Adjustment Frictions and the Cost of Environmental Regulatory Uncertainty

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Abstract

When regulators are appointed by elected government officials, political power shifts create regulatory uncertainty through regulator turnover. Regulator turnover can change how rules are enforced, generating fluctuations in enforcement intensity for regulated facilities. Moreover, adjusting pollution levels in response to new enforcement regimes often involves adjustment costs. This paper quantifies the welfare cost of such regulatory fluctuations in California's water quality enforcement, emphasizing the roles of adjustment costs and political inefficiency—that is, inefficiencies stemming from politically driven variation in enforcement intensity. Using linked data on enforcement, compliance, and regulator membership, I show that facility violations gradually adjust following regulator turnover, consistent with adjustment costs. Estimating a structural model of facility pollution decisions, I find substantial adjustment costs: past pollution influences abatement 3.5 times more than current fines, reflecting slow adjustments in abatement behavior. I estimate welfare losses equal to nearly one-third of total fines—28% from adjustment costs and 72% from political inefficiency—relative to a stable enforcement regime. While these adjustment costs raise costs for facilities, they also stabilize pollution outcomes by dampening responses to regulatory swings. However, uncertainty about future regimes weakens this stabilizing effect and amplifies adjustment costs. I further show that institutional stability improves welfare: doubling regulator term lengths to eight years reduces welfare losses by approximately half.

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1 Introduction

Regulations are central to how governments implement policies across sectors, from trade and finance to environmental protection. While essential, regulations also impose enormous economic costs—U.S. federal regulations were estimated to cost nearly \$3 trillion in 2022 (Crain and Crain, 2023). These costs can be furthered complicated by regulatory fluctuations, a common but understudied feature of regulations. Regulations and enforcement can vary as regulators differ in their preferences over competing policy goals. For instance, individual regulators or groups may disagree on penalty amounts for the same violation, depending on how they weigh a facility's compliance cost against the benefits of reduced pollution. Because regulators are often either elected officials or their appointees, politics and regulation are often closely linked: this creates an unstable regulatory environment that fluctuates with political turnover. Amid rising political polarization worldwide (Boxell et al., 2024), such fluctuations may intensify, yet their impacts on regulated parties and the overall society remain understudied.

A changing regulatory environment may induce regulated facilities to make costly adjustments to their pollution abatement choices and also generate uncertainty about future regulatory regimes. In this paper, I study welfare implications of regulatory fluctuations, focusing on the roles of adjustment cost and regulatory uncertainty. I first demonstrate the presence of adjustment frictions in facility response to regulator turnover, using a reduced-form approach. I then estimate a structural model of facility abatement that incorporates these frictions and dynamic evolution of penalties. Using the estimated model, I quantify the welfare cost of a fluctuating regulatory environment and decompose it into losses attributable to adjustment frictions and to regulatory uncertainty. Finally, I explore how institutional design, particularly regulators' term lengths, shapes welfare outcomes by influencing the stability of enforcement.

To understand the mechanism behind the adjustments, consider a regulated facility that chooses its pollution abatement level by trading off the private benefits of pollution (e.g., increased revenues or reduced abatement costs) against the potential costs. First, consider a case with no adjustment frictions. The potential costs then only include an increased probability of violation and penalties. As the penalty level increases, the facility would potentially want to increase its abatement level to lower the probability of violation. When penalties fluctuate across years due to changing regulators, abatement immediately responds and tracks those changes.

Next, introduce adjustment frictions and assume convex adjustment costs. The total costs to evaluate against private benefits then include an additional cost from changing abatement year to year. The facility then faces an intertemporal trade-off: as changing abatement between periods becomes costly, their current decisions then depend on both past abatement and expectations about future penalties. Thus, the facility is no longer able to flexibly adjust their abatement in response to a year's penalty levels. Moreover, under convex adjustment costs, uncertainty about future regulatory environments can limit smooth adjustments over time and amplify the total adjustment cost.

While these frictions impose additional cost to the facilities, they can also potentially mitigate political influence on pollution outcomes. Consider a scenario where regulators alternate between two political parties with regulatory preferences equally diverging from the first-best policy. Even though penalties alternate accordingly, the costly frictions may potentially constrain facilities' ability to respond to the changes. That is, they can act as a stabilizing force, preventing pollution outcomes from fluctuating along with extreme political shifts and consequently, alleviating welfare loss from inefficient pollution outcomes. Whether the additional adjustment cost to facilities (which decreases welfare) or the efficiency gains from mitigating political extremes (which increases welfare) dominates depends on several factors: magnitudes of adjustment frictions, preference spreads, and facilities' responsiveness in abatement to penalties. This trade-off is further complicated by uncertainty over future regulatory regimes, as adjustment decisions depend on expectations for future penalty levels.

I empirically quantify these trade-offs in the context of California's water quality regulations. Authorized by the Clean Water Act, the National Pollutant Discharge Elimination System (NPDES) program requires facilities to obtain a permit with limit specifications to discharge pollutants from a point source to water of the United States. In California, the nine Regional Water Quality Control Boards (regional boards) implement and enforce the program, including assessing monetary penalties for violations. Each regional board consists of seven members with a four-year term, all appointed by the governor. I exploit rich variation in regional board member composition to analyze the link between enforcement actions (i.e., penalty amounts) and political affiliations. To investigate how these political links affect pollution abatement at regulated facilities, I link a novel dataset on regional board membership to enforcement and violation data spanning 2000-2024.

Using information on assessed penalties from the membership-linked enforcement data, I derive a measure of enforcement stringency for each regional board, leveraging variation in member composition. Then, I estimate the dynamic effects of a change in board stringency on the number of violations at regulated facilities. I find that facilities gradually decrease the number of violations over a two-year period after a board transitions to a more stringent one. On average, the number of violations decreases by 0.38 standard deviations (and the compliance rate increases by 0.3 standard deviations) following a 1 standard deviation increase in board stringency. This gradual nature of the response suggests frictions in facilities' abatement adjustments.

After demonstrating that frictions exist, I assess their implications for welfare. To do so, I specify a model of facility pollution where facilities incur a convex adjustment cost to change pollution levels between periods. In each period and region, the representative facility chooses an optimal pollution level by trading off the private benefits of pollution against the expected penalty from non-compliance and adjustment costs. I assume each region has a constant marginal damage that represents the overall mean preference in the region. Instead of setting a fixed penalty at such mean for all periods—which is the first best scenario, penalties in each region and period are set by the period's regional board members with varying preferences for enforcement stringency. These members' preferences differ in two ways: (i) on average, Democratic- and Republican-appointed members weigh facility profits against environmental damage differently, leading to different mean party preferences, and (ii) members have idiosyncratic preferences that are distributed around their respective party means. Consequently, the penalty level changes whenever the board changes, and the change in penalty levels is likely to be the largest when the governor's party affiliation changes.

I estimate the model in a two-step procedure: first, I use Ordinary Least Squares (OLS) regressions on penalty amounts to recover parameters characterizing board preferences, leveraging variation in member composition across enforcement outcomes; then, I use these board preference estimates to estimate the facility profit parameters using Generalized Method of Moments (GMM). The main parameters of interest are the facility's marginal benefit of pollution and the marginal adjustment cost parameters, as they govern facilities' pollution decisions. My identification strategy leverages the transition path of facility violations following board turnover. The magnitude of the change in violations in response to a change of penalties identifies the slope of the marginal benefit of pollution, while the speed of the violation change identifies the relative slope of the marginal adjustment cost to the marginal benefit. This approach mirrors the key insight of my reduced-form evidence. Accordingly, I match the observed transition path of violations following a board turnover to the path predicted by the model in the second-step GMM estimation.

My model estimates reveal significant adjustment frictions: the marginal adjustment cost of pollution increases more than three times as fast as the marginal benefit decreases. This implies that past pollution levels influence current pollution decisions 3.5 times more than current penalty levels do and 2.6 times more than combined future penalty levels do. Moreover, a penalty of $9,360 per violation—more than triple the current Mandatory Minimum Penalties (MMP)—is required to achieve full compliance on average. As for the board preference parameters, my estimate of the relative party preference parameter suggests that on average, a board composed entirely of Democratic-appointed members impose a penalty that is 65 percent higher than a board composed of Republican-appointed members. I also find large heterogeneity in long-run regional average preferences as well as in board members' idiosyncratic preferences: the long-run average preferred marginal damage (under a fully Republican-appointed board) ranges from \$300 to $\$2,571$ across regions, and a member in the highest-preference tercile imposes a penalty that is 6.65 times the penalty imposed by a member in the lowest-preference tercile. These reflect large penalty disparities across regions and members in the data.

The estimated model allows for quantifying the welfare loss from regulatory fluctuations as well as decomposing the contributions of adjustment frictions and regulatory uncertainty to the loss. Using the estimated model, I simulate violations under predicted penalties implied by the realized sequence of regional boards, and I simulate forward from the initial violations set to steady-state violations under the initial boards. I discuss welfare by comparing to a first-best penalty regime: a fixed penalty at the long-run regional average. Given realized regional boards, I find that fluctuating penalties lead to substantial total welfare loss of \$30.00 million—equivalent to nearly one-third of total penalty assessments—over years 2001-2019 across seven regions. \$8.42 million of the total loss is attributed to adjustment costs. Under the assumption that Democratic- and Republican-appointed members deviate from the overall mean preference equally, the remaining \$21.58 million of the total loss comes from political inefficiency, stemming from inefficient violation outcomes relative to the social optimum. If instead, the overall mean preference perfectly aligns with one party, political inefficiency either decreases to \$21.39 million or increases to \$33.89 million.

To decompose how each factor contributes to the loss, I begin with a one-time political turnover exercise where the winning governor replaces the entire board with members of their party's mean preference. Absent adjustment frictions, violations fully respond to party preferences, resulting in large political inefficiency—loss stemming from violations induced by regulatory preferences deviating from the first-best levels. Under adjustment frictions and perfect anticipation of the election outcome, violations adjust early but slowly to the new penalty level, incurring a large adjustment cost to facilities but a smaller political inefficiency. That is, adjustment frictions constrain facilities' responses to party swings, mitigating political influence on violation outcomes. If instead, facilities are uncertain about the election outcome, this smoothing effect is weakened and the adjustment cost is amplified.

Applying the same decomposition to the realized boards from 2001-2019, I find that resolving uncertainty about future boards substantially improves welfare. Under perfect foresight, facilities can adjust earlier and more smoothly to upcoming regulatory changes, which reduces adjustment costs by 75% and lowers political inefficiency by 19%. In contrast, eliminating adjustment frictions entirely would save all adjustment cost but increase political inefficiency by 14%, relative to the baseline. Overall, in the presence of uncertainty, adjustment frictions lower total welfare: the additional costs of adjustment outweigh the gains from stabilizing abatement outcomes.

The trade-off posed by adjustment frictions depends on the magnitude, frequency, and predictability of regulator turnover. Therefore, I examine how board appointment structures—which determines regulatory stability—affect the welfare loss of regulatory fluctuations. Specifically, I simulate facility violations under alternative board member term lengths. When the term length is halved to two years, the total welfare loss increases by 23%. Crucially, 76% of this increased loss is driven by exacerbated adjustment cost stemming from more frequent and larger board turnover. Conversely, doubling the term length to eight years decreases the total welfare loss by 45%. Here, political inefficiency loss accounts for a majority of the loss (89%), as the need for adjustments diminishes under stable boards.

This paper contributes to three strands of literature. First, this paper is closely related to political economy studies that use political affiliation or ideology to explain disparities in policy outcomes. For instance, Innes and Mitra (2015) document a gap in local enforcement of the Clean Air Act between Democratic and Republican representatives, and Cohen and Yang (2019) and Hübert and Copus (2022) find that Democratic- and Republican-appointed judges make different sentencing and settlement decisions respectively. In particular, Lim and Yurukoglu (2018) link different regulatory characteristics to political ideology in electricity regulation. They find that conservative regulators who weigh utility profits more than consumer surplus grant higher returns but engage in less auditing, and quantify how these differences mitigate or exacerbate commitment problem and moral hazard program in regulation. While I also attribute fine disparities to partisan and individual preferences, my contribution lies in focusing on variability brought by regulator turnover, its associated welfare loss, and the mitigating role of adjustment frictions. In addition, this paper adds to the literature by examining how such loss varies with board appointment structures. While existing work studies the relationship between appointment structures and policy effectiveness (Besley and Case, 1995; Leaver, 2009; Alt et al., 2011; Gray, 2017), as far as I know, this is the first study to quantify the impact of term lengths on regulatory variability and its associated welfare cost.

Secondly, this paper is related to studies on the impacts of policy uncertainty on industry outcomes. I first contribute to the literature by quantifying the welfare cost of policy variability and uncertainty under adjustment frictions. The relationship between uncertainty and adjustment frictions is long established: for example, Pindyck (1982) provides a theoretical framework showing that the effects of uncertainty on firm capital stock or output are determined by the characteristics of adjustment costs. Several studies have also empirically shown that firm investment is negatively affected by the degree of uncertainty over policy or electoral outcomes (Bloom, 2009; Julio and Yook, 2012; Gulen and Ion, 2016). I provide an empirical estimate of adjustment frictions and reveal a novel channel through which frictions can be beneficial to social welfare, in the presence of externality: by adding private costs, facility behaviors are stabilized, partially offsetting welfare loss from extreme policies. Moreover, in contrast to most papers that focus on uncertainty around specific, large-scale policy changes (Dorsey, 2019; Gowrisankaran et al., 2025), I exploit frequent board turnover to characterize constant uncertainty over regulatory environment. This allows me to link penalty disparities to partisan or individual members and study how facility responses unfold over the term of a board. I further highlight the role of uncertainty over future regulatory environment in exacerbating adjustment costs by limiting smooth adjustments. My results also offer insights on how expectations about future policies change facilities' current behaviors. When their behaviors involve adjustment frictions, facilities move in advance toward expected future policies, instead of away, which is often suggested in the Green Paradox literature (Sinn, 2008; Smulders et al., 2012; Van der Werf, 2012).

Lastly, this paper contributes to the empirical literature on enforcement of environmental regulations. While ensuring effective enforcement has been one of the focuses in the literature, I illustrate that the effectiveness and implications of enforcement can vary substantially with political turnover. Previous research has studied various aspects of enforcement, including enforcement spillovers (Shimshack and Ward, 2005), penalties contingent on violation histories (Blundell et al., 2020) or on linkage plants owned by the same firms (Leisten and Vreugdenhil, 2024), regulatory discretion in enforcement (Kang and Silveira, 2021), or sanction costs (Shimshack and Ward, 2022). While Kang and Silveira (2021) also focus on penalty disparities in California water regulations, they quantify the benefits of boards using regulatory discretion to tailor penalties under asymmetric information. In contrast, I use novel board membership data to focus on the overall consequences of varying penalties driven by partisan and individual preferences on regulated facilities. Furthermore, I document that when the underlying regulatory environment is not stable, facilities bear an additional cost to comply—adjustment costs—beyond regular compliance costs. To my knowledge, while some papers quantify facilities' compliance costs (Trebbi and Zhang, 2022), this paper is the first to quantify the cost of adjustments, specifically to a varying regulatory environment.

The rest of the paper is organized as follows. Section 2 provides a brief overview of water quality enforcement and water board appointments in California. Section 3 describes my data and presents the reduced-form analysis that motivates the model. Section 4 specifies the model of facility pollution decisions, the relationship between penalty levels and regional boards, and the welfare benchmark. Section 5 introduces empirical specifications and explains my identification and estimation strategy. Section 6 discusses the estimation results, quantifies welfare implications, and presents counterfactual analyses on alternative term lengths. Section 7 concludes.

2 Institutional Background

This section provides background on California's water regulations institutional features. Section 2.1 describes regulatory enforcement of the National Pollutant Discharge Elimination System (NPDES) program and the common forms of pollution abatement processes at the facilities. Section 2.2 explains the appointment structure of regional water boards, which generates variation in regulatory enforcement that can be linked to political changes.

2.1 Regulation and Enforcement

Authorized by the federal Clean Water Act, the NPDES program regulates pollutant discharges from point sources into surface waters. In California, the State Water Resources Control Board and the nine Regional Water Quality Control Boards—created under the Porter-Cologne Water Quality Control Act—jointly governor the NPDES program along with other water regulations. The regions are divided by watersheds and each regional board conducts regulatory activities within its own jurisdiction.[1]

Facilities that discharge pollutants from point sources (e.g., pipes or man-made ditches) into California surface waters must obtain an NPDES permit. Permits specify allowable discharge limits and the monitoring and reporting requirements. Facilities are required to submit self-monitoring reports at regular intervals, and these reports constitute the primary source of violation detection. Once a violation is confirmed, the regional board evaluates it for informal or formal enforcement action. A common form of formal enforcement is the assessment of Administrative Civil Liability (ACL), which may result in monetary penalties.

ACL assessments follow the State Water Board's enforcement policy. Board staff first calculate an initial penalty amount using a prescribed formula based on violation severity, discharge volume, and extent of environmental harm. Regional boards may then adjust

[1] Water pollution damages and remediation options vary across watersheds; regional administration allows regulation to account for unique differences in climate, topography, geology, and hydrology.

the initial amount based on additional factors. Mandatory Minimum Penalties (MMPs) of $3,000 apply to violations classified as serious or chronic.[2] As specified in the Water Code, certain statutory exemptions from MMPs exist but often require board discretion and evaluation. Thus, for violations subject to MMPs, regional boards may determine whether to impose penalties and, if so, at what level (equal to or above the MMP).

Most facilities regulated under the NPDES program in California are wastewater treatment plants, but the program also covers facilities such as power plants and construction sites.[3] In the wastewater context, violations often stem from failures to operate or maintain existing pollution control equipment, rather than from infrequent capital installment or upgrades (see Shimshack and Ward (2005, 2022); Kang and Silveira (2021)). This pattern is also reflected in violation descriptions in the data, which frequently reference equipment failure, operator error, or wet-weather conditions.[4] Thus, this abatement process involves staffing or training decisions that are often not flexible to change.

2.2 Board Governance and Appointments

Each regional board is responsible for critical water quality decisions, including compliance decisions and enforcement actions, within its own region. As discussed in Section 2.1, regional boards play a central role in determining enforcement intensity. Critically, several features of the board appointment system allows me to link board members to their enforcement preferences as well as link board turnover to political changes. Prior to the Water Code amendments in 2012, each board had nine members serving part time; since then, each board has seven members.

Members serve four-year terms and are appointed by the governor with confirmation by the State Senate. Terms are staggered, with one or two terms expiring each September, and members may be reappointed without limit. Members may also leave before their term expires due to withdrawal by the governor, non-confirmation by the Senate, or resignation, though such cases are rare.[5] Vacancies are required to be immediately filled by the governor for the remainder of the term, although delays in appointments are frequent. These institutional features generate rich variation in board composition over time and across regions, allowing me to empirically gauge each member's link to

[2]A violation is classified as serious if it exceeds the effluent limit of a Group I pollutant by more than 40% or a Group II pollutant by more than 20%, or if the facility fails to submit reports for every 30 days. A violation is classified as chronic after the fourth or subsequent non-serious violation in a period of 180 days.

[3]In the sample, sewerage systems account for 50% of facilities, followed by missing 4-digit SIC code (17%), water supply (3%), electric services (3%), and construction sand and gravel (2%).

