following equations for any α by observing that equation (14) holds for both regimes:

$$\frac{\sum_{r=1}^{R} \Gamma_{post,r} \left[G_{post}^{-1}(\alpha)\right]^{r-1}}{e_{post}' \left[G_{post}^{-1}(\alpha)\right]} - \frac{\sum_{r=1}^{R} \Gamma_{pre,r} \left[G_{pre}^{-1}(\alpha)\right]^{r-1}}{e_{pre}' \left[G_{pre}^{-1}(\alpha)\right]} + \Psi_{pre} - \Psi_{post} = 0. \tag{17}$$

Note that, for each regime, equation (16) 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 (17) specifies an infinite number of equations. Assumption 5 suffices for a system consisting of equations (16) and (17) 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 (15), we identify $Q(\cdot)$ and, accordingly, $F(\cdot)$ and $f(\cdot)$. Lastly, using equation (12), we identify $b'(a)$ for $a \in \mathcal{A}_{pre} \cup \mathcal{A}_{post}$. □

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 (forthcoming). Once the regulator's objective function parameters are identified, we recover $F(\cdot)$ and $b'(\cdot)$ from (9).

Note that our model is over-identified because we can evaluate (17) 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 evaluating equation (9) at the upper bounds of $\mathcal{A}_j$'s.

5.3. **Estimation.** Our estimation procedure closely follows the identification strategy described above. It consists of four steps: first, we estimate the penalty schedules the distribution of negligence levels before and after the 2006 institutional changes;

second, we employ these estimates to compute estimates of $\tilde{\theta}(a, pre)$ and $\tilde{\theta}(a, post)$ for a finite set of negligence levels a; third, using the estimates from steps one and two, we estimate the parameters of the regulator's objective function; and, finally, employing the estimates from all previous steps, we obtain estimates of the distribution of cost types and the baseline private benefit function. We allow the primitives of the model to vary with observable attributes of the facilities. With this intent, let $\mathbf{x}_{i,t}$ denote the observed characteristics of facility i in quarter t. The vector $\mathbf{x}_{i,t}$ includes facility and county characteristics summarized in Table 1, as well as dummies for the regional water boards. Below we describe in details each step of the estimation procedure.

5.3.1. *Step 1.* We obtain estimates $\hat{\epsilon}_{pre}(k|\mathbf{x})$ and $\hat{\epsilon}_{post}(k|\mathbf{x})$ for the expected penalties $\mathbb{E}\left[\epsilon_{pre}(k|\mathbf{x})\right]$ and $\mathbb{E}\left[\epsilon_{post}(k|\mathbf{x})\right]$, respectively. When estimating $\mathbb{E}\left[\epsilon_{pre}(k|\mathbf{x})\right]$, we use quarterly violation observations from 2000–2001 and their associated penalty data; and, for $\mathbb{E}\left[\epsilon_{post}(k|\mathbf{x})\right]$, we use observations from 2009–2010. For both specifications, we consider only observations in which at least one violation occurred in the quarter. Specifically, we consider

$$\hat{\epsilon}_j(k|\mathbf{x}) = \begin{cases} \phi_0 + \phi_{1,j} k + \phi_3 \mathbf{x}_{i,t}, \text{ if } k > 0 \\ 0, \text{ if } k = 0, \end{cases} \tag{18}$$

for $j \in \{pre, post\}$. Under Assumption 1, $\phi_{1,j} > 0$ and $\phi_0 + \phi_3 \mathbf{x}_{i,t} > 0$ for all j and $\mathbf{x}_{i,t}$. We thus estimate (18) using a constrained OLS, ensuring that these conditions are satisfied. Given $\hat{\epsilon}_j(k|\mathbf{x})$, we estimate the marginal expected penalty, $\hat{e}_j'(a|\mathbf{x})$ using equation (1).