[4]Examples of equipment-related descriptions include clogged eductors, water main breaks, and pipe leaks. Wet weather indicates that violations are also affected by external factors beyond a facility's control; for example, storm events.

[5]According to the State Water Board, these incidents rarely happen.

enforcement outcome.[6]

3 Data and Empirical Evidence

This section introduces the data sources used in the analysis, presents descriptive statistics and key empirical patterns, and then provides reduced-form evidence of adjustment frictions. Section 3.1 describes data on facility compliance outcomes and board enforcement actions. Section 3.2 presents data on water board composition and political turnover. Section 3.3 offers empirical evidence of facility adjustment frictions, using a reduced-form analysis.

3.1 Compliance and Enforcement

I combine multiple reports from the California Integrated Water Quality System (CIWQS) to construct two main estimation samples used in the analyses: (1) a facility-quarter compliance panel and (2) violation-level ACL enforcement data.

For the compliance panel, I aggregate violation information from the Violation Report into facility-quarter observations for 2000-2024. To determine which facilities are regulated, I use permit information from the Facility-At-A-Glance Report and define any facility with an active permit in a given quarter as regulated.[7] The regulated facilities are unevenly distributed across the nine regional boards in California (see Figure 1).[8]

A facility is considered in compliance in a given quarter if it is regulated and records no violation during that period. I then aggregate the panel into region-quarter observations and define the compliance rate as the share of regulated facilities in compliance. Table 1 presents the summary statistics of the compliance data, where I aggregate $144,748$ facility-quarter observations at region-quarter level. On average, there are $1,484$ regulated facilities per quarter across eight regions, or roughly 183 facilities per region-quarter. The average compliance rate is 82 percent, ranging from 73 percent to 92 percent. The average number of violations is 1.17.

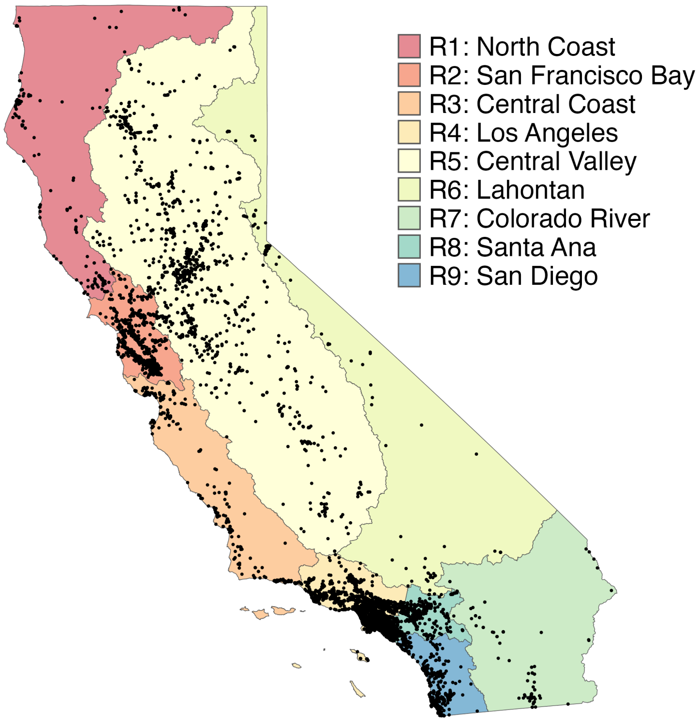
For the enforcement data, I merge penalty information from the Detailed ACL Report with linkage variables from the Violations with Linked Enforcement Actions Report, violation characteristics from the Violation Report, and MMP-type classifications from

[6] In particular, some members serve only partial terms, some serve multiple terms, some return after gaps in service, and some boards have persistent vacancies.

[7] Lags between the expiration of old permits and the issuance of new ones are common, especially during the COVID-19 pandemic. To avoid dropping facilities due to such lags, I treat a facility as continuously permitted if the gap between permits is less than 18 months.

[8] I exclude the Lahontan region from the structural estimation sample due to its small number of violations, limited enforcement actions, and infrequent board turnover.

Figure 1: Regional Water Boards and Regulated Facilities



Note: The map shows the boundaries of the nine regional boards and the locations of the regulated facilities in the sample.

Table 1: Descriptive Statistics

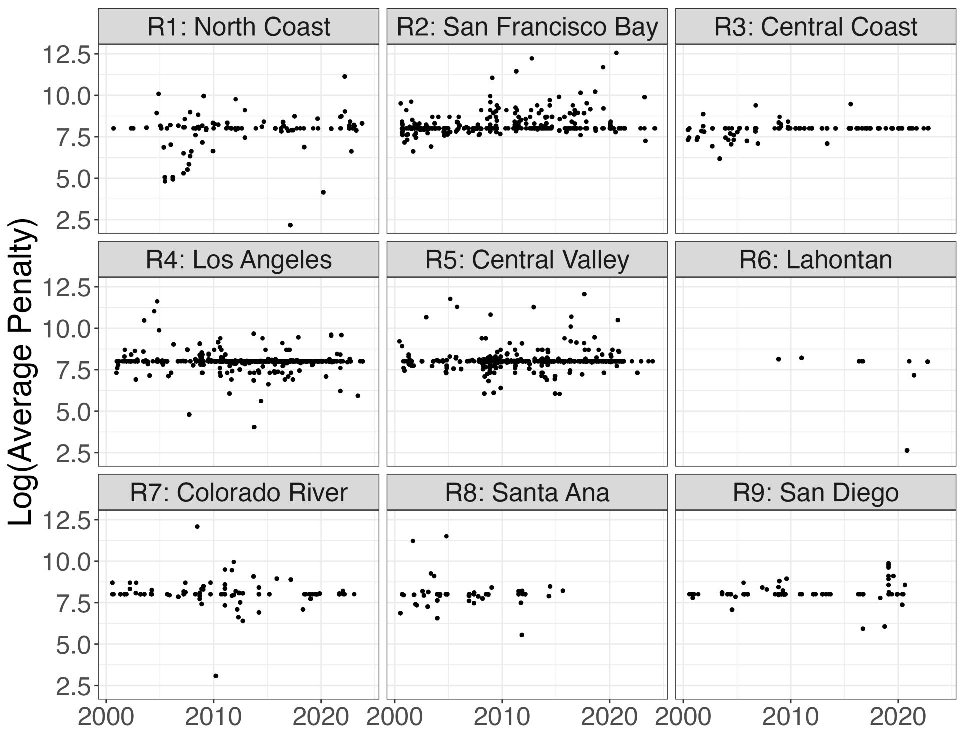
	N	Mean	St. Dev.	Pcl(25)	Pcl(75)
Compliance (at Region-Quarter Level)					
Number of Facilities	792	182.76	158.99	57	251
Compliance Rate	792	0.82	0.12	0.73	0.92
Avg. Number of Violations	792	1.17	1.37	0.29	1.53
Enforcement (at Enforcement Action Level)					
Number of Violations Linked	2068	20.55	80.51	2	16
Number of Nonexempt MMP Viol. Linked	2068	17.45	78.2	2	13
Avg. Penalty per Nonexempt MMP Viol. ($)	2068	4444.45	11716.6	2797.43	3350.22

Notes: The table presents the descriptive statistics of the compliance data at region-quarter level and the enforcement data at enforcement action level. The Lahontan region is omitted from both samples. Average penalty per nonexempt MMP violation is calculated as the total ACL amount divided by the number of nonexempt MMP violations linked. Penalty amounts are adjusted by the PCE index with a based year of 2012.

the Facility-At-A-Glance Report. Because a single ACL action can cover multiple violations, I compute the average ACL penalty per violation by dividing the total amount of assessment by the number of linked, non-exempt MMP violations.[9] I restrict the samples to the non-exempt violations with ACL actions taken after 2000, violation dates before 2020, and positive total penalty assessments.

As shown in Table 1, 17.45 out of 20.55 linked violations per ACL enforcement action on average are subject to MMP, and the mean penalty per non-exempt MMP violation is $4,444.45. As discussed in Section 2.1, average penalties may fall below or exceed the MMP. In practice, most observations cluster around the MMP threshold, but there is substantial variation on both sides (Figure A1). Figure 2 further shows the average penalty at the ACL action level over time and by region, with fines often fluctutating around the MMP.

Figure 2: Average ACL Penalty by Region



Notes: The figure plots log-transformed average ACL penalty amount per nonexempt MMP violation over time and by region. The penalty amount is presented in the raw amount prior to any PCE adjustment. The Lahontan region is omitted in the structural analyses due to very few ACL penalty observations.

Table 2 then reports the descriptive statistics for the mean enforcement outcomes of each regional board. There is significant variation in the mean penalty assigned across

[9] Penalty amounts are adjusted to 2012 dollars using the Personal Consumption Expenditures (PCE) deflator obtained from Federal Reserve Economic Data.

boards: on average, boards on the third quartile assign an average penalty that is 36% higher than boards on the first quartile. When a board transition occurs, on average, the absolute difference in average penalty between the two boards is as high as $4,112.85. 46% of board transitions are associated with an increase in penalty, while the rest are associated with a decrease in penalty.

Table 2: Descriptive Statistics (Boards)

	N	Mean	St. Dev.	Pcl(25)	Pcl(75)
Enforcement (at board level)					
Avg. Penalty per Nonexempt MMP Viol. ($)	236	5007.37	9865.61	2911.93	3966.67
Avg. Num. of Nonexempt MMP Viol. Linked	236	26.75	57.81	5	28.06
Change in Enforcement (at board change level)					
Difference in Avg. Penalty ($)	228	-1.4	14014.19	-876.07	814.31
Absolute Difference in Ave. Penalty ($)	228	4112.85	13394.31	224.77	1949.08
Penalty Increased	228	0.46	0.5	0	1

Notes: The table presents the descriptive statistics of the enforcement data aggregated at board level. A board is defined to be a unique combination of board members. For each board transition, outcomes about change in enforcement are calculated by subtracting values under the old board from those under the new board. Penalty Increased is a dummy variable that equals to one when the new board has a higher average penalty than the old board.

Finally, I supplement these data with facility characteristics from the Facility-At-A-Glance and Regulated Facilities reports in CIWQS. These include permit effective and termination dates, region, address, latitude, longitude, and four-digit SIC codes.[10] To approximate the downstream impact of each facility's discharge within a region, I merge facility coordinates with the flowline and hydrologic sequence data from United States Geological Survey's National Hydrography Dataset Plus and compute each facility's downstream distance to its closest regional boundary.[11]

3.2 Board Appointment

I compile regional water board appointment records from two sources: (1) appointment data obtained directly from the California Water Boards covering 1977-2024, and (2) the California Senate Weekly History records for 2000-2024, which I use to cross-validate

[10] About 15 percent of facilities lack valid SIC codes; I group these into a separate category rather than dropping them from the estimation sample.

[11] Facilities missing coordinates are geocoded using their addresses. Facilities geocoded outside California are dropped. If a facility still lacks a location, I assign the mean downstream distance for its region.

and fill missing appointment dates. The final dataset includes member name, region, appointment status, term start and end dates, Senate confirmation dates, and withdrawal dates when applicable.

Using these appointment records, I construct board composition at two levels of aggregation. First, I create a region-day panel of active boards members, which I use to attribute enforcement actions (ACLs) to the specified board in place at the time of the enforcement action. Second, I construct a region-quarter panel, which assigns facilities to the set of active board members governing their region in each quarter. A member is considered active in a period if any part of their appointment term overlaps with the end of a period.[12]

I define a board cohort (board hereafter) as a unique combination of active members.[13] Across the eight regions in my analysis, there are 286 unique board members during the sample period. On average, boards consist of 7.61 members prior to the 2012 amendments and 5.95 members afterward.[14] A typical member serves on 9.80 distinct boards over time, and an average board lasts 3.27 quarters. (See Figures A2a, A2b, and A3.)

For my structural analysis, I make two assumptions about firms' expectations of board turnover. First, I assume that firms expect a board member to remain in office until their official term expires and do not anticipate early withdrawal or removal.[15] Second, I assume that facilities do not expect any governor in their first term to remain in office for a second term. These assumptions allow facilities' expectations to evolve only with observed term duration and expiration.

To capture political variation in board composition, I classify members by the party affiliation of the governor who first appointed them. A member is then labeled Democratic-appointed or Republican-appointed based on their initial appointment.[16] Figure 3 shows the time series of the average share of Democratic-appointed members across boards, while Figure A4 further shows cross-region variation. These patterns reflect political swings in board composition, which I later exploit to measure party-specific enforcement stringency and capture corresponding regulatory changes.

[12]Because appointment delays are common, if the gap between consecutive terms for the same member is shorter than 90 days, I assume the member remains active during the gap.

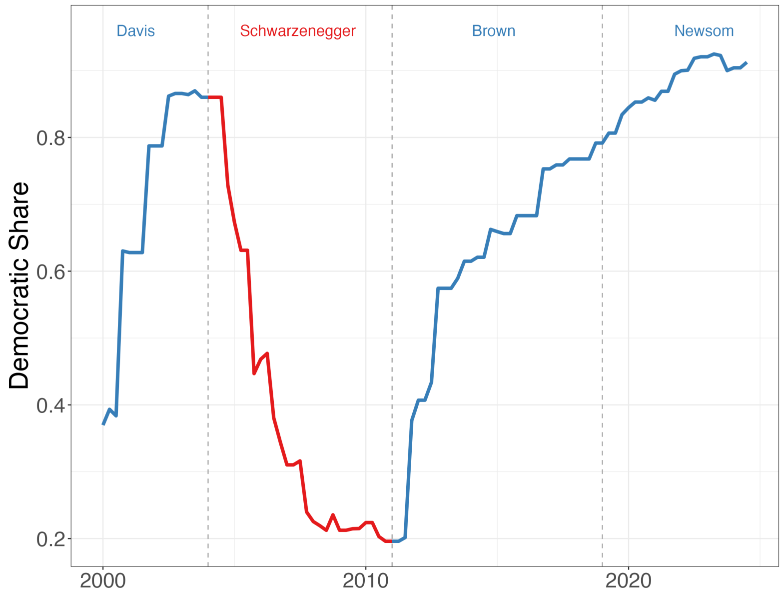
[13]If the same combination of members reappears after a gap—due to members expiration and later reappointments—I treat them as separate boards.

[14]In some region-quarters, the number of observed members exceeds the number of official board seats. This is likely due to missing resignation dates in the appointment record. When resignation information is unavailable, I assume a member remains active until their term expires or is formally withdrawn.

[15]Withdrawals by the governor or non-confirmation by the Senate do occur but are infrequent and thus unlikely to be anticipated by facilities.

[16]I also collect direct information on party affiliation for a subset of members (131 of 268 members) using news archives and official press releases. The correlation between a member's recorded party affiliation and the party of their appointing governor is 0.48, supporting the validity of the proxy.

Figure 3: Average Share of Democratic-Appointed Members



Notes: The figure plots the average share of Democratic-appointed members across regions and over time. Colors represent the political colors of the two parties. Names on the top of the figure are the names of the governor during a period.

3.3 Empirical Evidence of Adjustment Frictions

To motivate and empirically ground the model, I begin by examining how facilities respond to changes in enforcement stringency in a reduced-form analysis. This analysis relies on two sources of variation. First, variation in board composition allows me to link enforcement outcomes to individual board members. Second, the staggered timing of board turnover generates variation in enforcement over time within region. I use the first source of variation to construct a measure of enforcement stringency, and then use the second to study how facilities adjust to changes in enforcement.

3.3.1 Measuring Board Enforcement Stringency

I first estimate individual board member's enforcement stringency using variation in ACL penalty outcomes across violations. I attribute each ACL assessment in a region to all board members who were active on the enforcement date and estimate a member-level stringency measure based on the penalties associated with their terms.

Specifically, I estimate the following regression at violation level:

$$\log \text{Penalty}_{i\ell t} = \sum_{m \in \mathcal{M}} \gamma_m \mathbb{1}\left\{m \in \mathcal{M}_{b(\ell t)}\right\} + \mathbf{X}_{it}' \eta + \\ FE_\ell + FE_{\text{violation year}(i)} + FE_{\text{violation quarter}(i)} + FE_{\text{industry}(i)} + \varepsilon_{i\ell t}, \quad (1)$$

where $\log \text{Penalty}_{i\ell t}$ is the log average penalty for violation i enforced on day t in region ℓ; $\mathcal{M}_{b(\ell t)}$ is the set of active members on board b; and γ_m captures the mean contribution of member m to penalty severity. The vector $\mathbf{X}_{it}$ includes violation characteristics (such as violation type, priority status, and Group I or Group II pollutant) and facility characteristics (such as indicators of past or concurrent violations and downstream distance to regional boundaries). The specification includes region fixed effects, violation-year and violation-quarter fixed effects, and industry fixed effects (4-digit SIC). The estimated $\hat{\gamma}_m$ then serves as the measure for member m's enforcement stringency.[17]

To determine board b's stringency, I take average over stringency of members on the board and define the average as the board's stringency:[18]

$$\text{Stringency}_b = \frac{1}{|\mathcal{M}_b|} \sum_{m \in \mathcal{M}_b} \hat{\gamma}_m.$$

Thus, a board's stringency depends on board composition and changes with board turnover.

Table 3 reports the estimation results from Regression (1). Column (1) controls for the characteristics and region, year, quarter fixed effects, Column (2) adds industry fixed effects, and Column (3) further includes member dummies. Including member dummies increases the adjusted R^2 from 0.51 to 0.86, indicating that member composition explains a large share of the variation in penalty amounts. Once member effects are included, observed violation characteristics also play a much smaller role. This result is consistent with the presence of enforcement discretion by the regional boards, as discussed in Section 2.1.

3.3.2 Facility Responses to Changes in Enforcement Stringency

I next take the board stringency measures and study how facilities respond to changes in enforcement stringency caused by board turnover. For each board transition, I compute the change in enforcement stringency as the difference in stringency between the new and

[17] I jointly estimate stringency of members who always serve together during all valid ACL actions. Some members do not have estimates because they never observe ACL action during their terms (44% of all members in the sample) or because their terms are linear dependent with others (18%), leaving insufficient variation for identification.

[18] The average is taken over members that have a member estimate. On average, 80% of members on a board have an estimate.

Table 3: ACL Penalty Determinations

	Log (Average Penalty)		
	(1)	(2)	(3)
Violation Characteristics			
Chronic or Not	0.041	0.057	−0.021
	(0.065)	(0.071)	(0.025)
Report or Not	0.136	0.267***	0.087
	(0.083)	(0.065)	(0.049)
Priority or Not	0.027	−0.029	−0.069
	(0.072)	(0.103)	(0.047)
Group I Pollutant or Not	0.401*	0.325**	0.066**
	(0.181)	(0.114)	(0.022)
Group II Pollutant or Not	0.634**	0.494***	0.151**
	(0.243)	(0.125)	(0.048)
Facility Characteristics			
Any Other Current Violation (Quarter)	−0.186	−0.151	−0.057
	(0.116)	(0.109)	(0.035)
Any Past Violation (Semester)	−0.144	−0.070	0.026
	(0.135)	(0.119)	(0.038)
Downstream Distance within Region (Mi)		−0.0002	0.0003
		(0.001)	(0.0004)
Board Member Dummy			X
Industry FE		X	X
Region, Year, Quarter FE	X	X	X
Observations	35,387	35,387	35,387
R^2	0.307	0.512	0.862
Adjusted R^2	0.306	0.510	0.860

Notes: The table reports the estimation results of Regression (1). The dependent variable is log average ACL penalty of a violation. The independent variables include violation characteristics and facility characteristics. Column (1) includes region, year of violation, and quarter of violation fixed effects, Column (2) adds industry (4-digit SIC) of the violating facility fixed effects, and Column (3) adds board member dummies. The regression is run at the violation level, and the standard errors are clustered at region level. *p<0.1; **p<0.05; ***p<0.01.

the old boards:

$$\Delta \text{Stringency}_b = \text{Stringency}_b - \text{Stringency}_{b-1},$$

where $b - 1$ indicates the previous board.

I then examine how facility compliance outcomes evolve following these enforcement changes, focusing on whether responses occur immediately or gradually over a board's term. To capture the response over time, I interact $\Delta\text{Stringency}_b$ and quarter-of-term indicators and estimate the following regression at region, quarter level:[19]

$$Y_{\ell t} = \beta \Delta \text{Stringency}_{b(\ell t)} + \sum_{\tau=1}^{19} \alpha_\tau d_{\tau,\ell t} + \sum_{\tau=1}^{11} \beta_\tau d_{\tau,\ell t} \cdot \Delta \text{Stringency}_{b(\ell t)} + FE_\ell + FE_t + \eta_{\ell t}, \quad (2)$$

where $Y_{\ell t}$ is either facility compliance rate or average number of violations in region ℓ in quarter t; $d_{\tau,\ell t}$ is an indicator of the τ-th quarter of board $b(\ell t)$'s term; and FE_ℓ and FE_t are region and year-quarter fixed effects.[20] The coefficients β_τ then trace the dynamic response of facility behavior to changes in enforcement stringency. In order to see the dynamic response clearly, I run Regression (2) on a sub-sample of boards which stay for at least eight quarters, where facilities have enough time to respond under relatively stable environments.[21]

Figure 4 plots the estimated β_τ using number of violations as the outcome variable, from the sub-sample of longer boards (see Figure A5 for the compliance rate results). A one-unit increase in board stringency reduces number of violations by 1 on average, corresponding to a 0.38 standard deviation decrease of violations following a one standard deviation increase of ΔStringency. Similarly, the compliance rate increases by 0.13, corresponding to a 0.29 standard deviation increase of compliance following a one standard deviation increase of ΔStringency. These results suggest that facility respond to board stringency changes in an expected way: when the board transitions into a more stringent cohort, facilities comply more and reduce violations. I also test for asymmetric responses with respect to the direction of stringency change in Section A.2.3.

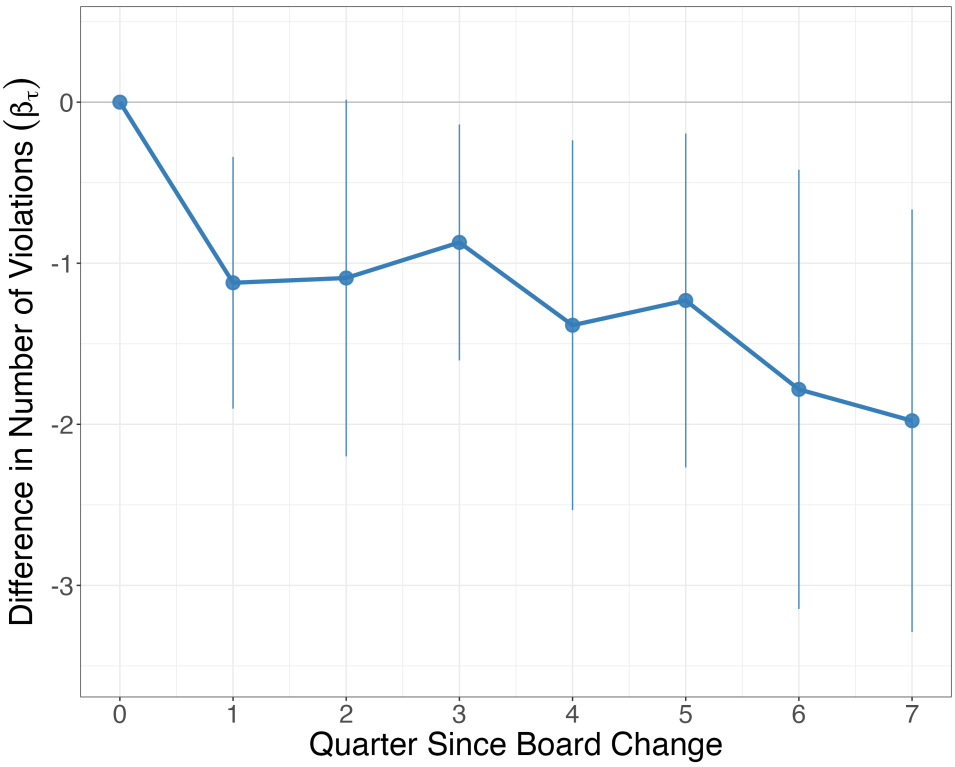
Importantly, the adjustment is gradual. As seen in Figure 4 and Figure A5, the β_τ estimates grow in magnitude over a board's term: compliance increases quarter by quarter, and violations decrease progressively. This gradual, rather than immediate, feature of the responses is consistent with adjustment frictions—facilties do not instantly adapt to new enforcement environments but rather adjust gradually over time.

[19] In this regression, I focus on post-turnover periods for three reasons. First, board turnovers recur over time, so the pre-periods associated with a given turnover mechanically overlap with the post-periods of the previous board. Second, the analysis is designed to capture facilities' dynamic responses to board turnovers, which materialize in the post-turnover periods. Third, when both pre- and post-turnover periods are included, I find no evidence of differential pre-trends (see Section A.2.2).

[20] If a board transition occurs during a quarter, I assign the new board to the entire region-quarter.

[21] Even though the staggered structure makes one or two members expiring each year, due to reappointments or delays in appointments, many boards serve less or more than four quarters. Under boards who stay a short period of time, it is likely that facilities do not have enough time to respond to the board changes.

Figure 4: Violation Changes after Board Transitions Over Time



Notes: The figure plots the estimates and 95% confidence intervals of β_τ for $\tau \leq 7$ from Regression (2). β_τ captures the difference in number of violations from quarter 1 for each unit increase in board stringency.

4 Model

This section develops the theoretical framework of the empirical model. Section 4.1 specifies the decision problem of a representative facility. Section 4.2 models how the fines are determined under different regional water boards, and Section 4.3 defines the social planner benchmark and welfare.

4.1 Facility Pollution Decisions

I consider a finite-horizon setting with representative facilities operating in multiple regions. Time is indexed by $t \in \{1, \cdots, T\}$ and region by $l \in \{1, 2, \cdots, L\}$. Facilities are assumed to be identical across regions and share the same profit function. In each period, a facility chooses a pollution level $x_{\ell t}$, which generates private benefits but also increases the probability of regulatory violations (i.e., the probability of receiving fines). Let $u_{\ell t}$ denote the per-violation fine imposed by region ℓ's water board at time t.

In this setting, pollution represents the extent of abatement efforts and can be adjusted continuously. This choice captures incremental operational decisions—such as amount of care and maintenance, training, or staffing—that influence violations.[22] Pollution level $x_{\ell t}$ is therefore a continuous control variable that maps into a stochastic violation outcome.

A key feature of the model is that facilities face adjustment frictions when changing pollution levels. Specifically, altering pollution intensity from one period to the next incurs a cost, which introduces state dependence and makes the pollution problem dynamic. Given past pollution $x_{\ell t-1}$ and current fine $u_{\ell t}$, a facility's per-period profit is

$$\Pi(x_{\ell t}, x_{\ell t-1}, u_{\ell t}) = B(x_{\ell t}) - P(x_{\ell t})u_{\ell t} - A(x_{\ell t-1}, x_{\ell t}),$$

where $B(x_{\ell t})$ is the net private benefit from polluting $x_{\ell t}$ units (e.g., increased revenues or reduced abatement costs), and $A(x_{\ell t-1}, x_{\ell t})$ is the adjustment cost of changing pollution levels from $x_{\ell t-1}$ to $x_{\ell t}$, and $P(x_{\ell t})$ is the expected number of violations given pollution choice $x_{\ell t}$. Pollution $x_{\ell t}$ affects the distribution of realized violations, which are modeled to be stochastic due to external shocks such as weather,[23] and expected violations $P(x_{\ell t})$ is increasing in $x_{\ell t}$.[24]

Therefore, the facility chooses pollution dynamically by trading off private benefits and costs from expected fines and adjustments: at t, the facility in region ℓ chooses pollution to maximize the expected discounted sum of profits:

$$\max_{\{x_{\ell s}\}_{s=t}^{T}} \Pi(x_{\ell t}, x_{\ell t-1}, u_{\ell t}) + \sum_{s=t+1}^{T} \delta^{s-t}\mathbb{E}\left[\Pi(x_{\ell s}, x_{\ell s-1}, u_{\ell s})|\mathcal{I}_{\ell t}\right],$$

where δ is the discount factor and $\mathcal{I}_{\ell t}$ is the facility's information about future board composition at time t, which is used to form expectations about future fines. Here, conditional on state variables $\{x_{\ell t-1}, u_{\ell t}, \mathcal{I}_{\ell t}\}$, the facility chooses the optimal sequence of pollution: $\{x_{\ell s}\}_{s=t}^{T}$.

To obtain a tractable and interpretable model, I impose the following functional form assumptions: (i) quadratic private net benefit of pollution, $B(x) = g_0 x - \frac{1}{2}gx^2$, where the marginal benefit is linear and diminishing, (ii) quadratic adjustment cost, $A(x_{-1}, x) = \frac{1}{2}k(x - x_{-1})^2$, where the marginal adjustment cost is linear and increasing in the difference in pollution levels: $\frac{\partial A}{\partial x}(x_{-1}, x) = k(x - x_{-1})$, and (iii) the expected number of violations is equal to the pollution choice $P(x) = x$; that is, on average, a unit of pollution generates

[22] This specification is motivated by the institutional evidence discussed in Section 2.1: most violations arise from failures in equipment operation or maintenance rather than discrete capital investments or upgrades.

[23] As discussed in Section 2.1, for example, storms and runoff events create random compliance shocks (Kang and Silveira, 2021; Shimshack and Ward, 2022).

[24] Equivalently, facilities face random compliance shocks given abatement effort. While I do not impose a specific distributional assumption, one interpretation is that violations follow a Poisson process with mean $P(x_{\ell t})$ increasing in pollution $x_{\ell t}$.

one violation.[25]

To build intuition, consider the static framework without adjustment costs. Under the functional form assumptions, the first-order condition for per-period profit maximization given fine u is

$$g_0 - gx = u \;\;\Leftrightarrow\;\; x^{\mathrm{SS}}(u) = \frac{g_0 - u}{g},$$

where $x^{\mathrm{SS}}(u)$ denotes the steady-state pollution level under fine u, i.e., the level a facility would choose if the fine were expected to remain constant indefinitely.

With adjustment frictions, facilities smooth pollution adjustments over time. Solving the static profit maximization in the final period, the first-order condition implies that the optimal pollution in the final period T is

$$\begin{aligned} x^*_{\ell T} &= \frac{k}{k+g} x^*_{\ell T-1} + \frac{g}{k+g} \frac{g_0 - u_{\ell T}}{g} \\ &= \frac{k/g}{k/g+1} x^*_{\ell T-1} + \frac{1}{k/g+1} x^{\mathrm{SS}}(u_{\ell T}). \end{aligned}$$

Denoting $\phi_{T,-1} \equiv \frac{k/g}{k/g+1}$ and $\phi_{T,0} \equiv \frac{1}{k/g+1}$, $x^*_{\ell T}$ becomes an weighted average of $x^*_{\ell T-1}$ and $x^{\mathrm{SS}}(u_{\ell T})$:

$$x^*_{\ell T} = \phi_{T,-1} x^*_{\ell T-1} + \phi_{T,0} x^{\mathrm{SS}}(u_{\ell T}). \tag{3}$$

Solving dynamic optimization by backward induction gives the optimal pollution in all periods. For any $t \leq T$, the optimal pollution in region ℓ at t is

$$x^*_{\ell t} = \phi_{t,-1} x^*_{\ell t-1} + \phi_{t,0} x^{\mathrm{SS}}(u_{\ell t}) + \sum_{\iota=1}^{T-t} \phi_{t,\iota} x^{\mathrm{SS}}(\mathbb{E}\left[u_{\ell t+\iota} | \mathcal{I}_{\ell t}\right]), \tag{4}$$

where the weights $\{\phi_{t,\iota}\}$ are functions of discount factor δ and k/g, which is the ratio of the slope of marginal adjustment cost to the slope of marginal benefit of pollution, and satisfy $\sum_{\iota=-1}^{T-t} \phi_{t,\iota} = 1$. The exact forms of $\{\phi_{t,\iota}\}$ are as follows: for $\iota \leq T - t$,

$$\phi_{t,-1} = \frac{k/g}{S_t}, \quad \phi_{t,0} = \frac{1}{S_t}, \text{ and } \quad \phi_{t,\iota} = \delta \frac{k/g \phi_{t+1,\iota}}{S_t}, \tag{5}$$

where for $t < T$,

$$S_t = k/g + 1 + \delta k/g \left(1 - \frac{k/g}{S_{t+1}}\right) \quad \text{and} \quad S_T = k/g + 1. \tag{6}$$

This expression has a simple economic interpretation: pollution today is a weighted

[25] This normalizes the unit of pollution to the unit of mean number of violations.

average of past pollution $x^*_{\ell t-1}$, current static optimum (i.e., current steady-state pollution $x^{\mathrm{SS}}(u_{\ell t})$), and future expected optima (i.e., future steady-state pollution $x^{\mathrm{SS}}(\mathbb{E}[u_{\ell t+\iota}|\mathcal{I}_{\ell t}])$). These weights $\{\phi_{t,\iota}\}$ summarize the tension between costs from moving away from the past pollution and benefits from moving toward pollution under current and future fines as well as the tension between current and future profits. For instance, when k is large relative to g, i.e., $k/g > 1$ or the marginal adjustment cost increases faster than the marginal benefit falls, adjustment cost dominates and decisions are more persistent (due to $\phi_{t,-1} > \phi_{t,0}$ for any t): the facility stays closer to its past pollution level rather than adjusting quickly to the new fine.

4.2 Fine Determinations

Pollution generates not only private benefits for facilities but also external social costs. Let $\Theta_\ell(x)$ denote the total social damage from pollution x in region ℓ, with marginal damage $\Theta'_\ell(x) = \theta_\ell$. I assume that marginal damage is constant over pollution levels, varies across regions, and is time-invariant.[26] The welfare-maximizing fine induces facilities to fully internalize the social cost and choose the socially optimal pollution level. That is, the socially efficient fine equals the marginal damage: $u^{\mathrm{FB}} = \theta_\ell$.

However, in practice, fines are often determined by regulators who may not share the social planner's objective. Individual board members may differ in their beliefs or preferences about benefits and costs of reducing pollution (e.g., reduced pollution damage against increased facility compliance costs), and thus may prefer to set different fines. Suppose there is an underlying distribution of preferred marginal damages in the society that centers around the true marginal damage θ_ℓ. Individual board members drawn from this distribution hold different preferences for marginal damages and set fine equal to their preferred damage. For instance, a board member who values facility compliance cost more than benefits from reduced damage would prefer a smaller marginal damage level and hence a lower fine.

I model this by assuming that each board member has a preferred marginal damage:

$$\tilde{\theta}_m = \theta_{\ell(m)} \alpha_m \omega_m,$$

where $\theta_{\ell(m)}$ is the true marginal damage in the member's region, α_m captures systematic preference differences by political appointment, and ω_m captures idiosyncratic heterogeneity across members.[27] I assume $\alpha_m = \alpha^{\mathrm{D}}$ if m is Democratic-appointed and $\alpha_m = \alpha^{\mathrm{R}}$

[26] This reflects the localized nature of water pollution: damages depend on watershed characteristics and differ geographically.

[27] Idiosyncratic preferences may reflect differences in professional expertise, environmental ideology, or regulatory experience of the board members.

if m is Republican-appointed. That is, Democratic- and Republican-appointed members differ systematically in their enforcement preferences, but members of the same party can still disagree due to individual heterogeneity ω_m. I assume ω_m is distributed with mean one. The functional form then suggests members with different preferences, α_m and ω_m, scale the true marginal damage differently.

I assume board members' preferences are time-invariant and truthfully revealed, so that a given board member prefers the same fine under any circumstances.[28] Region ℓ's board at time t consists of members $\mathcal{M}_{\ell t}$, and I model the board's fine to be set as an aggregation of the members' preferred marginal damages.[29] Assuming equal influence across members and a Cobb-Douglas aggregation, the board sets fine equal to

$$u_{\ell t} = \tilde{\theta}_{\ell t} \equiv \prod_{m \in \mathcal{M}_{\ell t}} \tilde{\theta}_m^{\frac{1}{|\mathcal{M}_{\ell t}|}} = \theta_\ell \prod_{m \in \mathcal{M}_{\ell t}} (\alpha_m \omega_m)^{\frac{1}{|\mathcal{M}_{\ell t}|}} . \tag{7}$$

Under this structure, fines change whenever board composition changes. Thus, fine levels fluctuate with board turnover.

I assume that facilities observe true marginal damage θ_ℓ, all preferences, including party mean preferences α^{D} and α^{R}, and individual members' idiosyncratic preferences ω_m for all members that have been appointed to the boards, and appointment history of board members and governors. Given any board composition, facilities know the fine level set by the board.

I further assume that facilities form expectations about future fines based on these preferences and members' terms,[30] and a perceived probability of governors' party affiliation. I assume that the facility expects a Republican candidate to win any gubernatorial election with probability r. The facility's information set $\mathcal{I}_{\ell t}$ therefore includes θ_ℓ, α^{D}, α^{R}, ω_m for the region's past and current members, r, and the terms of the governor and all members on region ℓ's board at t.

4.3 First-Best Fines and Welfare Definitions

As discussed in Section 4.2, since the marginal damage of pollution is constant over time and region-specific, the socially efficient fine is also a constant, region-specific fine that internalizes externality. Under the assumption that the society's mean preference of marginal damage lies at θ_ℓ, a benevolent social planner who maximizes the overall welfare

[28] This abstracts from strategic behavior within boards and between boards and facilities.

[29] I assume that board members set fines solely based on their preferred marginal damage and they do not consider facility adjustment costs.

[30] For example, if a member's term ends at $t+3$, a facility at t expects that member to influence fines only until $t+3$, and expects member n's position to be filled by a new appointee with mean-zero ω_m and α_m of the party of the appointing governor.

sets the fine in region ℓ equal to

$$u_{\ell t}^{\mathrm{FB}} = u_{\ell}^{\mathrm{FB}} = \theta_{\ell}.$$

Facing this first-best fine u_{ℓ}^{FB}, a facility in region ℓ then chooses a constant pollution level in each period:

$$x_{\ell}^{\mathrm{FB}} = x^{\mathrm{SS}}(\theta_{\ell}),$$

which is the steady-state pollution level under the first-best fine. This first-best allocation serves as a benchmark throughout the analysis. In Section 6.2 and 6.3, I compare welfare under alternative scenarios and define welfare loss in a scenario as its deviation from the first-best welfare.