We also estimate $G_{pre}(\cdot|\mathbf{x})$ and $G_{post}(\cdot|\mathbf{x})$. In principle, we could directly apply the argument of Lemma 2 to estimate the negligence level distributions non-parametrically. However, given our sample size and our intent to condition the estimates on $\mathbf{x}_{i,t}$, non-parametric estimation is not feasible. Instead, we impose a parametric functional form to the observed distribution of emission violations, which allows us to estimate the conditional distribution of negligence employing standard regression techniques for count data. 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

$$h(\nu) = \frac{\delta^\delta}{\Gamma(\delta)} \nu^{\delta-1} \exp(-\nu\delta),$$

where δ is a positive parameter. Assume that ν is i.i.d. across facilities and, within each facility, over periods. 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

$$\nu_{i,t} \exp\left(\beta_{0,j} + \beta_1 \mathbf{x}_{i,t}\right), \tag{19}$$

where $j \in \{pre, post\}$. This distribution of violations is equivalent to a negative binomial distribution with mean $\exp\left(\beta_{0,j} + \beta_1 \mathbf{x}_{i,t}\right)$ and variance $\exp\left(\beta_{0,j} + \beta_1 \mathbf{x}_{i,t}\right)$ $\left(1 + \nu_{i,t}^{-1} \exp\left(\beta_{0,j} + \beta_1 \mathbf{x}_{i,t}\right)\right)$. Then the estimation of the distribution of negligence levels amounts to estimating the parameters δ and β. We estimate these parameters by MLE. See Cameron and Trivedi (2013) for details about this estimator.

5.3.2. *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:

$$\hat{a}_l(\mathbf{x}) \equiv \hat{G}_{pre}^{-1}\left[\hat{G}_{post}\left[\hat{a}_{l-1}(\mathbf{x})|\mathbf{x}\right]|\mathbf{x}\right],$$

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

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.

5.3.3. *Step 3.* Equation (16) 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 (17), 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 $G_{post}^{-1}(\alpha) > 0$ 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 $\mathbf{x}$. 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 $r = \{1, \ldots, R\}$.

5.3.4. *Step 4.* From the empirical analogue to (15) with $\alpha_0 = 0$, we estimate the quantile function associated with the distribution of types, conditional on $\mathbf{x}$, as

$$\hat{Q}_j\left(\alpha|\mathbf{x}\right) \equiv \hat{\theta}_0^j(\mathbf{x}) \exp\left(\int_{\hat{G}_j\left[\hat{a}_0^j(\mathbf{x})|\mathbf{x}\right]}^{\alpha} \left[\sum_{r=1}^{R} \Gamma_{j,r}(\mathbf{x}) \frac{\left[\hat{G}_j^{-1}(u|\mathbf{x})\right]^{r-1}}{e_j'\left[\hat{G}_j^{-1}(u|\mathbf{x})|\mathbf{x}\right]} - \Psi_j(\mathbf{x})\right] \frac{1}{(1-u)} du\right),$$

for $j \in \{pre, post\}$. Given our restriction that $Q_{pre}(\cdot) = Q_{post}(\cdot)$, an estimator of the quantile function of $F(\cdot|\mathbf{x})$, which we denote by $\hat{Q}\left(\cdot|\mathbf{x}\right)$, is:

$$\hat{Q}\left(\alpha|\mathbf{x}\right) = \hat{\pi}_{pre}(\mathbf{x})\hat{Q}_{pre}\left(\alpha|\mathbf{x}\right) + \left[1-\hat{\pi}_{pre}(\mathbf{x})\right]\hat{Q}_{post}\left(\alpha|\mathbf{x}\right),$$

where the scalar $\hat{\pi}_{pre}(\mathbf{x})$ is a weight that depends on the relative frequency of observations from the pre-2008 regime, conditional on the observable characteristics $\mathbf{x}$. An estimator for $F(\cdot|\mathbf{x})$, or $\hat{F}(\cdot|\mathbf{x})$, is the inverse of $\hat{Q}\left(\cdot|\mathbf{x}\right)$. Note that under Assumption 2, the inverse of $\hat{Q}\left(\cdot|\mathbf{x}\right)$ is guaranteed to exist. Finally, we define

$$\hat{b}'\left(a|\mathbf{x}\right) \equiv \left\{\hat{\pi}_{pre}(\mathbf{x})\hat{e}_{post}'\left(a|\mathbf{x}\right) + \left[1-\hat{\pi}_{pre}(\mathbf{x})\right]\hat{e}_{pre}'\left(a|\mathbf{x}\right)\right\} / \hat{Q}[\hat{F}\left(a|\mathbf{x}\right)|\mathbf{x}].$$