The total welfare loss in any scenario has two sources—adjustment cost, arising when facilities make changes in pollution, and political inefficiency, arising from fines (or equivalently, board preferences) that differ from the true marginal damage θ_{ℓ}.

First, since the first-best fines are constant over time, facilities face no incentive to change their pollution levels over time and therefore incur no adjustment cost. Under any alternative fine path $\{u_{\ell t}\}$ where fines are not constant, welfare is reduced by the cost of adjusting pollution between periods in response to the changes in fines. Given initial pollution $x_{\ell 0}$, the adjustment cost component of welfare loss is

$$AdjCost = \sum_{t=1}^{T} \sum_{\ell=1}^{L} \delta^{t-1} N_{\ell t} A(x_{\ell t-1}, x_{\ell t}), \tag{8}$$

where $\{x_{\ell t}\}$ is the optimal pollution path under fine path $\{u_{\ell t}\}$ and $N_{\ell t}$ denotes the number of facilities in region ℓ at t. Note that per-period adjustment cost increases with the magnitude of pollution changes, and because adjustment costs are assumed convex, the total adjustment cost is smaller with multiple gradual changes than few abrupt changes.

Second, political inefficiency captures the welfare loss due to fines that differ from true marginal damage, which drives pollution away from the first-best level x_{ℓ}^{FB}. Since such fine deviations arise from board preference differences, this welfare loss represents political inefficiency. The political inefficiency component of welfare loss includes any gap between private benefit and social damage of pollution across pollution distortion:

$$PoliticalIneffi = \sum_{t=1}^{T} \sum_{\ell=1}^{L} \delta^{t-1} N_{\ell t} \int_{x_{\ell}^{\mathrm{FB}}}^{x_{\ell t}} \left(B'(z) - \theta_{\ell}\right) dz. \tag{9}$$

Note that the per-period political inefficiency increases with deviation of the actual pollution from the first-best level, and that the marginal benefit $B'(x)$ determines how rapidly this deviation is translated into welfare loss.

Thus, the total welfare loss in a scenario equals the sum of adjustment cost and political inefficiency of all regions and periods:

$$TotalLoss = AdjCost + PoliticalIneffi. \tag{10}$$

5 Empirical Specification

This section discusses how I take the model in Section 4 to data. Section 5.1 presents an empirical model and specifies the two sets of model parameters to estimate: the board preference parameters and the facility profit parameters. Section 5.2 illustrates what data variations I use to separately identify the main parameters of interest, marginal benefit and marginal adjustment cost of pollution, and how they are related to my reduced-form evidence in Section 3.3. Lastly, Section 5.3 discusses the two-step estimation strategy: I first estimate board preference parameters using Ordinary Least Squares (OLS) and the ACL enforcement data; then, I use the board preference estimates and the model solutions to estimate facility profit parameters with Generalize Method of Moments (GMM) and the compliance data.

5.1 Empirical Model

I assume the fine amounts in data are observed with measurement errors. Let $\tilde{u}_{i\ell t}$ denote the fine observed in the data for violation i in region ℓ at time t, and recall that $u_{\ell t}$ is the true fine set by the board. I assume

$$\tilde{u}_{i\ell t} = u_{\ell t}\tilde{\varepsilon}_{i\ell t},$$

where $\tilde{\varepsilon}_{i\ell t}$ is a measurement error with mean one.

From fine determination specified in Equation (7), the board fine equals the aggregate preferred marginal damage of its members. Thus, the observable fine is

$$\begin{aligned}\tilde{u}_{i\ell t} &= \tilde{\theta}_{\ell t}\tilde{\varepsilon}_{i\ell t} \\ &= \theta_\ell \prod_{m\in\mathcal{M}_{\ell t}} (\alpha_m\omega_m)^{\frac{1}{|M_{\ell t}|}}\,\tilde{\varepsilon}_{i\ell t}.\end{aligned} \tag{11}$$

The first set of parameters to estimate are the board preference parameters, which include parameters on true marginal damages, partisan mean preferences, and individual preferences: $\Theta^{\text{Board}} = (\theta_\ell, \alpha^{\text{D}}, \alpha^{\text{R}}, \omega_m)'$.

As for the facility problem discussed in Section 4.1, I assume a period is a quarter in the data and set discount factor $\delta = 0.95$. Given the discount factor, the weights $\{\phi_{t,\iota}\}$ in Equation (4) become a function of k/g and t alone. I further assume that the end of the sample period $\tilde{T}$ is far from the final period in the model T, so the weights converge to time-invariant forms and thus are identical across periods in the sample. Using the recursive structure of $\{\phi_{t,\iota}\}$, I obtain the convergent weights for all periods $t \leq \tilde{T}$ as

$$\phi_{t,-1} \to \phi_{-1} = \frac{k/g}{S}, \quad \phi_{t,0} \to \phi_0 = \frac{1}{S}, \text{ and } \quad \phi_{t,\iota} \to \phi_\iota = \frac{\delta^\iota (k/g)^\iota}{S^{\iota+1}}, \tag{12}$$

where

$$S = \frac{k/g + 1 + \delta k/g + \sqrt{(k/g + 1 + \delta k/g)^2 - 4\delta (k/g)^2}}{2}. \tag{13}$$

As $\phi_\iota \to 0$ as ι increases, I truncate at $\tilde{T}'$ future periods.[31] (See discussion of convergent weights in Section A.3.)

Then, for all $t \leq \tilde{T}$,

$$\sum_{\iota=1}^{T-t} \phi_{t,\iota} x^{\text{SS}}(\mathbb{E}\left[u_{\ell t+\iota} | \mathcal{I}_{\ell t}\right]) = \sum_{\iota=1}^{\tilde{T}'-t} \phi_{t,\iota} x^{\text{SS}}(\mathbb{E}\left[u_{\ell t+\iota} | \mathcal{I}_{\ell t}\right]) = \sum_{\iota=1}^{\tilde{T}'-t} \phi_{\iota} x^{\text{SS}}(\mathbb{E}\left[u_{\ell t+\iota} | \mathcal{I}_{\ell t}\right]),$$

and Equation (4) becomes

$$x^*_{\ell t} = \phi_{-1} x^*_{\ell t-1} + \phi_0 x^{\text{SS}}(u_{\ell t}) + \sum_{\iota=1}^{\tilde{T}'-t} \phi_\iota x^{\text{SS}}(\mathbb{E}\left[u_{\ell t+\iota} | \mathcal{I}_{\ell t}\right]).$$

Next, I substitute steady-state pollution, and express fines using board preferences and board composition. The equation then becomes

$$x^*_{\ell t} = \phi_{-1} x^*_{\ell t-1} + \phi_0 \frac{g_0 - \tilde{\theta}(\mathbf{X}_{\ell t}; \Theta^{\text{Board}})}{g} + \sum_{\iota=1}^{\tilde{T}'-t} \phi_\iota \frac{g_0 - \tilde{\theta}(\mathbb{E}\left[\mathbf{X}_{\ell t+\iota} | \mathcal{I}_{\ell t}\right]; \Theta^{\text{Board}})}{g}, \tag{14}$$

where $\mathbf{X}_{\ell t}$ is the vector of observed board composition and $\tilde{\theta}(\cdot)$ is a function that maps $\mathbf{X}_{\ell t}$ into $\tilde{\theta}$ using Θ^{Board} and Equation (7). Thus, the optimal pollution choice can be written as a function of $x_{\ell t-1}$, $\mathbf{X}_{\ell t}$, and $\mathbb{E}\left[\mathbf{X}_{\ell t+\iota} | \mathcal{I}_{\ell t}\right]$. Let $x^*(\cdot)$ denote such function.

Since I do not observe pollution directly but only observe number of violations, I next convert the model solution of pollution into number of violations. In the model, the expected number of violations equals the pollution choice. Let V denote the number of violations. Note that under the functional form assumption (in Section 4.1), $V_{\ell t} | (x_{\ell t-1}, \mathbf{X}_{\ell t}, \mathcal{I}_{\ell t})$ is a discrete random variable with the expected value equal to $x^*(x_{\ell t-1}, \mathbf{X}_{\ell t}, \mathcal{I}_{\ell t})$:[32]

[31] In estimation, I assume $\tilde{T}'$ is 20 quarters after the end of the sample period $\tilde{T}$.

[32] One example is the Poisson distribution (as in Kang and Silveira (2021)): $V_{\ell t} | (x_{\ell t-1}, \mathbf{X}_{\ell t}, \mathcal{I}_{\ell t}) \sim$

$$\mathbb{E}[V_{\ell t}|x_{\ell t-1}, \mathbf{X}_{\ell t}, \mathcal{I}_{\ell t}] = x^*(x_{\ell t-1}, \mathbf{X}_{\ell t}, \mathcal{I}_{\ell t}) = x_{\ell t}.$$

In the data, I observe $N_{\ell t}$ facilities in region ℓ at t. The number of violations at each facility, $v_{i\ell t}$, is independently drawn from the same distribution with expected value of $x_{\ell t}$; that is, the mean number of violations in region ℓ at t also has an expected value of $x_{\ell t}$. Therefore, the model solution in Equation (14) can be written in terms of the average number of violations in a region, period:

$$V^*_{\ell t} = \phi_{-1} V^*_{\ell t-1} + \phi_0 \frac{g_0 - \tilde{\theta}(\mathbf{X}_{\ell t}; \Theta^{\text{Board}})}{g} + \sum_{\iota=1}^{\tilde{T}'-t} \phi_\iota \frac{g_0 - \tilde{\theta}(\mathbb{E}\left[\mathbf{X}_{\ell t+\iota}|\mathcal{I}_{\ell t}\right]; \Theta^{\text{Board}})}{g}. \quad (15)$$

Recall that $\{\phi_\iota\}$ are functions of k/g. Thus, the second set of parameters to estimate are the facility profit parameters: $\{k, g, g_0\}$, where k is the slope of the marginal adjustment cost, g_0 and g are the intercept and slope of the marginal benefit of pollution. As k only enters the model solution together with g, I estimate $\Theta^{\text{Firm}} = (k/g, g, g_0)'$ in implementation and discuss identification accordingly.

5.2 Identification

Here, I discuss identification of the facility profit parameters, focusing on how I separately identify the adjustment cost parameter k/g from the slope of the marginal benefit of pollution g. The key source of identifying variation comes from the transition path of facility pollution responses to board turnover. To illustrate the idea of identification clearly, I abstract future expectations from the following arguments.

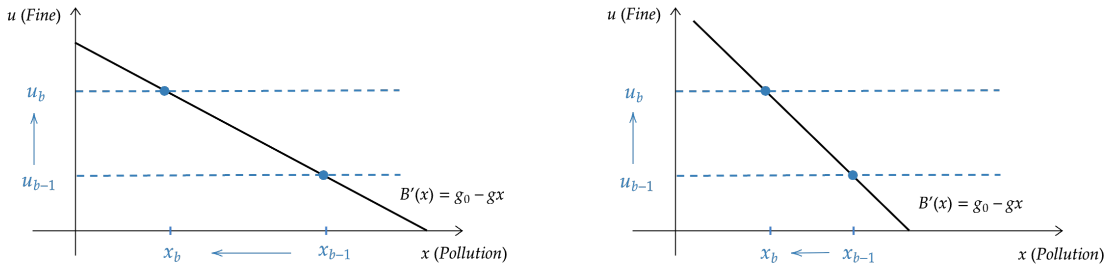
To begin with, I first consider the case without adjustment frictions. In this static setting, the facility chooses pollution so that its marginal benefit equals marginal cost; that is, the current fine level. Then, consider a one-time board transition to a new steady-state board (a board who is expected to stay for all of the remaining periods). When the board transitions into a new board with a different preference, i.e., fine level, the size of facility response in pollution is determined by the slope of marginal benefit, g. As shown in Figure 5, pollution is less responsive to the change in fines when the marginal benefit of pollution declines quickly (i.e., high g).

Now, reintroduce adjustment frictions. The ratio of the slopes k/g, which is the relative magnitude of the rate of change in marginal adjustment cost to marginal benefit, determines the speed of adjustment toward the new steady state after a board transition. Intuitively, marginal benefit pulls pollution toward the new optimal level, while marginal

$Poisson(\lambda)$ where the parameter $\lambda = \mathbb{E}[V_{\ell t}|x_{\ell t-1}, \mathbf{X}_{\ell t}, \mathcal{I}_{\ell t}] = x^*_{\ell t}$ and that expectation of a Poisson random variable equals its parameter, λ.

Figure 5: Identification of Marginal Benefit g

(a) Small g (b) Large g

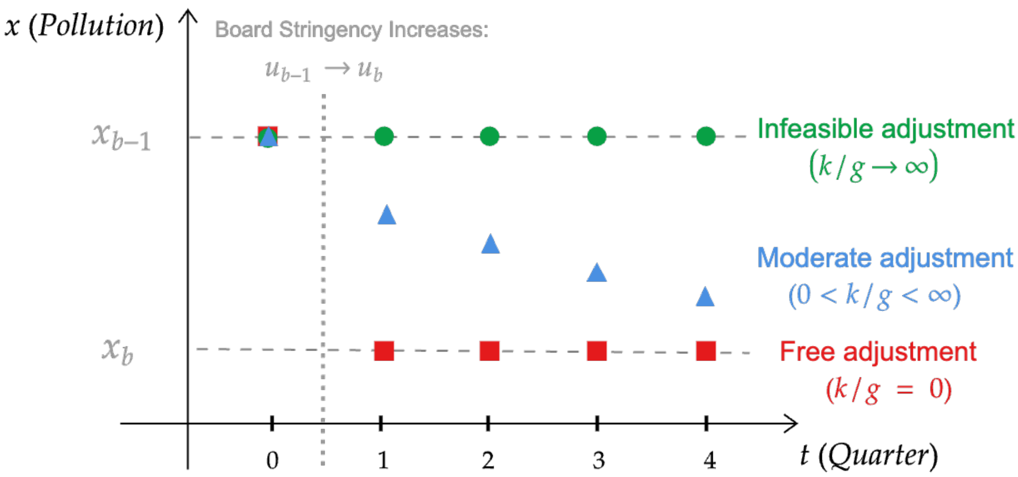


Notes: This figure plots the change in optimal pollution levels when the board transitions from a low-fine board to a high-fine board under different slopes of marginal benefit of pollution g. Panel (a) corresponds to a small slope and Panel (b) corresponds to a large slope.

adjustment cost penalizes movement away from the previous level of pollution.

Figure 6 illustrates how the transition path varies with k/g for a given g. Under free or infinitely small adjustment cost ($k/g = 0$ or $k/g \to 0$), the optimization problem becomes static and pollution immediately jumps to the new steady-state level. In contrast, if the adjustment cost is infinite ($k/g \to \infty$), pollution remains at the old steady-state level, because the benefit from matching the new fine level is not able to offset the infinite cost of moving. Then, any adjustment cost in between, i.e., $0 < k/g < \infty$ results in pollution slowly shifting toward the new steady state, and the transition becomes slower as k increases.

Figure 6: Identification of Relative Marginal Adjustment Cost k/g



Note: The figure plots the transition paths of realized pollution following a board change under different adjustment costs.

To sum up, when considering a thought experiment in which a board transition occurs once and the new board is expected to stay indefinitely (and the facility has enough time to adjust), g determines the difference between the starting and the converging pollution levels, and k/g determines the rate of convergence. That is, transition paths of pollution following board turnover identify g and k/g, which mirrors the evidence in Figure 4.

In practice, however, enforcement regimes change frequently due to repeated board turnover. Pollution often may not fully converge before the next regulatory change. In such settings, pollution levels may reflect both current fines and incomplete adjustment from past boards, making the pollution level informative about both g and k/g. Even in this case, the adjustment speed remains uniquely determined by k/g. In Section 5.3, I construct moments for GMM estimation based on the dynamic responses to board changes.

5.3 Estimation

I estimate the model in two steps. In the first step, I estimate the board preference parameters Θ^{Board} using OLS and the violation-level ACL enforcement data. In the second step, I use the estimated board preferences and the model prediction of average number of violations in Equation (15) to estimate the facility profit parameters Θ^{Firm} using GMM and the compliance data.

5.3.1 Board Preference Parameters

From Equation (11), the observed fine can be written as

$$\tilde{u}_{\ell t} = \theta_\ell \prod_{m \in \mathcal{M}_{\ell t}} (\alpha_m \omega_m)^{\frac{1}{M_{\ell t}}} \tilde{\varepsilon}_{i\ell t},$$

where $M_{\ell t} = |\mathcal{M}_{\ell t}|$ is the number of active members on the board. Arranging the terms gives

$$\tilde{u}_{\ell t} = \theta_\ell \alpha^{\text{R}} \left(\frac{\alpha^{\text{D}}}{\alpha^{\text{R}}} \right)^{s_{\ell t}} \prod_{m \in \mathcal{M}_{\ell t}} \omega_m^{\frac{1}{M_{\ell t}}},$$

where $s_{\ell t}$ is the share of Democratic-appointed members on the board.

Taking a log transformation results in log fine being linear in regional and board composition:

$$\log(\tilde{u}_{i\ell t}) = \log\left(\alpha^{\text{R}} \theta_\ell\right) + \log\left(\frac{\alpha^{\text{D}}}{\alpha^{\text{R}}} \right) s_{\ell t} + \frac{1}{M_{\ell t}} \sum_{m \in \mathcal{M}_{\ell t}} \log \omega_m + \varepsilon_{i\ell t}, \tag{16}$$

where $\varepsilon_{i\ell t} = \log(\tilde{\varepsilon}_{i\ell t})$. This also suggests the following violation-level OLS regression:

$$\log(\tilde{u}_{i\ell t}) = \sum_{\ell' \in L} \log\left(\alpha^{\mathrm{R}}\theta_\ell\right) \mathbb{1}\left\{\ell = \ell'\right\} + \log\left(\frac{\alpha^{\mathrm{D}}}{\alpha^{\mathrm{R}}}\right) s_{\ell t} + \sum_{m \in \mathcal{M}} \log \omega_m \frac{1}{M_{\ell t}} \mathbb{1}\left\{m \in \mathcal{M}_{\ell t}\right\} + \varepsilon_{i\ell t}. \tag{17}$$

Here, $\tilde{u}_{i\ell t}$ is the average penalty amount per nonexempt MMP violation for violation i in region ℓ enforced at quarter t, $\mathbb{1}\left\{\ell = \ell'\right\}$ is the region dummy, $\mathcal{M}$ is the set of all members in the data, and $\frac{1}{M_{\ell t}}\mathbb{1}\left\{m \in \mathcal{M}_{\ell t}\right\}$ is the member dummy scaled by the inverse of the board size.

Instead of directly estimating Equation (17) using one OLS regression, I estimate the parameters by running two OLS regressions sequentially.[33] First, I regress log-transformed fine amount $\log(\tilde{u}_{i\ell t})$ on scaled member dummies $\frac{1}{M_{\ell t}}\mathbb{1}\left\{m \in \mathcal{M}_{\ell t}\right\}$ and obtain an estimate for each member. The estimate for member m represents their contribution to the average fine amount inclusive of the regional damage and party preference. Second, I regress these member estimates on region dummies and the Democrat dummy, to capture the mean contribution in a region or party, and obtain estimates for $\log\left(\alpha^{\mathrm{R}}\theta_\ell\right)$ and $\log\left(\frac{\alpha^{\mathrm{D}}}{\alpha^{\mathrm{R}}}\right)$. The residuals from the second regression then become the estimates for $\log \omega_m$, which captures the individual contribution to fine amount, net of region or party influence.