6. Results

6.1. **Estimates.** Table 5 presents the penalty schedule estimates, ϕ's in (18), and the estimates of the negligence distributions, δ and β's in (19). Consistent with the preliminary results discussed in Section 3, the estimated slope of the penalty schedule after the 2006 institutional changes ($\hat{\phi}_{1,post}$) is larger than its counterpart before 2006 ($\hat{\phi}_{1,pre}$). 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 period prior to 2006. Furthermore, $\hat{\beta}_{0,pre} - \hat{\beta}_{0,post} < 0$; the facilities decrease negligence levels after the changes.

Given these first-stage estimates, we proceed with the remaining estimation steps to estimate the model primitives. We do so separately for each of the 244 facilities that were active in the first quarter of 2005. Table 6 presents our estimates of $Med(\Theta)b'(1)$, the median marginal compliance costs, evaluated at a negligence level equal to one. The table also reports, for the periods before and after the 2006 institutional changes, the parameters associated with the regulators' preferences: γ, the

Table 5. Enforcement Schedule and Negligence Distribution Estimates

	Penalty Schedule†	Negligence Distribution
$\phi_{1,pre}$	509.69	
	(214.53)	
$\phi_{1,post}$	2,719.45	
	(133.02)	
$\beta_{0,post} - \beta_{0,pre}$		-0.62
		(0.10)
δ		12.34
		(0.52)
ϕ_3's and β_1's:		
Major	8,163.046	0.10
	(2,514.55)	(0.11)
First permitted in 1982-1987	1,631.27	-0.28
	(1,395.67)	(0.15)
First permitted after 1987	18,773.03	-0.34
	(8,503.67)	(0.27)
Water bond proposition %	-104.33	-0.08
	(116.66)	(0.01)
Turnout %	-49.58	-0.05
	(182.14)	(0.01)
Population density per sq. miles (log)	748.07	0.08
	(1,314.28)	(0.11)
Household income (log)	4,713.80	3.77
	(6,672.41)	(0.52)
Irrigation water use %	-2,105.37	2.44
	(5,316.62)	(0.33)
Total precipitation	0.00	0.02
	(30.11)	(0.01)
Region FE	Yes	Yes
Number of observations	837	8,195

Notes: Unit of analysis is at the facility-quarter level. The estimated parameters of the penalty schedules consist of constrained OLS results in which the dependent variable is the total amount of penalties associated with effluent MMP violations occurring in the quarter, and in which we only include facility-quarter observations in the periods 2000-2001 and 2009-2010 with at least one effluent MMP violation. The estimated parameters of the negligence distributions are based on a Poisson-Gamma regression in which the dependent variable is the number of effluent MMP violations occurring in the quarter, and in which all facility-quarter observations in the periods 2002-2005 and 2011-2014 are employed. The Gamma distribution in the latter regression is characterized by δ. See Section 3 for a description of the regressors. Bootstrap standard errors are in parenthesis.

†: Measured in 2010 USD.

perceived environmental cost per violation; and ψ, the enforcement cost. To facilitate the exposition, the results are aggregated by facility attributes: location (coastal and inland) and size (major and minor).

The marginal compliance costs are higher for inland facilities than for coastal ones. Also, the marginal environmental costs (enforcement costs) are higher (lower) for coastal facilities, both before and after the institutional changes. These results are consistent with the statistics presented in Table 2, which show that coastal facilities violate substantially less, relative to facilities regulated by inland regional water boards. In words, inland facilities violate more because (i) it is more costly for them to reduce violations; (ii) regulators perceive their violations to be less damaging; and (iii) it is more costly to impose fines to inland facilities. The comparison between major and minor facilities is not as clear. While the marginal compliance costs for major facilities are always higher, the environmental costs for minor, inland facilities are higher than those for major facilities located in the same regions. In coastal regions, the environmental costs are higher for major facilities.

The results in Table 6 also show how the estimated model rationalizes the increases in compliance after the 2006 reforms. For all groups of facilities considered, the environmental costs increased and the enforcement costs decreased. These trends may reflect that the digitalization of the self-reports made it easier for the regional boards to issue fines against violating facilities and the Office of Enforcement provided support and incentive for the regional boards to enforce the regulation.