Additionally, I impose two assumptions on members' terms to obtain an estimate for each of the members. Since some of the dummies of members in a region are identical or linearly dependent, depending on the combinations and timings of their terms,[34] without imposing assumptions or restrictions, one or more member dummies need to be dropped from the regression. I assume that for members whose dummies are identical (i.e., always on the board together in all fine observations), they have the same preference which is the average of the combined preference. For members whose dummies are linearly dependent, I assume that for any minimal linearly dependent set of members,[35] the very first fine of that set is only attributed to the earliest member;[36] that is, later members have no or

[33]Since members do not move between regions, directly estimate Equation (17) in one regression would require one of the region dummies or member dummies to be dropped from the regression to avoid colinearity. The second step of the estimation requires an estimate for each region and member to construct aggregate board preferences, so I separately run two regressions to avoid any parameter from being dropped and at the same time, still capture the average contribution of each component.

[34]For example, member A and member B are always together on the board during the same enforcement observations and are never separately observed, so there is no enough variation to separate the two members' contributions. Similarly, when only two unique combinations of three members are observed with enforcement outcomes, the variation is not enough for three separate parameters of the three members.

[35]I define a minimal linearly dependent set of members to be a set where the members' dummies are linearly dependent and if any combination of the dummies of a proper subset of the members is linearly independent.

[36]If there are members appointed at the same time, I assume the first fine is attributed to the one with a longer term.

negligible effects on the very first fine assessment. I repeat the operation until there is no linearly dependent set and all member dummies can be estimated.

Once I obtained the OLS estimates of $\log(\alpha^{\mathrm{R}}\theta_\ell)$, $\log(\frac{\alpha^{\mathrm{D}}}{\alpha^{\mathrm{R}}})$, and $\log\omega_m$, I take exponential transformation to obtain estimates for the following combinations of the board parameters: $\tilde{\Theta}^{\text{Board}} = (\alpha^{\mathrm{R}}\theta_\ell, \frac{\alpha^{\mathrm{D}}}{\alpha^{\mathrm{R}}}, \omega_m)'$.[37]

5.3.2 Facility Profit Parameters

With combinations of the board preference parameters estimated in the first step, I next estimate the facility profit parameters Θ^{Firm}. Given the estimated combinations of board preference parameters $\hat{\tilde{\Theta}}^{\text{Board}}$, observed board composition $\mathbf{X}_{\ell t}$, and information set $\mathcal{I}_{\ell t}$, I construct the current fines and the expected future fines as

$$\hat{\tilde{\theta}}_{\ell t} = \tilde{\theta}(\mathbf{X}_{\ell t}; \hat{\tilde{\Theta}}^{\text{Board}}) \quad \text{and} \quad \mathbb{E}_t[\hat{\tilde{\theta}}_{\ell t+\iota}] = \tilde{\theta}(\mathbb{E}\left[\mathbf{X}_{\ell t+\iota}|\mathcal{I}_{\ell t}\right]; \hat{\tilde{\Theta}}^{\text{Board}}).$$

The information set $\mathcal{I}_{\ell t}$ includes number of members $M_{\ell t}$, term index and party affiliation of each of the member on the board, term index and party affiliation of the governor, and the perceived probability of a Republican candidate winning a gubernatorial election r. I set r to be the long-run share of Republican governors in California (over 50 years): $r = 0.46$. (See Section A.4 for details in the derivation of expected board composition.)

I aggregate the facility-quarter compliance panel into region-quarter observations by taking average of the number of violations, inclusive of facilities in compliance (i.e., zero violations):

$$\bar{V}_{\ell t} = \frac{1}{N_{\ell t}} \sum_{i=1}^{N_{\ell t}} v_{i\ell t},$$

where $v_{i\ell t}$ is the number of violations at facility i in region ℓ, quarter t. I take the average violation in a region in the first quarter of the sample period to be the initial violation for that region: $\bar{V}_{\ell 0}$.

For each $t \geq 1$, I estimate $V^*_{\ell t-1}$ by the sample analogue of the mean of $V_{\ell t-1}$ in data: $\hat{V}_{\ell t-1} = \bar{V}_{\ell t-1} = \frac{1}{N_{\ell t-1}} \sum_{i=1}^{N_{\ell t-1}} v_{i\ell t-1}$. Using the constructed fines and $\bar{V}_{\ell t-1}$, Equation (15) generates the model prediction for the average number of violations in region ℓ at t:

$$\hat{V}_{\ell t} = \phi_{-1}\bar{V}_{\ell t-1} + \phi_0 \frac{g_0 - \hat{\tilde{\theta}}_{\ell t}}{g} + \sum_{\iota=1}^{\tilde{T}'-t} \phi_\iota \frac{g_0 - \mathbb{E}_t[\hat{\tilde{\theta}}_{\ell t+\iota}]}{g}. \tag{18}$$

Based on the identification idea in Section 5.2, I construct three moment conditions to

[37] Note that I can only obtain combinations of the board parameters Θ^{Board}. These combinations suffice for the second-step estimation. However, for counterfactual analyses in Section 6.2, I need to impose an additional assumption on the relative location of α's and the truth in order to separate θ_ℓ and α's.

identify $\Theta^{\text{Firm}} = (k/g, g, g_0)'$. For each board transition from board $b-1$ to b, I measure the normalized change in violations (to per-unit change in board preferences) between the last quarter of the previous board and quarter q of the new board:

$$\gamma_{\ell b,q} = \frac{V_{\ell b,q} - V_{\ell b-1,Q_{b-1}}}{\tilde{\theta}_b - \tilde{\theta}_{b-1}},$$

where Q_{b-1} denotes the final quarter of board $b-1$. Let $\hat{\gamma}_{\ell b,q}$ denote the model-predicted counterpart generated from Equation (18). I define the moment conditions as

$$\mathbb{E}\begin{bmatrix} \gamma_{\ell b,4} - \hat{\gamma}_{\ell b,4} \\ \\ \frac{\gamma_{\ell b,4}}{\gamma_{\ell b,2}} - \frac{\hat{\gamma}_{\ell b,4}}{\hat{\gamma}_{\ell b,2}} \\ \\ V_{\ell t} - \hat{V}_{\ell t} \end{bmatrix} = 0.$$

The first moment corresponds to the normalized level of change in violations one year after a board change, and the second moment corresponds to the speed of the change, which is approximated by the rate at which violation change grows in one year versus six months. These two moment conditions characterize the transition path of facility response in violations to board turnover and identify k/g and g. The last moment regards the average number of violations in each region, quarter and identifies the intercept parameter g_0.

I estimate $(k/g, g, g_0)$ using GMM by minimizing the empirical analog of the moment conditions, weighting each moment by the inverse of its empirical standard deviation. I calculate bootstrap standard errors of the estimates by resampling the ACL enforcement data at the board level and resampling the violation data at the facility level.

6 Results

This section presents the estimation results and counterfactual analyses. Section 6.1 reports estimates of the two sets of model parameters: the board preference parameters and the facility profit parameters. Section 6.2 uses these estimates to quantify welfare consequences of regulatory variability and decompose them into components due to adjustment frictions and uncertainty over future regulators. Section 6.3 explores how alternative board appointment structures affect welfare implications.

6.1 Estimation Results

Table 4 reports the estimated model parameters along with the 95% bootstrapped confidence intervals. I begin with the first-stage OLS estimates of the combinations of board preference parameters. The estimated Republican-preferred marginal damage ($\alpha^{\mathrm{R}}\theta_\ell$) ranges from \$299.72 per violation in the North Coast Region to \$2,571.01 per violation in the Central Valley Region. The substantial spatial heterogeneity reflects the localized nature of water pollution damages.

Table 4: Parameter Estimates

Model Component	Parameter	Estimate	95% Confidence Interval
Board Preference			
Relative Democratic Preference	$\alpha^{\mathrm{D}}/\alpha^{\mathrm{R}}$	1.65	(1.37, 1.88)
Republican-Preferred Marginal Damage:			
Region 1: North Coast	$\alpha^{\mathrm{R}}\theta_1$	299.72	(228.99, 403.56)
Region 2: San Francisco Bay	$\alpha^{\mathrm{R}}\theta_2$	2,152.82	(1,818.06, 2,645.36)
Region 3: Central Coast	$\alpha^{\mathrm{R}}\theta_3$	305.99	(200.67, 415.07)
Region 4: Los Angeles	$\alpha^{\mathrm{R}}\theta_4$	2,179.19	(1,995.68, 2,435.07)
Region 5: Central Valley	$\alpha^{\mathrm{R}}\theta_5$	2,571.01	(2,308.89, 2,863.85)
Region 7: Colorado River Basin	$\alpha^{\mathrm{R}}\theta_7$	2,245.85	(1,867.60, 2,801.60)
Region 8: Santa Ana	$\alpha^{\mathrm{R}}\theta_8$	1,600.89	(1,125.74, 1,543.98)
Region 9: San Diego	$\alpha^{\mathrm{R}}\theta_9$	1,548.06	(1,381.35, 1,775.37)
Facility Profit			
Relative Adjustment Cost	k/g	3.51	(1.03, 13.25)
Marginal Benefit of Pollution (Slope)	g	4,439.46	(2,683.26, 16,368.87)
Maringal Benefit of Pollution (Intercept)	g_0	9,360.10	(7,453.21, 18,511.71)

Notes: The table reports the board preference estimates from the OLS Regression (17) and the facility profit estimates from GMM. The 95% confidence intervals are calculated based on bootstrap estimates with resampling enforcement data at the board level and compliance data at the facility level.

I also find systematic differences in enforcement preferences by political appointment. The estimated relative Democratic preference to Republican ($\frac{\alpha^{\mathrm{D}}}{\alpha^{\mathrm{R}}}$) is 1.65: meaning that, on average, Democratic-appointed members prefer marginal damages 65% higher than Republican-appointed members. In addition, there is large heterogeneity across individual members (ω_m), even within party. A member in the highest tertile imposes a penalty that is 6.65 times the penalty imposed by a member in the lowest tertile, indicating substantial within-party variation in enforcement preferences.

Turning to the second-stage GMM estimates, Table 4 shows that the relative adjustment cost parameter, which is estimated as the ratio of the slope of marginal adjustment cost to the slope of marginal benefit of pollution k/g, is 3.51. This implies that the marginal adjustment cost increases 3.51 times faster than the marginal benefit decreases. Regarding the implied weights in the optimal pollution choice, it suggests that facilities place 60% weight (ϕ_{-1}) on past pollution, 17% (ϕ_0) on current fines, and 23% ($\sum_{\iota=1}^{\tilde{T}'-t} \phi_\iota$) on expected future fines when choosing current pollution levels. The large weight on past behaviors indicates substantial adjustment frictions and past dependence in pollution decisions.

Moreover, the slope estimate of the marginal benefit (g) implies that the marginal benefit of pollution decreases by \$4,439.46 per additional violation, which is slightly above the current MMP of \$3,000. The intercept estimate (g_0) implies that achieving full compliance on average would require a fine of \$9,360.10 per violation, which is more than three times the current MMP. These estimates jointly imply that in the absence of fines, facilities would generate 2.11 violations on average per region-quarter, which is almost twice the observed average in the data. Lastly, the implied marginal adjustment cost increases at a rate of \$15,563.73 per additional violation difference (k). I also test robustness of the facility parameter estimates with respect to different assumed values for the perceived probability of Republican winning in Section A.5.

Table 5 reports model fit for the three targeted moments explicitly used in GMM estimation. The model closely matches the moments on the latter two moments.

Table 5: Model Fit

Moment	Data	Model
Violation Change in 1 Year	0.028	0.009
Ratio of Violation Changes in 1 Year to 6 Months	1.494	1.284
Average Number of Violations	1.160	1.160

Note: The table reports the targeted moments in the data and their predictions by the model.

6.2 Welfare Implications and Decomposition

Using the estimated model parameters from Table 4, I quantify the welfare consequences of regulatory variability and decompose welfare loss into two channels: adjustment frictions and uncertainty about future regulators. Welfare is defined relative to the first-best benchmark introduced in Section 4.3. I begin by illustrating welfare decomposition in a simplified scenario of one-time political turnover (Section 6.2.1), and then implement the same decomposition using actual historical board turnover in the data (Section 6.2.2).

To define welfare loss components, I impose a normalization assumption on partisan preferences relative to the first-best. I assume that Democratic and Republican preferences lie symmetrically around the first-best, so that

$$\frac{\alpha^{\mathrm{D}} + \alpha^{\mathrm{R}}}{2} = 1.$$

This assumption allows me to separately identify θ_ℓ, α^{D}, and α^{R} from the estimated combinations. Under this normalization, I obtain $\alpha^{\mathrm{D}} = 1.24$ and $\alpha^{\mathrm{R}} = 0.76$. This implies that Democratic-appointed members prefer marginal damages (or fines) 24% above the true marginal damages (or first-best fines), while Republican-appointed members prefer marginal damages 24% below the true marginal damages.[38]

6.2.1 One-time Political Turnover

To build intuition for welfare decomposition, I begin with a simplified political transition designed to isolate the role of adjustment frictions and regulatory uncertainty. Suppose all regions initially have boards composed of average Republican-appointed members who impose a fine of $\alpha^{\mathrm{R}}\theta_\ell$. A one-time gubernatorial election is announced at the start of quarter 1 and held at the end of quarter 4. Starting in quarter 5, the entire board is replaced by mean members appointed from the winning governor's party.[39] I use the estimated model to simulate realized fines, expected fines, and facility violations.

To shed lights on how the two channels—adjustment frictions and regulatory uncertainty—affect welfare, I run simulations under three scenarios: (i) *free adjustment scenario* where adjustment cost is set to zero ($k = 0$),[40] (ii) *full information scenario* where adjustment cost is as estimated ($k = \hat{k}$ in Table 4) but facilities have perfect foresight about future boards, and (iii) *baseline scenario* where adjustment cost is as estimated ($k = \hat{k}$ in Table 4) and facilities are uncertain about future boards and need to form expectations. In this one-time turnover exercise, the only source of uncertainty is the election result; that is, under *full information*, facilities are fully informed of the election outcome starting

[38] Section A.6 reports results under two alternative assumptions: (1) Democratic preference equals the first-best and (2) Republican preference equals the first-best. These alternative assumptions yield similar qualitative conclusions.

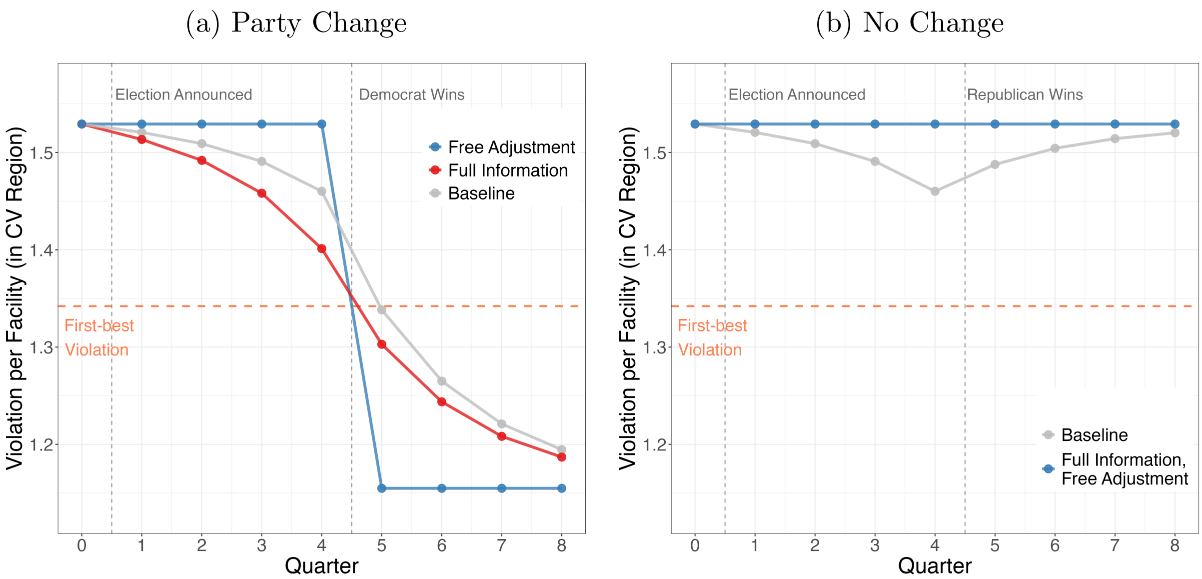
[39] This abstracts away from idiosyncratic member preferences in order to focus on political changes.

[40] The assumption about expectations is not relevant in this scenario because when adjustment is free, facilities only optimize pollution based on current fines alone and the future no longer matters to the current decision.

from quarter 1 and under *baseline*, facilities form expectations using r, i.e., the probability that a Republican candidate wins the election.

Figure 7a and 7b show the simulated violation paths in the Central Valley region under the outcomes of Democratic governor winning and Republican governor winning the election. Consider the former case where Democratic governor wins the election. The incoming Democratic board raises fines from $\alpha^{\mathrm{R}}\theta_\ell$ to $\alpha^{\mathrm{D}}\theta_\ell$ beginning in quarter 5. Under *free adjustment*, facility violations respond immediately and drop to the Democratic steady-state violation level in quarter 5. Once adjustment frictions are added in, under *full information scenario*, violations adjust gradually downward and may not reach the Republican level of violations soon due to adjustment costs. Under *baseline*, uncertainty about the future board leads to a slower and less smooth adjustment: facilities only partially anticipate Democratic enforcement prior to the election and fully update only once uncertainty is resolved. The visible kink at quarter 5 reflects this discrete resolution of uncertainty.

Figure 7: Violation Paths under One-Time Political Turnover



Notes: The figure plots the simulated violation path in the Central Valley Region in the two potential cases of a one-time political turnover exercise. Panel (a) plots the case of party change (Democratic wins) and Panel (b) plots the case of no party change (Republican wins).

Now consider the case where Republican governor wins and the board remains unchanged (Figure 7b). The *free adjustment* and *full information* scenarios coincide: violations remain unchanged at the Republican level. However, under *baseline* scenario, uncertainty temporarily induces partially downward adjustments before the election, reflecting the positive possibility of a future Democratic board. Once the Republican winning outcome is revealed, violations gradually return to the initial level. This illustrates that uncertainty can induce unnecessary adjustments (and thus unnecessary adjustment costs), even when no political change occurs in the end.

I then discuss intuitions behind the welfare implications of these dynamics before showing the welfare results. As defined in Equation (9), political inefficiency arises from any mismatch in marginal private benefit and marginal damage of pollution aggregated over violation distortion. That is, the magnitude of political inefficiency is increasing in the distance between the realized violation and the first-best violation. Under *free adjustment*, violations fully respond to political changes, resulting in the largest violation distortion. In contrast, adjustment frictions constrain facilities' ability to flexibly respond to politics, stabilizing violations and limiting political inefficiency. Resolving uncertainty early further strengthens this stabilizing effect, by allowing violations to respond earlier, but only in the case of party change. On the other hand, the sum of adjustment cost (as defined in Equation (8)), is smaller as the changes in violations between periods are smoother. Thus, uncertainty over future regulators amplifies the adjustment cost by preventing smooth adjustments over time.