Table 7 compares the distribution of the number of quarterly violations across facilities, as predicted by the estimated model, with the distribution observed in the data. The model fits the data well. In particular, it is able to reproduce both the relatively high probability of no violations happening at the facility-quarter level and the shift in the distribution of violations that took place following the 2006 institutional changes.

6.2. **Explaining the Regulators' Preferences.** What drives the heterogeneity in the regulators' preferences? We now examine whether the estimated regulators' parameters presented in Table 6 reflect the environmental preferences of local constituents, measured as the percentage of voters supporting Proposition 84 in 2006 at the county level. Figure 4 shows the correlation between this measure and the estimated values of γ and ψ for each facility. The figures indicates a positive correlation between the environmental costs, as perceived by the regulator, and the local preferences for water quality—both before and after the 2006 institutional changes. A

Table 6. Primitive Estimates by Region and Facility Types

	Marginal Compliance Cost ($Med(\Theta\|\mathbf{x})b'(1\|\mathbf{x})$)	Environmental Cost per Violation ($\gamma(\mathbf{x})$)		Enforcement Cost per Penalty ($\psi(\mathbf{x})$)	
		Before	After	Before	After
Coastal, Major	2,749	3,927	7,793	1.10	1.08
	(425)	(2,322)	(2,706)	(0.06)	(0.05)
Coastal, Minor	820	2,163	5,178	1.08	1.04
	(278)	(646)	(890)	(0.06)	0.05)
Inland, Major	4,193	1,707	5,780	1.14	1.13
	(881)	(4,161)	(4,954)	(0.08)	(0.06)
Inland, Minor	1,488	1,980	5,925	1.14	1.05
	(440)	(1,676)	(1,953)	(0.07)	(0.04)
Total	2,558	2,861	6,677	1.11	1.08
	(408)	(1,901)	(2,311)	(0.06)	(0.05)

Notes: This table compares our average estimates of the median marginal compliance costs, evaluated at a negligence level equal to one, as well as ψ and γ by facility attributes, before and after the 2006 institutional changes. Inland regions comprise Central Valley, Lahontan, and Colorado River Basin, while we classify other regions as coastal. Bootstrap standard errors in parenthesis.

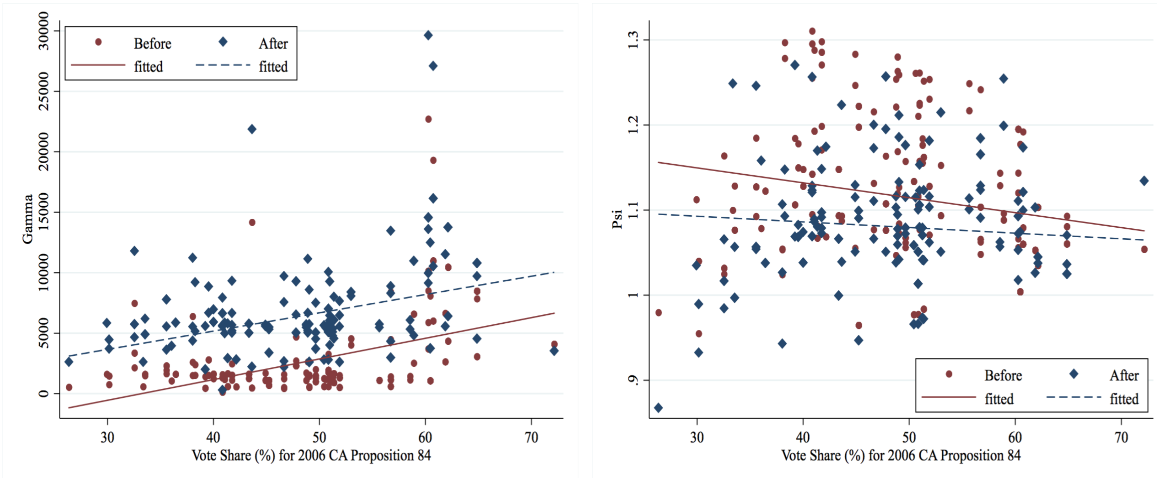
Table 7. Number of Violations: Data vs. Fitted Model

Number of violations	Before		After	
	Data	Model	Data	Model
0	0.79	0.80	0.86	0.84
1	0.07	0.06	0.04	0.06
2	0.04	0.03	0.02	0.03
3	0.03	0.02	0.02	0.02
4	0.02	0.01	0.01	0.01
5 and more	0.07	0.08	0.05	0.05

Notes: This table compares the distribution of the number of violations in the data with the one predicted by the fitted model, before and after the 2006 institutional changes.

possible interpretation of these results is that the regulator's preferences reflect those of the population in the facility location—either because the governor tends to intentionally appoint regional board members that will tailor the enforcement standards to local preferences and needs, or because the qualified individuals available to be appointed for the regional board positions, which are unpaid and part-time, typically have preferences for environmental policy that are similar to the ones of voters in

FIGURE 4. γ and ψ Estimates versus Local Environmental Preferences



(A) γ Estimates (B) ψ Estimates

Notes: This figure shows the correlation between the estimated regulator parameters for each facility (γ and ψ on panels (A) and (B), respectively) and the environmental preferences of local constituents, measured as the percentage of voters supporting Proposition 84 in 2006 at the county level. The panels report estimates both for the period prior to the 2006 institutional changes and the period after them.

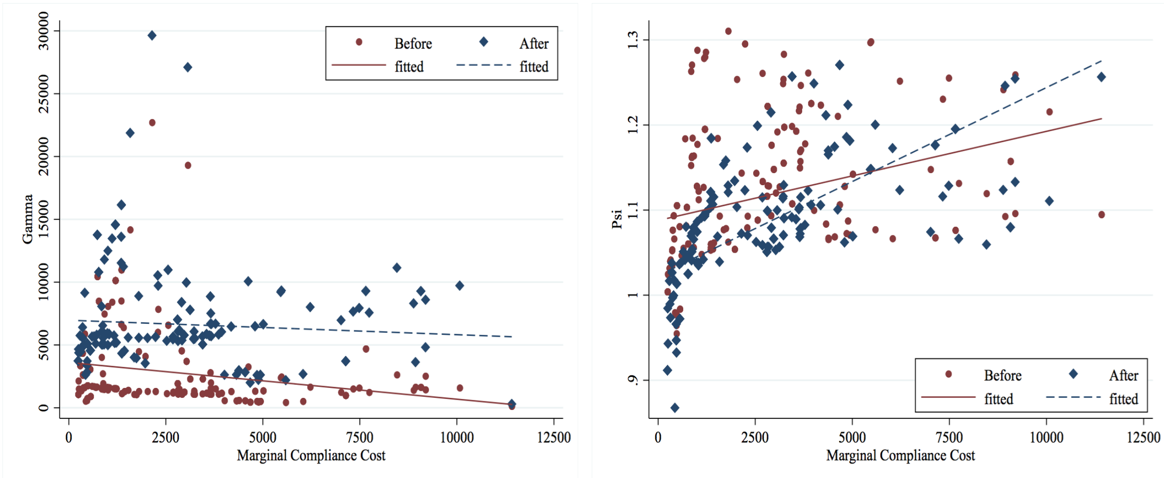
their regions. The correlation between the enforcement costs and local preferences for environment is negative, which suggests that regulators in regions where voters value the environment relatively highly have more resources or face lower political costs for issuing fines against facilities than regulators in other regions.

Figure 5 shows the correlation between the γ and ψ estimates and the estimated $Med(\Theta)b'(1)$, the median marginal compliance costs for each facility, evaluated at a negligence level equal to one. Although there is no clear relationship between the marginal costs and the γ estimates, the figure indicates that ψ, the regulator's marginal enforcement costs, increase as the facilities' marginal compliance costs get higher. This pattern, which holds both before and after the 2006 institutional changes, suggests that it is more costly for the regulators to issue penalties against facilities for whom compliance is relatively costly.