Figure 8a and Figure 8b reports the cumulative welfare loss over the first eight quarters.[41][42] In the case of party change (Figure 8a), fully responding to the political change under *free adjustment* results in large political inefficiency. Adjustment frictions increase adjustment cost but at the same time, greatly mitigate political inefficiency by stabilizing facility behaviors. Resolving uncertainty early further reduces political inefficiency as well as adjustment costs. On the other hand, in the case of no party change (Figure 8b), adjustment frictions alone do not constrain political influence on violations, but only when combined with uncertainty do they stabilize violations. Here, being uncertain about the future raises adjustment cost but reduces political inefficiency.

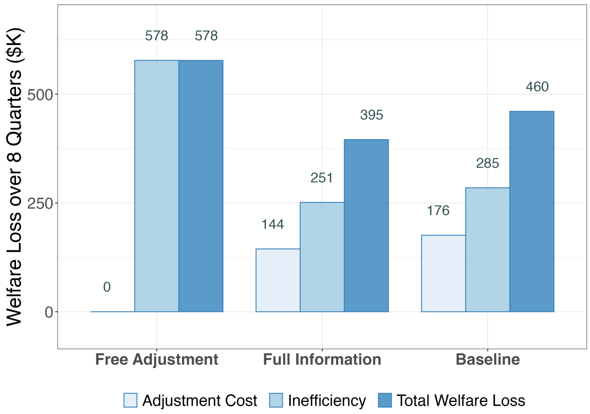
In the presence of adjustment frictions, uncertainty about future regulators complicates welfare in two ways: first, it prevents smooth adjustments across periods, increasing adjustment cost; second, it prevents early adjustments to the incoming regulators, changing political inefficiency. However, the effect of uncertainty on political efficiency is ambiguous and depends on the true state of regulations. To better interpret the effect of uncertainty on welfare, I consider the ex-ante welfare calculated prior to state realization using the probability r of Republican governor winning. As shown in Figure 8c, uncertainty increases adjustment cost but reduces political inefficiency.

[41] Welfare is aggregated over the first eight quarters for comparison, since differences between scenarios diminish over time as facilities eventually adjust. In the model, facilities make decisions with expectations up to 40 quarters.

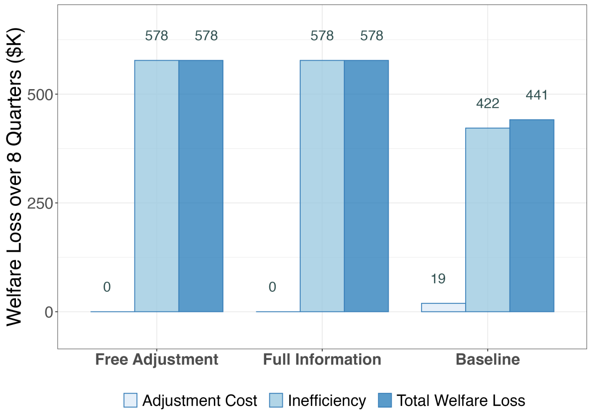
[42] The model predicts average violation in a region, quarter. I convert per-facility losses to regional totals by multiplying by the number of regulated facilities in that region as of Q1 2012.

Figure 8: Welfare Loss under One-Time Political Turnover

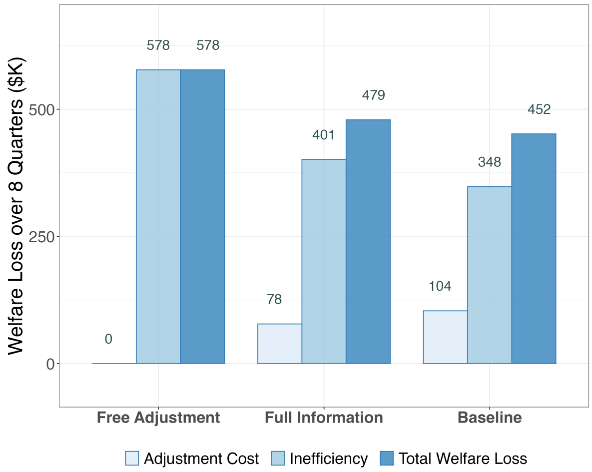
(a) Party Change



(b) No Change



(c) Ex-Ante



Notes: The figure plots the total welfare loss and its components under counterfactual scenarios: *free adjustment*, *full information*, and *baseline*. Panels (a) and (b) plot the welfare outcomes in the case of party change and no party change respectively. Panel (c) plots the ex-ante welfare outcomes, which is the weighted average of Panel (a) and Panel (b) with each weighted by $1 - r$ and r.

6.2.2 Sample Period 2001-2019

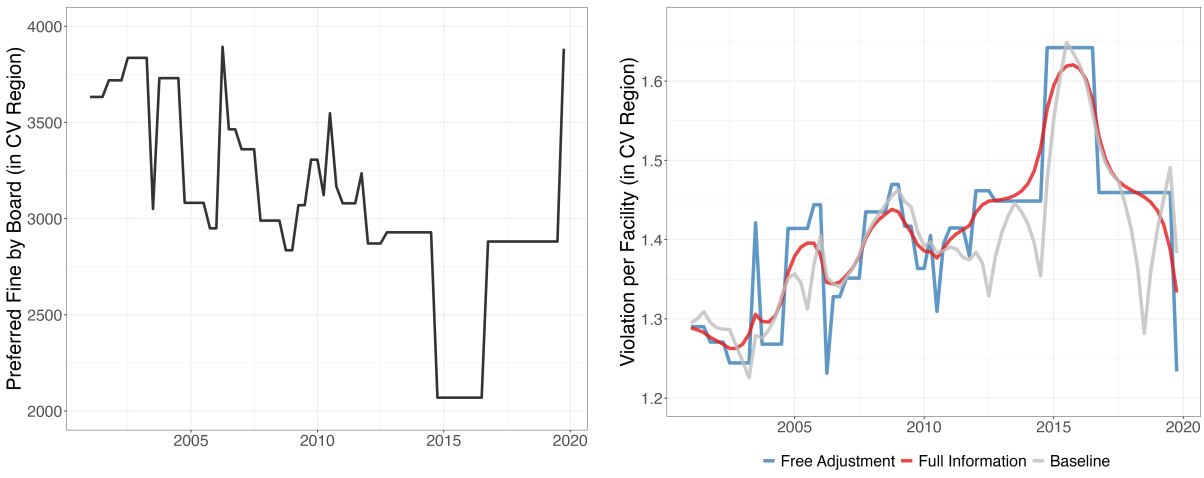
After illustrating welfare implications in a simplified one-time political turnover, I now quantify the same welfare decomposition using the actual, realized sequence of board turnover in California. Specifically, I use the realized governor party affiliations, regional board membership, and the estimated model parameters from Table 4 to predict fines and violations under the three counterfactual scenarios: *free adjustment*, *full information*, and *baseline scenarios*. Under *full information*, facilities perfectly foresee future fines. Under *baseline*, facilities form expectations using the belief structure described in Sections 5.3 and A.4.

I restrict the simulation samples to 2001-2019, using steady-state violations under the realized boards in the fourth quarter in 2000 as the initial violations. This avoids mechanically negative predicted violations, which can arise from extreme member-level fine estimates based on limited data.[43] I also exclude years after 2020 to avoid distortions from the COVID-19 pandemic, which coincided with a sharp decline in the number of regulated facilities–likely due to delayed renewals rather than actual facility exit.[44] Finally, I aggregate welfare measures across seven regions, excluding the North Coast Region, where frequent negative predictions make welfare comparison less reliable.

The simulated violation paths under the three scenarios share similar features as the one-time political turnover exercise. Figure 9a and 9b plot the predicted fines and violations for the Central Valley Region. In all scenarios, violations move inversely with fines. Under *free adjustment*, violations move in the exact opposite direction of the fines. In contrast, under *full information* and *baseline*, violations respond more gradually, as their responses are constrained by adjustment costs. Violations under *full information* follow a much smoother path, reflecting better smoothing across time when the future is fully anticipated. However, under *baseline*, violations sometimes move temporarily in the wrong direction due to incorrect expectations about future regulators.

Figure 9: Simulated Fines and Violations

(a) Fine (b) Violation



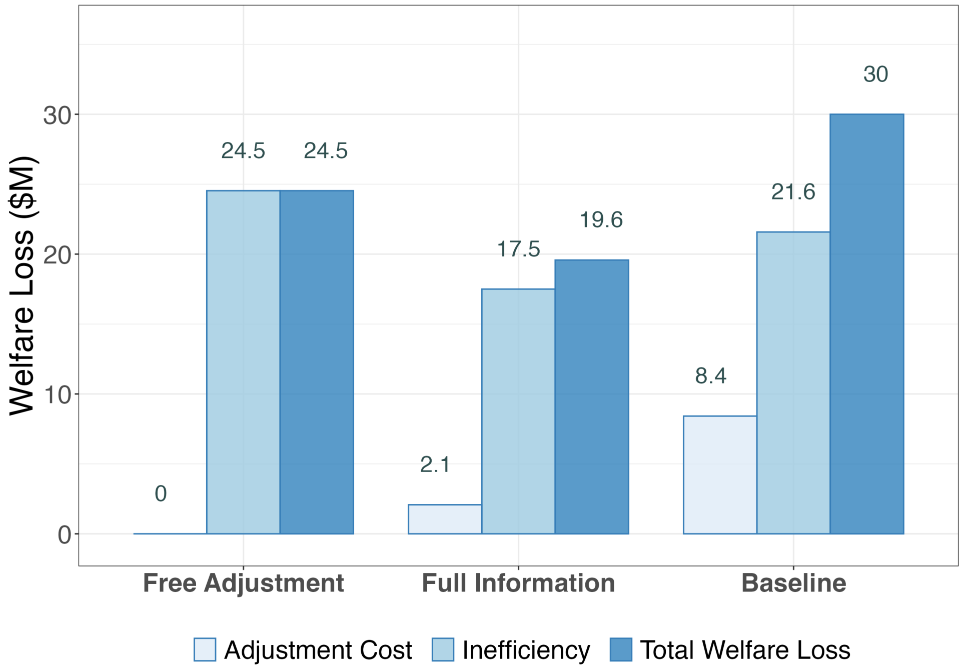
Note: The figure plots the simulated fine path and violation path in the Central Valley Region over 2001-2019, using the realized sequence of regional boards.

Figure 10 presents the aggregated welfare loss across seven regions over 2001-2019.

[43]Negative predicted violations artificially inflate political inefficiency because they imply deviations from the first-best that are not economically meaningful. They also generate implausibly large adjustment costs during transitions (between positive and negative values of violations). As pollution decision s can be past dependent, starting the simulation at a non-negative violation level ensures valid welfare comparisons across scenarios.

[44]A facility is defined as regulated in a quarter if it has an active permit during the quarter. The observed sharp decline in the number of active permits after 2020 likely reflects administrative delays instead of permanent closures.

Figure 10: Welfare Loss during 2001-2019



Note: The figure plots the total welfare loss and its components under counterfactual scenarios: *free adjustment*, *full information*, and *baseline*.

Overall, a varying regulatory environment produces a total welfare loss of \$30.00 million, equivalent to 33% of total penalty assessment in the same period. The total welfare loss is composed of \$8.42 million from adjustment costs borne by the regulated facilities and \$21.58 million from political inefficiency borne by the society. When adjustment frictions are removed, the adjustment cost disappears, but political inefficiency increases to \$24.53 million, as facilities fully respond to fine fluctuations. Maintaining frictions but resolving uncertainty reduces both sources of welfare loss: adjustment costs fall by 75% and political inefficiency falls by 19%, yielding an overall welfare gain of \$10.42 million.

Even though adjustment frictions impose additional costs on facilities, they stabilize violations and limit the loss from inefficient political or administrative changes. However, uncertainty about future regulators undermines this stabilizing role by causing facilities to delay or misdirect their adjustments, and further amplifies the adjustment costs. During the 2001-2019 period, the stabilizing benefits of adjustment frictions were substantial but not sufficient to offset the additional adjustment costs.

6.3 Alternative Board Appointment Structures

The magnitude and direction of adjustment frictions' welfare effects depend critically on three features of the regulatory environment: the magnitude, frequency, and predictability of regulator turnover. All of these features are shaped by the appointment structure of the boards. Thus, I examine how alternative board appointment structures—specifically, board member term lengths—affect the welfare cost of regulatory fluctuations.

I retain most of the institutional features observed in the data: each governor serves a four-year term, each regional board consists of seven members, and member terms are staggered. To isolate the effect of term length, I impose two simplifying assumptions: (i) no governor serves a second term, and (ii) no member is reappointed. These assumptions abstract from complicated expectation formation regarding potential reelection or reappointment.

Under these settings, shorter board member terms lead to more frequent and larger board changes year to year because more terms expire each year, leading to greater regulator variability and higher adjustment needs for facilities. In contrast, longer member terms make boards more stable over time, as fewer terms expire each year and turnover becomes less frequent, which also reduces uncertainty about future board composition. However, longer terms also increase the possibility that some extreme members remain on boards for extended periods, which can potentially amplify political inefficiency.

The current board member term length is four years. I compare welfare outcomes under this and two alternative term-length scenarios: two and eight years. In each simulation, I generate a sequence of governors drawn from a Bernoulli distribution with probability r of electing a Republican and for each region, a sequence of idiosyncratic member preferences drawn (with replacement) from the empirical distribution of estimated ω_m for that region.[45] Simulated members are appointed to the regional boards in a fixed order across scenarios. Each member's preference reflects both the appointing governor's party (which is determined by when the member is appointed to the board and the governor draw for that period) and their idiosyncratic preference draw. I take average of welfare outcomes over 100 simulations for each term-length scenario to account for variation in political and individual draws.[46]

Table 6 reports the average total welfare loss and its component under each term-length scenario. Among these three alternative term lengths, welfare improves with longer member term lengths: halving term lengths from four to two years increases total welfare loss by 23% , while doubling term lengths from four to eight years reduces total welfare loss by 45%. These welfare differences primarily reflect differences in the frequency of board turnover and preference volatility. When board members have longer

[45] In each simulation, the same simulated sequences of governors and idiosyncratic member preferences in each region are used across the three scenarios. However, because longer terms require fewer total members to fill positions over time, the number of simulated members used decreases with member term lengths.

[46] Averaging over simulations allows the average welfare comparison to incorporate disutility from the variance of draws. This is relevant for policy implications because appointment structures can influence the expected variance of future welfare outcomes.

Table 6: Counterfactual Analyses: Alternative Board Member Term Lengths

	2 Years (1)	4 Years (2)	8 Years (3)
Adjustment Cost (Billion $)	95.212	53.118	13.824
Political Inefficiency (Billion $)	196.862	183.462	117.342
Total Welfare Loss (Billion $)	292.074	236.581	131.166
Share of Adjustment Cost in Total Loss	0.326	0.225	0.105

Notes: The table reports the total welfare loss and its components under counterfactual scenarios with alternative board member term lengths. The last row reports the ratio of adjustment cost to total loss in each scenario.

terms, facilities adjust less frequently as well as adjust to smaller regulatory changes, reducing both adjustment costs and variance in inefficient board preferences.

The trade-off between shorter versus longer terms can be seen in the share of adjustment cost of total welfare loss: the portion of total loss due to adjustment cost declines from 32% under two-year terms to 11% under eight-year terms. Thus, as boards become more stable, adjustment frictions matter less for welfare, and political inefficiency becomes the dominant source of welfare loss.[47]

7 Conclusion

In this paper, I quantify the welfare cost of regulatory fluctuations induced by political and administrative turnover. I find that these fluctuations impose substantial social costs—equivalent to nearly one-third of total fine assessments between 2001 and 2019. Using detailed data on compliance, enforcement, and board composition in California's water regulations, I identify and estimate sizable adjustment frictions in facilities' pollution abatement decisions.

Using the estimated model, I show that while these frictions impose additional costs on regulated facilities, they also partially insulate pollution outcomes from inefficient regulatory swings. By stabilizing abatement outcomes, these frictions mitigate welfare loss that would otherwise arise from political variability. However, uncertainty about future regulators weakens this stabilizing role and amplifies adjustment costs. Counterfactual simulations suggest that institutional stability matters: doubling board member term

[47]This also suggests that, as term lengths increase (beyond eight years), the political inefficiency component of welfare loss may continue to grow and eventually outweigh the benefits of board stability at some point.

lengths to eight years reduces welfare losses by 44%.

The analysis has several limitations. First, the estimated adjustment frictions are an aggregation across potentially heterogeneous facilities and adjustment processes. Due to limited data on facility characteristics, the model is set up to characterize a representative facility within each region. As most of the regulated facilities in this context are wastewater treatment plants, the simplification may be reasonable. However, future work could extend and estimate the model to incorporate richer heterogeneity in facilities' profits or adjustments.

Second, the quantified adjustment costs represent the overall cost and potentially aggregate from a wide range of adjustment actions and procedures. Without data on specific operational or maintenance actions, it is difficult to model or separate different types of adjustments. Future research could use more granular operational data to investigate the source of frictions and inform policies that target the exact causes of the frictions.

Finally, the measure of political links of enforcement intensity relies on the party affiliation of the first appointing governors. Additional information on board members' political ideology, network, or professional background would enable a more precise mapping between politics and regulator behaviors, which could then inform policies on the board selection processes.

Despite these limitations, the paper reveals an understudied dimension of regulatory burden—adjustment frictions—and demonstrates their dual role: they create private costs yet also mitigate inefficiencies from regulatory instability. The paper highlights the broader relevance of adjustment frictions amid rising political instability and polarization, and the results underscore the value of institutional stability in regulatory design. These mechanisms and insights extend to many other regulatory settings characterized by changing regulations or enforcement discretion, including trade policy, financial regulation, workplace safety, and many other environmental policies.

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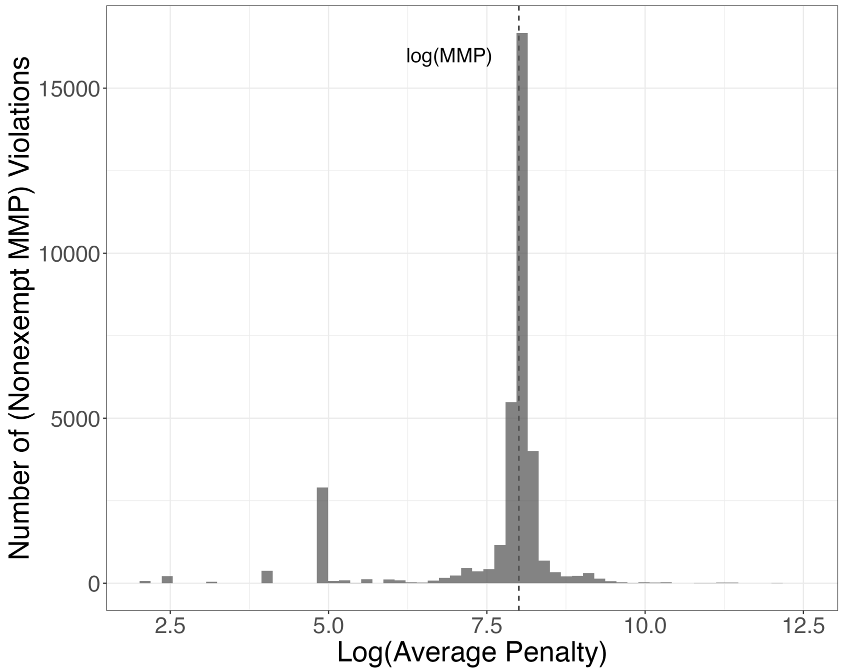
A Appendix

A.1 Additional Descriptive Statistics

This section presents additional descriptive statistics and the results of the reduced-form analysis discussed in Section 3. Figure A1 shows the variation in average penalty per nonexempt MMP violation at violation level. While a majority of violations have penalty equal to MMP, there are violations on both sides of the MMP.