6.3. **Counterfactual Analyses: Changing Enforcement Discretion.**

6.3.1. *The Role of Heterogeneity in Regulators' Preferences.* We now investigate how the regulator's discretion affects compliance and penalties. With this intent, we use the estimated model to consider two counterfactual scenarios. First, we assume that all facilities are subject to the same regulator, who has values of γ and ψ associated

FIGURE 5. γ and ψ Estimates versus Compliance Costs



(A) γ Estimates (B) ψ Estimates

Notes: This figure shows the correlation between the estimated regulator parameters for each facility (γ and ψ on panels (A) and (B), respectively) and the estimated median marginal compliance costs, evaluated at a negligence level equal to one. The panels report estimates both for the period prior to the 2006 institutional changes and the period after them.

with a hypothetical facility with observable characteristics $\mathbf{x}_{i,t}$ equal to the average across all 244 facilities active in the first quarter of 2005. Specifically, based on the fitted penalty schedule and negligence distribution for the average facility, obtained from step 1 of the estimation procedure, we apply estimation steps 2 and 3 to recover the corresponding regulator parameters. For convenience, we refer to the regulator with these parameters as the uniform regulator throughout the current section. Comparing the outcomes in this counterfactual scenario with those from our baseline model allows us to assess the effects of regulator heterogeneity on compliance behavior and penalty actions. In Table 8, we report results both for the period prior to the 2006 institutional changes and the one after them. As with the estimation results, we aggregate the counterfactual outcomes by facility attributes. We focus on the distribution of two outcomes across the facilities: (i) the violation frequencies; and (ii) $e\left(1|\mathbf{x}_{i,t}\right)$, the expected penalties schedule, evaluated at a negligence level equal to one.

Columns (3) and (4) of Table 8 contain the outcomes in the scenarios with the uniform regulator, while columns (1) and (2) present the baseline scenario estimates. Under the uniform regulator, the mean violation frequency falls for all groups of facilities. For major, inland facilities, facing the uniform regulator leads to a decrease in the mean violation frequency by roughly thirty percent. Interestingly, the mean expected penalty across the facilities also decreases under the uniform regulator for almost all groups of facilities. That is, the uniform regulator is able to achieve higher average compliance levels with lower average penalties.

Figure 5 provides an explanation for this seemingly counterintuitive result. Facilities with high compliance costs tend to face regulators with high enforcement costs. Homogenizing the regulators' objectives across the facilities thus tends to cause the enforcement costs to fall for facilities with relatively high compliance costs. This change makes enforcement, on average, more effective. Evidently, our results do not allow us to take any conclusion concerning welfare, as we do not consider the facilities' actual compliance costs and the social costs of environmental violations. Notice that our model primitives are defined from the perspectives of the facility administrators and the regulator.

Another interesting aspect of having an uniform regulator is that it substantially decreases the dispersion in violation frequencies across the facilities. The standard deviation of the violation frequencies falls for all groups both before and after the 2006 institutional changes, by roughly 20 percent. Since the regulators' preferences reflect environmental preferences of local constituents, it might be beneficial, from a welfare perspective, that they drive the dispersion in compliance frequencies across facilities.

6.3.2. *Uniform Penalty Schedule.* We address a scenario in which the uniform regulator considered previously must impose the same penalty schedule to all facilities, regardless of their observed characteristics. Specifically, we analyze the case in which the regulator assumes that all facilities have the same distribution of compliance costs as a facility with the average observable characteristics $\mathbf{x}_{i,t}$. Columns (5) and (6) of Table 8 present the results.

Since the penalty schedule in this scenario is devised by the uniform regulator, it is convenient that we first compare the outcomes under uniform penalties with those from the previous counterfactual exercise, in which the uniform regulator could set different schedules to different facilities, depending on their compliance cost distribution. Comparing these two counterfactual scenarios helps us to isolate the role of the regulator's information on compliance and penalties.

For all groups of facilities, the average violation frequency increases substantially under an uniform penalty schedule, relative to the scenario with a flexible schedule set by the uniform regulator. For major, inland facilities, for example, the increase is

Table 8. Effects of Enforcement Discretion

	Baseline scenario		Uniform regulator		Uniform penalties	
	Before (1)	After (2)	Before (3)	After (4)	Before (5)	After (6)
Violation frequency						
Mean						
Coastal, Major	1.20	0.64	1.18	0.58	1.66	0.78
Coastal, Minor	1.07	0.57	0.86	0.39	0.85	0.44
Inland, Major	1.78	0.96	1.23	0.66	2.63	1.18
Inland, Major	1.57	0.84	1.52	0.76	1.58	0.80
Total	1.38	0.74	1.22	0.61	1.74	0.82
Standard deviation						
Coastal, Major	1.31	0.70	0.99	0.59	1.66	0.77
Coastal, Minor	0.64	0.34	0.40	0.21	0.52	0.27
Inland, Major	1.04	0.57	0.71	0.45	1.86	0.89
Inland, Major	1.09	0.59	1.01	0.57	1.40	0.68
Total	1.17	0.63	0.90	0.53	1.64	0.76
Expected penalty $(e(1\|\mathbf{x}_{i,t}))$						
Mean						
Coastal, Major	8,733	10,242	7,320	9,060	6,691	8,900
Coastal, Minor	4,103	4,954	4,250	5,973	6,691	8,900
Inland, Major	10,142	11,097	9,844	11,405	6,691	8,900
Inland, Major	5,182	5,905	4,824	6,257	6,691	8,900
Total	7,744	8,901	6,968	8,609	6,691	8,900
Standard deviation						
Coastal, Major	4,684	5,230	4,459	4,054	-	-
Coastal, Minor	2,232	2,865	1,521	1,805	-	-
Inland, Major	3,132	3,173	4,074	4,087	-	-
Inland, Major	3,792	4,148	2,809	2,962	-	-
Total	4,517	4,992	4,271	4,124	-	-

Notes: This table presents the results of two counterfactual scenarios that reduce the enforcers' discretion. In the first one (columns (3) and (4)), every facility is under a regulator with the same preferences, which we compute based on a hypothetical facility with observable characteristics equal to the average across all facilities. The regulator separately considers the compliance cost distribution of each facility, so different facilities can still face different penalty schedules. In the second counterfactual (columns (5) and (6)), each facility is subject to the same penalty scheduled, devised by a regulator that considers a facility with average observable characteristics. See the text for details. The outcomes obtained from the fitted model are presented in columns (1) and (2). The table reports the results both for the period prior to the 2006 institutional changes and the period after them.

of 100 percent or larger, depending on the period that we compare. To understand this result, notice that the uniform penalty is similar to the average penalty in the uniform regulator scenario, meaning that the uniform penalty is harsher for some facilities than a flexible schedule, while, for other facilities, the uniform penalty is relatively lenient. Since the facilities with higher compliance costs are the ones that tend to face the strictest penalties under a flexible enforcement schedule, switching to an uniform penalty schedule leads to more violations overall. Similarly, the dispersion of the violation frequencies across the facilities increases substantially under an uniform penalty schedule. Therefore, preventing the regulator from setting stricter penalties for high-cost facilities leads to more violations and increases the dispersion in compliance across the facilities. These results illustrate the importance of the regulators' expertise about the facilities' compliance costs in the design of the penalty schedule.

Finally, we compare the outcomes under the uniform penalty schedule with those from the baseline scenario. Here, the differences between the mean violation frequencies are less clear. Considering facilities located in coastal areas, for example, the transition from the baseline scenario to the one with uniform penalties leads to an increase in violation frequencies for major facilities and a decrease for minor facilities. These contrasting results are not surprising in light of the previous discussion. Having an uniform regulator leads to lower violation frequencies overall, but constraining this regulator to set an uniform penalty schedule tends to increase the frequency of violations. The net result of these two effects differs depending on the characteristics of the facility.

7. Conclusion

We provide an empirical framework to evaluate regulatory discretion by identifying and estimating a model of strategic interactions between a regulator and privately-informed dischargers. Applying our framework to data on the regulation of wastewater treatment facilities in California, we estimate the environmental preferences and enforcement costs of the regulator and the distribution of facilities' compliance costs. We find that if the regulator's objective function were homogeneous across facilities, both violation frequencies and penalties would decrease. But it is unclear whether these outcomes would be beneficial to society, as our results suggest that the regulator preferences and enforcement costs reflect environmental preferences of local constituents. We also consider the case in which the regulator must set an uniform penalty schedule to all facilities. We show that, under this scenario, the mean and the dispersion of the violation frequencies across facilities could increase substantially. The latter finding indicates that the compliance cost heterogeneity across facilities is large, and that the regulator expertise to allocate penalties is valuable.

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