Figure A1: Average Penalty per Violation



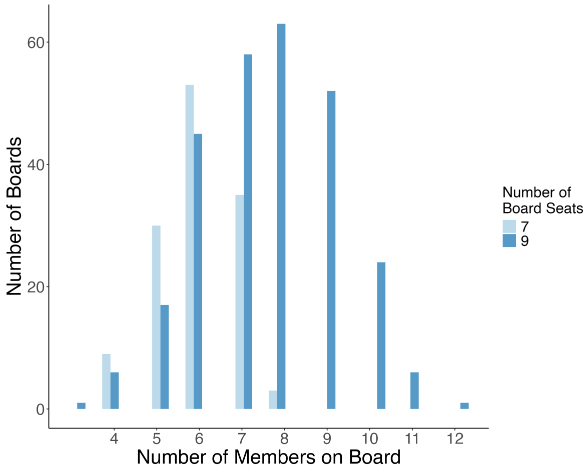
Notes: This figure plots the histogram of average ACL penalty amount per nonexempt MMP violation at the violation level. The vertical, dashed line represents the log MMP.

Figure A2a and A2b show descriptive statistics for regional boards. As seen in Figure A2a, there are often vacancies on regional boards due to delay in appointment. There are also boards with more members than designated, often in the earlier periods, which is likely resulted from delayed updates in membership records. Figure A2b then shows the number of boards (i.e., unique combination of board members) a board member ever served in the sample period. On average, a member serves 9.8 boards, reflecting frequent board turnover and large variation in member composition.

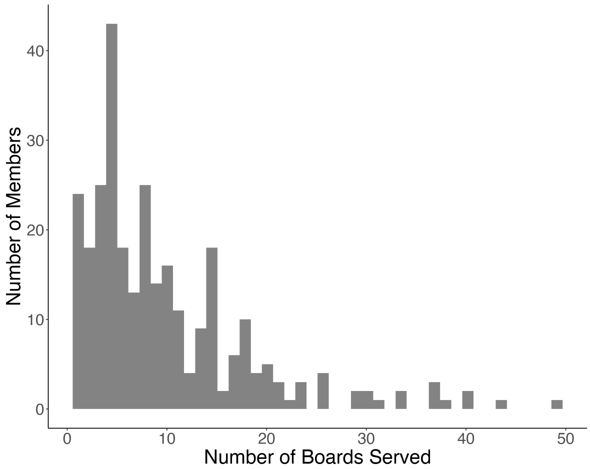
Figure A3 shows the number of continuous quarters served by boards. As member terms are staggered across years, a regular board is supposed to serve one year in in the absence of off-cycle exit or appointment as well as reappointment of members. The large variation in the number of quarters served reflects frequent off-cycle turnover and

Figure A2: Regional Board Turnover

(a) Number of Board Members per Board

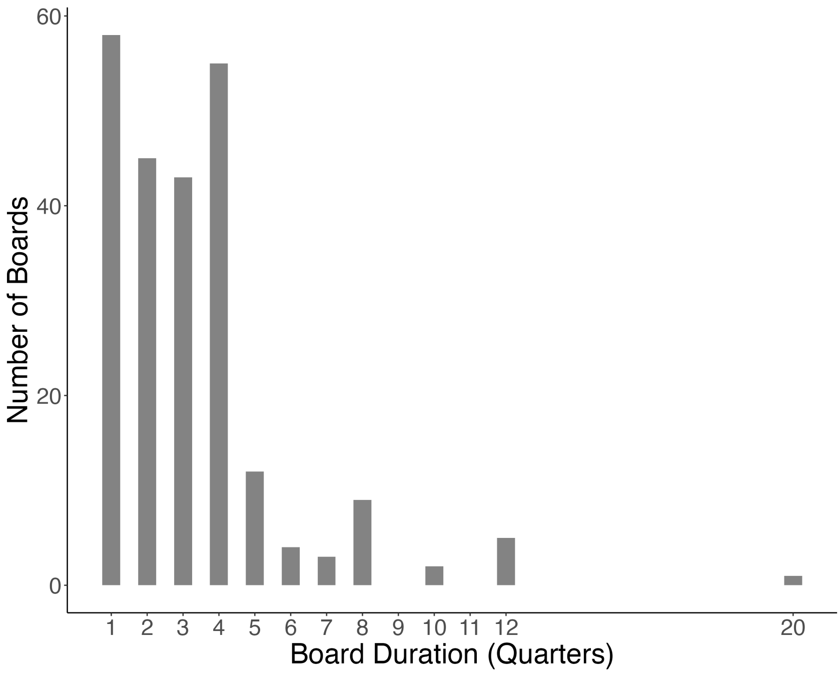


(b) Number of Boards Served per Member



Notes: The figure plots the number of board members per board and the number of board served by board members. In both Panel (a) and (b), boards are defined by unique member composition.

Figure A3: Lengths of Regional Boards

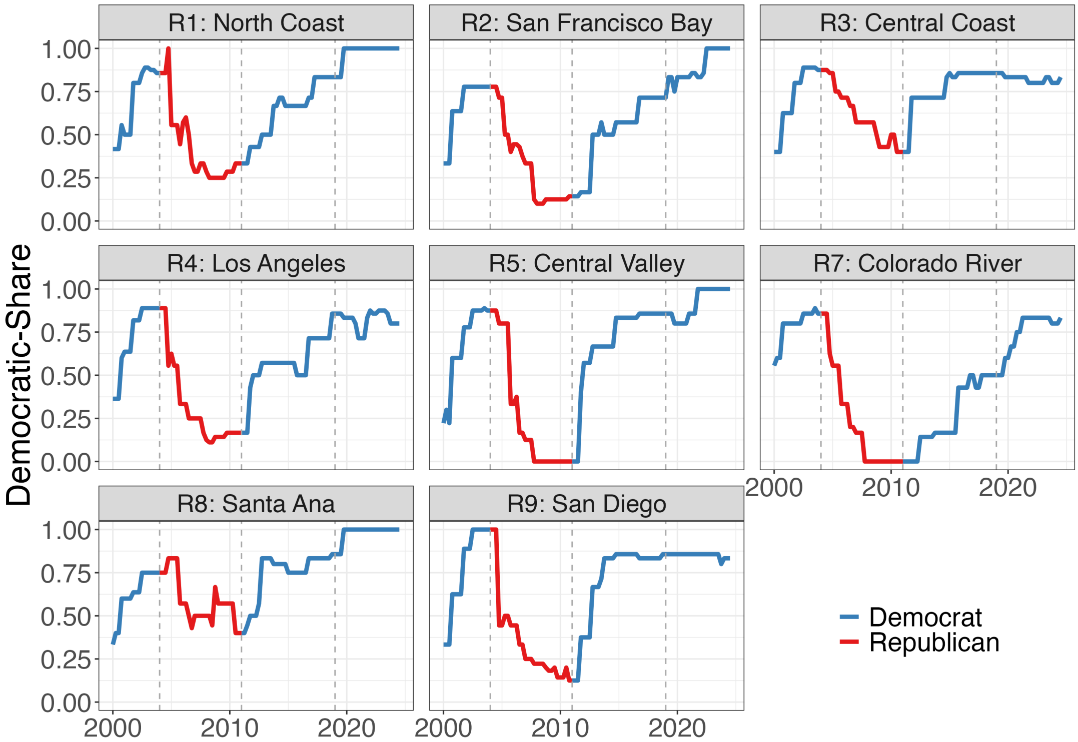


Notes: The figure plots the histogram of the number of quarter served at the board level. Here, board is defined by unique member composition

reappointment, and thus similarly, rich variation in member composition.

Figure A4 then shows the share of Democratic-appointed members on each regional board over time. While the fluctuations roughly follow the party switch of governors, the level of Democratic share and magnitude of the swing vary across regions. These differences can come from different board sizes, different numbers of vacancies to appoint, or appointing or reappointing members from different parties.[48]

Figure A4: Share of Democratic-Appointed Members



Notes: The figure plots the number of board members per board and the number of board served by board members. In both Panel (a) and (b), boards are defined by unique member composition.

A.2 Additional Empirical Evidence of Adjustment Frictions

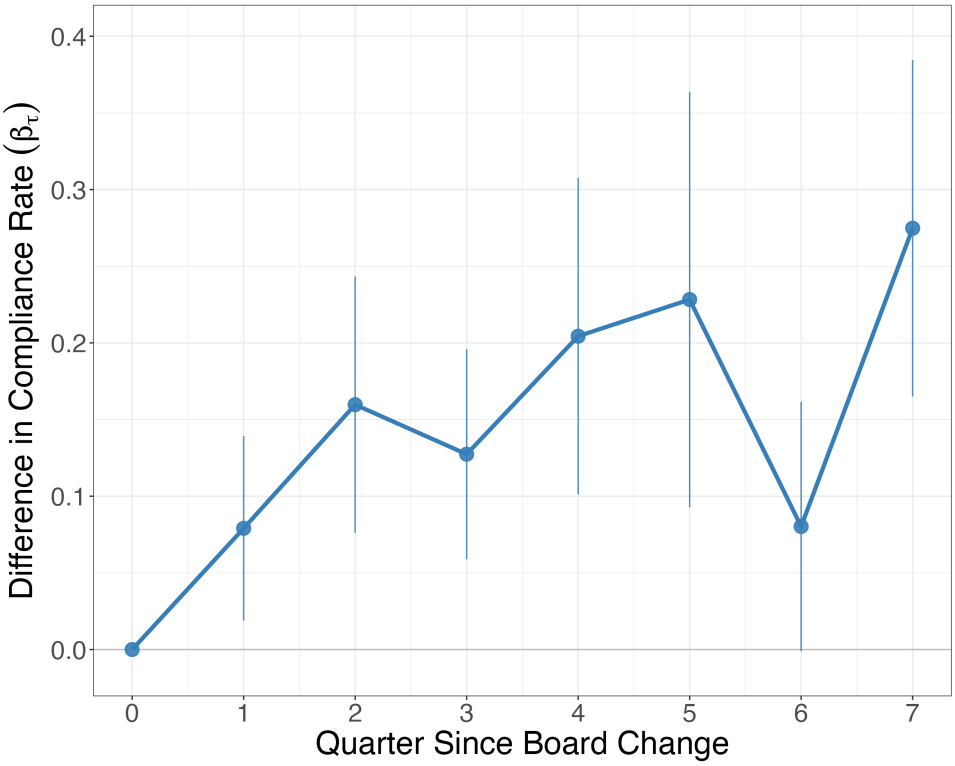
A.2.1 Compliance Rate as Outcome

Figure A5 plots the estimated β_τ from Regression (2), using compliance rate as the outcome variable. Similar to Figure 4, facilities respond gradually to board transitions: compliance increases gradually over the term of the new board after the board switches to a one-unit more stringent board. The average increase in compliance rate is 0.29 standard deviation after a one standard deviation increase of ΔStringency. Since member

[48]Member idiosyncratic preferences ω_m allow for the possibility that a governor may choose to reappoint a member from a different party. For example, a Democratic governor may reappoint a Republican-appointed member because the member has an idiosyncratic preference that is very close to Democratic preferences.

terms expire every four quarters, the drop in the seventh quarter likely reflects facilities' expectation that the board is likely to change and a less stringent board may come in.

Figure A5: Compliance Changes after Board Transitions Over Time



Notes: The figure plots the estimates and 95% confidence intervals of β_τ for $\tau \leq 7$ from Regression (2) where the outcome variable is average compliance rate. β_τ captures the difference in compliance rates from quarter 1 for each unit increase in board stringency.

A.2.2 Pre-Trend Analysis

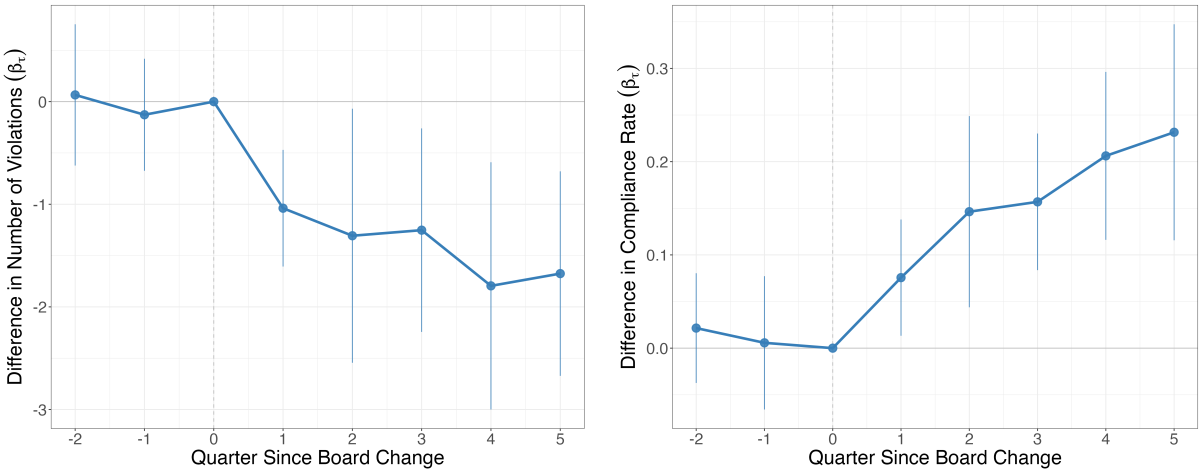
Figure A6 shows the regression estimates of Regression (2) when both pre-turnover periods and post-turnover periods are included (see Figure A6a for the number of violations and Figure A6b for the compliance rate as the outcome variable). Since the events of board turnovers recur over time, the pre-turnover periods of a given turnover mechanically overlap with the post-turnover periods of the previous board. To avoid overlapping event windows, I assign the last two post-periods of the previous board to the two pre-periods for a given board turnover.

Estimation results from the modified specification indicate no statistically significant differential pre-trends prior to board transition for either compliance outcome, whether measured by the number of violations or by the compliance rate. Moreover, the estimated post-turnover responses are similar to those in the baseline specifications shown in Figures 4 and A5.

In light of this lack of evidence for detectable pre-trends, the baseline specifications abstract from pre-turnover periods in order to characterize how facilities' compliance responses to board transitions evolve over time across as many post-turnover periods as possible.

Figure A6: Pre-Trends in Facility Response to Board Transitions

(a) Violation Changes (b) Compliance Changes



Notes: The figure plots the estimates and 95% confidence intervals of β_τ for $\tau \geq -2$ and $\tau \leq 5$ from a regression similar to Regression (2), where the last two post-periods of the previous board are defined as the two pre-periods of a given board turnover. Panels (a) and (b) show the estimates for the outcome variable of number of violations and compliance rate respectively.

A.2.3 Heterogeneity Analysis

To explore heterogeneity in facility response with respect to the direction of board stringency change, i.e., increasing pollution when stringency decreases versus decreasing pollution when stringency increases, I consider the following regression:

$$\begin{aligned} Y_{\ell t} =& \beta \Delta \text{Stringency}_{b(\ell t)} + \gamma_0 Inc_{b(\ell t)} + \gamma \Delta \text{Stringency}_{b(\ell t)} \cdot Inc_{b(\ell t)} + \sum_{\tau=1}^{19} \alpha_\tau d_{\tau,\ell t} + \\ & \sum_{\tau=1}^{11} \beta_\tau d_{\tau,\ell t} \cdot \Delta \text{Stringency}_{b(\ell t)} + \sum_{\tau=1}^{11} \gamma_\tau d_{\tau,\ell t} \cdot \Delta \text{Stringency}_{b(\ell t)} \cdot Inc_{b(\ell t)} + FE_\ell + FE_t + \eta_{\ell t}, \end{aligned} \tag{19}$$

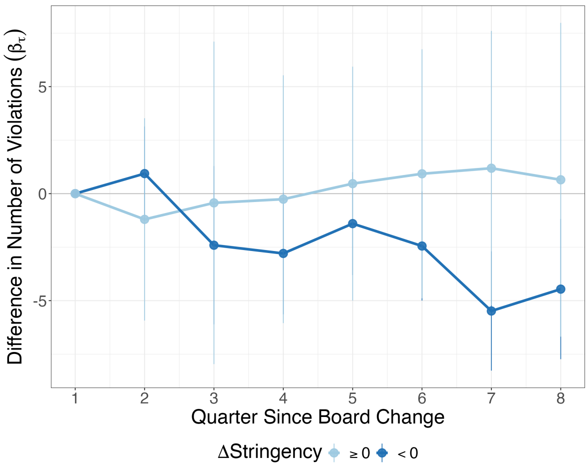
where $Inc_{b(\ell,t)}$ equals 1 if $\Delta \text{Stringency}_{b(\ell,t)} \geq 0$ and equals 0 otherwise.

Figures A7a and A7b show the regression estimates of Regression (19) for the number of violations and the compliance rate as the outcome variable respectively. The sample of boards that persist for at least 8 quarters includes 5 board transitions with a stringency increase, 1 transition with no stringency change, and 11 transitions with a stringency decrease. I plot the estimates of β_τ for the group of ΔStringency < 0 and $\beta_\tau + \gamma_\tau$ for the group of ΔStringency ≥ 0.

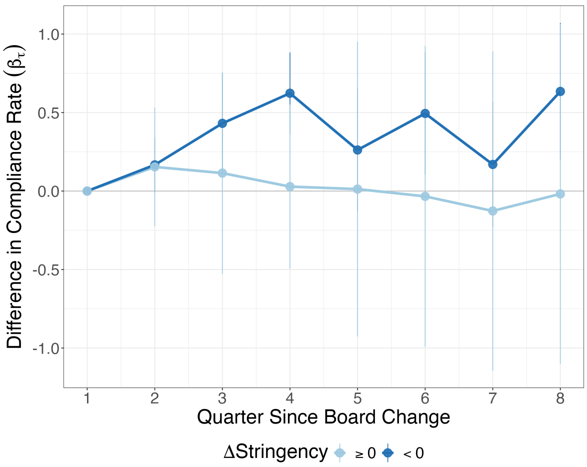
The results suggest that the gradual responses shown in the baseline specifications (Figures 4 and A5) mostly come from the group experiencing board transitions to less stringent boards and their corresponding responses in raising pollution. For the group experiencing stringency increases, their compliance outcomes remain nearly the same throughout the periods after boards transition into more stringent ones. These suggest that both direction of abatement adjustments incur sizable adjustment costs, with increasing pollution being less costly than decreasing pollution.[49]

Figure A7: Heterogeneity in Facility Response to Board Transitions by the Direction of Stringency Change

(a) Violation Changes



(b) Compliance Changes



Notes: The figure plots the estimates and 95% confidence intervals of β_τ for the group of ΔStringency < 0 and $\beta_\tau + \gamma_\tau$ for the group of ΔStringency ≥ 0, both for $\tau \leq 7$ from Regression (19). Panels (a) and (b) show the estimates for the outcome variable of the number of violations and the compliance rate respectively.

A.3 Convergent Weights in Model Solution

This section provides details on the weights in the model solution of facilities' optimal pollution decision (see Equation (12) and (13)). The convergent weights can be found by solving the fixed point of the recurrence sequence of S_T.

[49] I attribute the different shapes of transition paths to the differences in adjustment costs instead of marginal benefits of pollution because it is more likely that when facing boards with different stringency, facilities incur a different adjustment cost, as a result of different adjustment actions, rather than incur a different benefit of pollution.

As shown in Equation (6),

$$S_t = k/g + 1 + \delta k/g \left(1 - \frac{k/g}{S_{t+1}}\right) \quad \text{and} \quad S_T = k/g + 1.$$

Redefine the sequence to be

$$A_{t+1} = k/g + 1 + \delta k/g \left(1 - \frac{k/g}{A_t}\right) \quad \text{and} \quad A_0 = k/g + 1.$$

Suppose there exists a fixed point A^* such that $A_t \to A^*$ as $t \to \infty$. Then, it satisfies

$$A^* = k/g + 1 + \delta k/g \left(1 - \frac{k/g}{A^*}\right).$$

Solving the quadratic equation gives two roots:[50]

$$A^{*1} = \frac{k/g + 1 + \delta k/g + \sqrt{(k/g + 1 + \delta k/g)^2 - 4\delta(k/g)^2}}{2}$$

or

$$A^{*2} = \frac{k/g + 1 + \delta k/g - \sqrt{(k/g + 1 + \delta k/g)^2 - 4\delta(k/g)^2}}{2}.$$

Define $f(A) = k/g + 1 + \delta k/g \left(1 - \frac{k/g}{A}\right)$. Then, its derivative is $f'(A) = \frac{\delta(k/g)^2}{A^2}$. For the root to be stable, the following has to be hold: $|f'(A^*)| < 1$. That is, $A^* > \sqrt{\delta}k/g$. Therefore, the larger root A^{*1} is more likely to be the stable fixed point.

That is, as $t \to \infty$, $A_t \to A^*$ where

$$A^* = \frac{k/g + 1 + \delta k/g + \sqrt{(k/g + 1 + \delta k/g)^2 - 4\delta(k/g)^2}}{2}.$$

This implies that as T is far from the last period in the sample $\tilde{T}$, i.e., $T - \tilde{T} \to \infty$, for any $t \leq \tilde{T}$, the denominator of the weight converges to S:

$$S_t \to S = \frac{k/g + 1 + \delta k/g + \sqrt{(k/g + 1 + \delta k/g)^2 - 4\delta(k/g)^2}}{2}.$$

Then, the convergent weights can be obtained using S and Equation (5):

$$\phi_{t,-1} \to \phi_{-1} = \frac{k/g}{S}, \quad \phi_{t,0} \to \phi_0 = \frac{1}{S}, \text{ and } \quad \phi_{t,\iota} \to \phi_\iota = \frac{\delta^\iota (k/g)^\iota}{S^{\iota+1}}.$$

[50] For $k/g > 0$, the discriminant $(k/g + 1 + \delta k/g)^2 - 4\delta(k/g)^2$ is positive.

A.4 Expectations for Future Boards

I discuss the details of how I assume facilities to form expectations for future boards. In each period, facilities use their information on the current governor's and board members' terms to form expectation about future board composition, and then use information on the underlying preferences to translate expected board composition to expected fines.

Recall that a board's preferred marginal damage of pollution $\tilde{\theta}_{\ell t}$ is function of board preference parameters Θ^{Board} and observed board composition $\mathbf{X}_{\ell t}$: $\tilde{\theta}_{\ell t} = \tilde{\theta}(\Theta^{\text{Board}}; \mathbf{X}_{\ell t})$. Similarly, for any expected future board composition given today's information, the expected preferred marginal damage is: $\mathbb{E}\left[\tilde{\theta}_{\ell t+\iota} \middle| \mathcal{I}_{\ell t}\right] = \tilde{\theta}(\Theta^{\text{Board}}; \mathbb{E}\left[\mathbf{X}_{\ell t+\iota} \middle| \mathcal{I}_{\ell t}\right])$. The exact form of the board composition vector is

$$\mathbf{X}_{\ell t+\iota} = \begin{pmatrix} \mathbb{1}\{\ell = 1\}_{\ell t} \\ \vdots \\ \mathbb{1}\{\ell = L\}_{\ell t} \\ s_{\ell t} \\ \frac{1}{M_{\ell t}} \mathbb{1}\{1 \in \mathcal{M}_{\ell t}\}_{\ell t} \\ \vdots \\ \frac{1}{M_{\ell t}} \mathbb{1}\{M \in \mathcal{M}_{\ell t}\}_{\ell t} \end{pmatrix},$$

and the exact form of the expected future board composition is

$$\mathbb{E}\left[\mathbf{X}_{\ell t+\iota} \middle| \mathcal{I}_{\ell t}\right] = \begin{pmatrix} \mathbb{1}\{\ell = 1\}_{\ell t} \\ \vdots \\ \mathbb{1}\{\ell = L\}_{\ell t} \\ \mathbb{E}\left[s_{\ell t+\iota} \middle| \mathcal{I}_{\ell t}\right] \\ \frac{1}{M_{\ell t}} \mathbb{E}\left[\mathbb{1}\{1 \in \mathcal{M}_{\ell t+\iota}\} \middle| \mathcal{I}_{\ell t}\right]_{\ell t} \\ \vdots \\ \frac{1}{M_{\ell t}} \mathbb{E}\left[\mathbb{1}\{M \in \mathcal{M}_{\ell t+\iota}\} \middle| \mathcal{I}_{\ell t}\right]_{\ell t} \end{pmatrix},$$ [51]

which includes regional dummies, Democratic share of the board, and member dummies scaled by the inverse of the board size at t.

The expected Democratic share for board at $t + \iota$ is calculated using the party information of the current members whose terms lasting until $t+\iota$ and the number of vacancies in each period between t and $t + \iota$. Any vacancy in a period is expected to be filled by

[51] Note that the functional forms of how expected board membership depends on current information change with different appointment structures. Here I lay out the form for the appointment structure in the data, where every member's term is four years, Governor's term is four years, and Governor appoints members from their party (assumed). In counterfactual exercises where I inspect different appointment structures, those expectations need to be updated accordingly.

a member appointed by the governor of that period, and thus the newly filled member is expected to have the same party as the governor. That is, any vacancy between the current period and the last period of the current governor's term is expected to be filled with members from the current governor's party. On the other hand, any vacancy after the current governor's term is expected to be filled by a Republican-appointed member with a probability of r (i.e., probability of Republican winning a gubernatorial election).

Specifically, the expected Democratic share of a board can be obtained as

$$\mathbb{E}\left[s_{\ell t+\iota}\middle|\mathcal{I}_{\ell t}\right] = \frac{1}{M_{\ell t}}\Bigg\{\left|\mathbb{E}\left[\mathcal{M}_{\ell t+\iota}\middle|\mathcal{I}_{\ell t}\right] \cap \mathcal{M}_{\ell t} \cap \mathcal{D}\right| + \sum_{\iota'=\min\{1,\iota-3\}}^{\iota} \left|\mathbb{E}\left[\mathcal{M}_{\ell t+\iota'-1} \setminus \mathcal{M}_{\ell t+\iota'}\middle|\mathcal{I}_{\ell t}\right]\right| \times \mathbb{E}\left[\mathbb{1}\left\{\mathrm{Gov}_{t+\iota'} \in \mathcal{D}\right\}|\mathcal{I}_{\ell t}\right]\Bigg\},$$

where $\mathcal{D}$ is the set of gemocratic Governors and Democratically-appointed members. For any t being Gov_t's s period in their current term, the expected party affiliation of $\mathrm{Gov}_{t+\iota}$ is

$$\mathbb{E}\left[\mathbb{1}\left\{\mathrm{Gov}_{t+\iota'} \in \mathcal{D}\right\}|\mathcal{I}_{\ell t}\right] = \begin{cases} \mathbb{1}\left\{\mathrm{Gov}_t \in \mathcal{D}\right\} & \text{if } \iota \leq 16 - s \\ 1 - r & \text{otherwise} \end{cases}.$$

Similarly, a member is expected to be on the board in period $t+\iota$ only if the member's current term covers period $t+\iota$. Since each term consists of four years, the expected member dummies for board at $t+\iota$ is then

$$\mathbb{E}\left[\mathbb{1}\left\{m \in \mathcal{M}_{\ell t+\iota}\right\}|\mathcal{I}_{\ell t}\right] = \begin{cases} 1 & \text{if } t \text{ is } m\text{'s } s \text{ periond in current term and } \iota \leq 16 - s \\ 0 & \text{otherwise} \end{cases}.$$

Note that since each governor and each member has a four-year term, at any period t, the board is expected to be completely new after four years (i.e., 16 quarters).

In Section 6.3, I change each member's term length from four years to two or eight years. I then update the expected member dummies for future board to be

$$\mathbb{E}\left[\mathbb{1}\left\{m \in \mathcal{M}_{\ell t+\iota}\right\}|\mathcal{I}_{\ell t}\right] = \begin{cases} 1 & \text{if } t \text{ is } m\text{'s } s \text{ periond in current term and } \iota \leq Z - s \\ 0 & \text{otherwise} \end{cases},$$

where $Z = 8$ for two-year terms and $Z = 32$ for eight-year terms. As governors' terms remain to be four years, expectations about governors' party stay the same.

A.5 Alternative Republican Winning Probabilities

Table A1 presents the second-stage GMM estimation results for the facility profit parameters under different calibrated values for the perceived probability of a Republican governor r. In the baseline specification, r is set equal to the long-run share of Republican governors in California (over 50 years).

Here I test the following alternatives: (i) short-run share of Republican governors in California (over 25 years), (ii) maximum share of respondents reporting an intention to vote Republican in gubernatorial elections in California,[52] and (iii) a stylized 50-50 win probability for both parties. All of the three estimates are robust to different values of r. Out of the values tested, the relative adjustment cost (k/g) is increasing and the marginal benefit parameters are decreasing (g and g_0) in the size of r.

Table A1: Alternative Probabilities of Republican Winning

Model Component	Parameter	$r = 0.28$	$r = 0.46$	$r = 0.5$	$r = 0.64$
Relative Adjustment Cost	k/g	3.499	3.506	3.507	3.512
Marginal Benefit of Pollution (Slope)	g	$4,541$	$4,439$	$4,418$	$4,346$
Marginal Benefit of Pollution (Intercept)	g_0	$9,488$	$9,360$	$9,333$	$9,242$

Notes: The table reports the GMM estimates of facility profit parameters with respect to different calibrated values for the perceived probability of Republican winning gubernatorial elections (r). The baseline specification uses the long-run share of Republican governors over 50 years ($r = 0.46$). The alternatives include the short-run share of Republican governors over 25 years ($r = 0.28$), a stylized equal probability ($r = 0.5$), and the maximum polling results indicating an intention to vote Republican ($r = 0.64$).

A.6 Alternative First-Best Assumptions

In Section 6.3, I assume that true marginal damages lie in between the two parties' preferences. Here, I show the results of welfare decomposition under two alternative assumptions: (1) Democratic preference equals the truth (i.e., $\alpha^{\mathrm{D}}\theta_\ell = \theta_\ell$) and (2) Republican preference equals the truth (i.e., $\alpha^{\mathrm{R}}\theta_\ell = \theta_\ell$). Since I estimate the ratio of the two parties' preference $\alpha^{\mathrm{D}}/\alpha^{\mathrm{R}}$ to be 1.65 (see Table 4), any assumption about their relative location to the first-best, 1, changes the magnitudes proportionally.

The relative location assumption only affects the calculations of the political inefficiency component and does not affect the adjustment cost component. Recall that

[52] The maximum is taken over polling data extracted from Public Policy Institute of California for gubernatorial elections over years 2002 to 2022. To approximate the public's perceived probabilities right before the elections, only the poll closest to the election date is used for each election. I only test the maximum because the mean and the minimum are 0.48 and 0.40 respectively, which are both fairly close to the baseline value of 0.46.

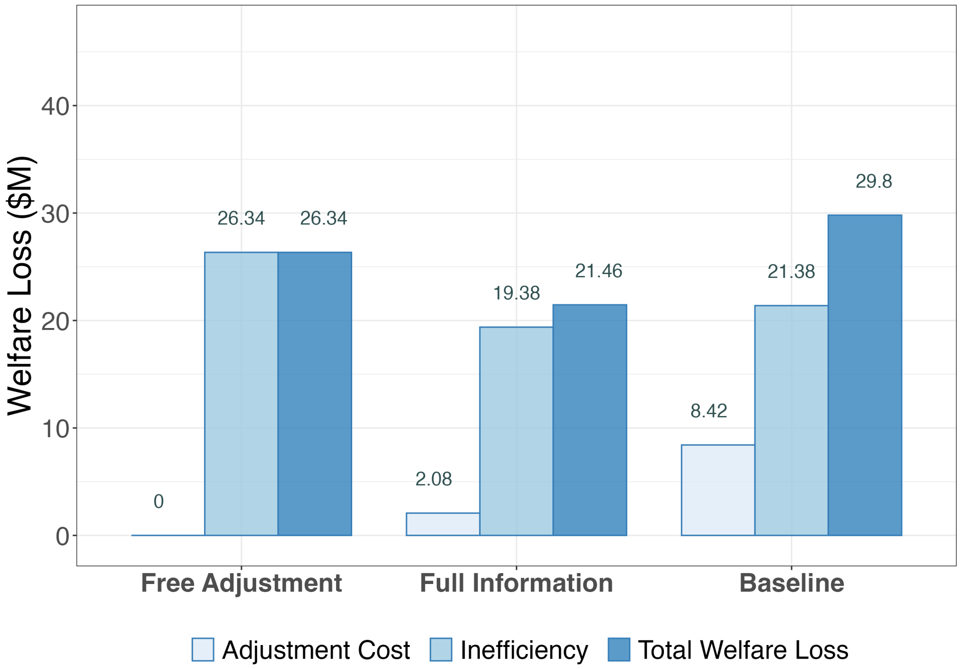
the relative party preference enters fine determinations together with the Republican-preferred marginal damage of pollution: a board's preferred damage $\theta_\ell \left(\alpha^{\mathrm{R}}\right)^{1-s_{\ell t}} \left(\alpha^{\mathrm{D}}\right)^{s_{\ell t}} = \theta_\ell \alpha^{\mathrm{R}} \left(\alpha^{\mathrm{D}}/\alpha^{\mathrm{R}}\right)^{s_{\ell t}}$. That is, any prediction of fines, and thus violations, does not require separate identification of α^{D}, α^{R}, and θ_ℓ. The relative location assumption allows for separating α^{D}, α^{R}, and θ_ℓ and use them to calculate political inefficiency.

Under the assumption that Democratic mean preference coincides with the first-best: $\alpha^{\mathrm{D}} = 1$, the estimated $\alpha^{\mathrm{D}}/\alpha^{\mathrm{R}}$ of 1.65 then implies $\alpha^{\mathrm{R}} = 0.61$. Figure A8a presents the welfare outcomes using the historical board turnover in the data. Compared to Figure 10, the relative rankings of political inefficiency across counterfactual scenarios remain the same, while the magnitudes slightly increase in the *free adjustment* and *full information* scenarios and decrease in the *baseline*. The trade-off of adjustment frictions also changes: while the net effect on welfare is still negative, its size drops from \$5.5 to \$3.5 million.

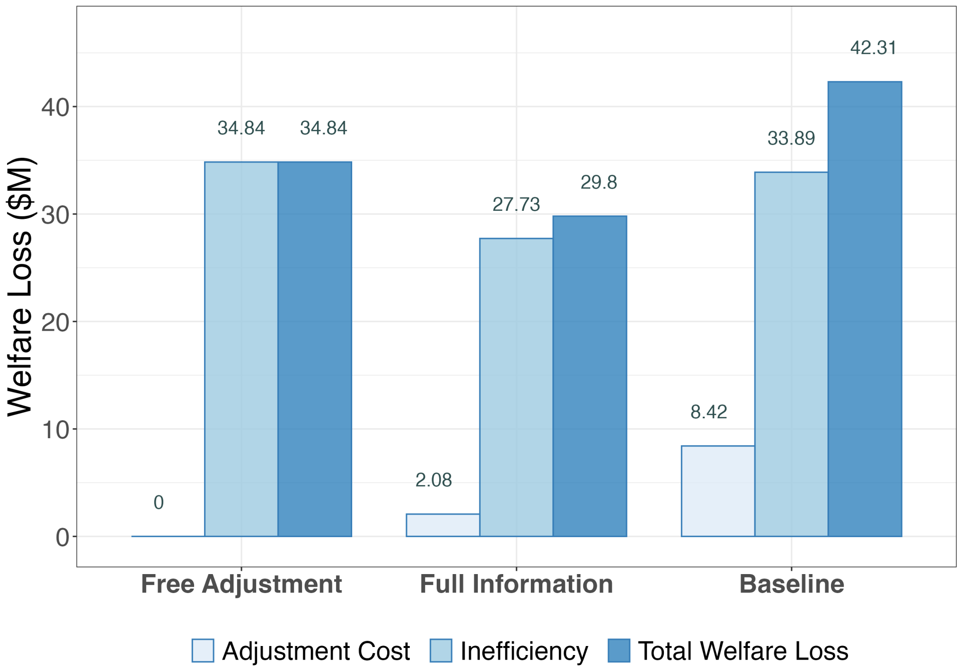
On the other hand, under the assumption that Republican mean preference coincides with the first-best: $\alpha^{\mathrm{R}} = 1$, the estimated $\alpha^{\mathrm{D}}/\alpha^{\mathrm{R}}$ of 1.65 then implies $\alpha^{\mathrm{D}} = 1.65$. Figure A8b then presents the welfare outcomes using the historical board turnover in the data. Compared to Figure 10, the relative rankings of political inefficiency across counterfactual scenarios remain the same, while the magnitudes largely increase all scenarios. This is likely due to the fact that most of the historical boards are closer to Democratic preferences than to Republican preferences. The trade-off of adjustment frictions also changes: while the net effect on welfare is still negative, its size increases from \$5.5 to \$7.5 million.

Figure A8: Welfare Loss during 2001-2019 under Alternative First-Best Assumptions

(a) Democratic Mean Being First-Best



(b) Republican Mean Being First-Best



Notes: The figure plots the total welfare loss and its components under counterfactual scenarios: *free adjustment*, *full information*, and *baseline*, with different assumptions on the relative location of partisan preferences and the first-best. In Panel (a), losses are calculated using $\alpha^{\mathrm{D}} = 1$ and $\alpha^{\mathrm{R}} = 0.61$. In Panel (b), losses are calculated using $\alpha^{\mathrm{D}} = 1.65$ and $\alpha^{\mathrm{R}} = 1$.