Legalizing Social Norms: How State Environmental Laws Reduce Facility Pollution

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Abstract

Every U.S. state enacts 12 new environmental laws per year on average, with substantial heterogeneity across states; yet the efficacy of these laws has remained unexplored. We argue that these laws function as legalized social norms — reflecting public concern and regional needs and collectively shape corporate behavior. Using a novel dataset of 11,249 state-level environmental laws, we find that a one-standard deviation increase in such laws reduces facility-level pollution by 7.9%, with punitive laws 6.1% more effective than non-punitive ones (3.5%). Industry-specific regulations are particularly impactful, likely due to heightened scrutiny of polluting sectors. The effect is stronger in Democratic-leaning states, where environmental norms are more salient. Importantly, these laws effectively mitigate pollution without harming sales or employment, and they exert only a negligible influence on creditworthiness, indicating compliance occurs via abatement activities rather than output cuts. To identify causality, we utilize instrumental variables based on media coverage and climate public opinion, showing that public pressure predicts legal change, which in turn curbs pollution.

JEL classifications: G32, Q52, Q58, L25

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1. Introduction

In 2022, the United States generated 13 million tons of toxic chemicals through production-related processes, underscoring the extensive industrial activity and its adverse effects on human health and the environment (EPA, 2023). The enactment of crucial environmental bills at the federal as well as state levels is a direct response to the pressing issues caused by climate change (Bartram et al., 2022). In *West Virginia v. Environmental Protection Agency* (2022, Case No. 20–1530), the Supreme Court decision restricted the Environmental Protection Agency (EPA)'s authority to set state-level carbon emission limits under the 1970 Clean Air Act. Moreover, a landmark Supreme Court decision, *Loper Bright Enterprises v. Raimondo* (2024, Case No. 22–451), issued on June 24, conferred considerable power to federal agencies for interpreting ambiguous statutes by overturning Chevron deference [2]. Hence, the involvement of state governments becomes increasingly important in serving as a safeguard for environmental conservation (NCEL, 2024). With the growing public concern about environmental pollution, state legislatures have increasingly enacted environmental laws aimed at controlling polluters' behavior (Scarlett, 2019). Understanding whether these laws effectively curb pollution and whether such laws impose financial consequences on facilities is a critical concern at the nexus of environmental economics, public policy, and finance.

Given the significant role that state-level legislation plays, this paper investigates how the growing number of environmental laws affects facility-level pollution. We conjecture that these laws are not arbitrary top-down mandates but rather reflect the social norms and public

[2] In Loper Bright Enterprises v. Raimondo, 603 U.S. ___ (2024), the U.S. Supreme Court overturned the Chevron deference, which had regulated administrative law since Chevron U.S.A., Inc. v. Natural Resources Defense Council, Inc., 467 U.S. 837 (1984). Under Chevron, courts deferred to a government agency's reasonable interpretation of unclear statutes. In Loper Bright, the Court determined that such deference contradicts the Administrative Procedure Act, asserting that courts must autonomously interpret statutory wording without yielding to agency interpretations.

pressures within each state. As such, they are likely to cause genuine behavioral change within the facilities. Specifically, we expect that these norm-reflective environmental laws signaling a high public awareness and public pressure on environmental matters which will reduce corporate environmental pollution. Such laws, especially when structured using both punitive and non-punitive measures, will achieve environmental goals without compromising the financial health of facilities.

There is ample evidence about the influence of federal legislation on corporate environmental behavior. However, limited evidence exists concerning state-level environmental laws. Although federal laws establish a comprehensive regulatory framework, they frequently lack the granularity required to tackle localized environmental challenges, which are more efficiently managed by state-level laws that align with local societal values (Ewick and Silbey, 1998) and are tailored to regional needs (Seltzer et al., 2022). While the US has robust federal environmental laws managed by the EPA, enforcement and implementation are largely left to state governments, leading to significant variations across states (Seltzer et al., 2022). Some states have adopted even stricter environmental standards than those mandated by the EPA (Bushnell et al., 2017, Chircop et al., 2023). The importance of state-level laws echoes the influence of California's stringent auto pollution laws[3] in the 1970s, which shaped federal regulations (Carlson, 2009). Therefore, states have the capacity to implement innovative programs that motivate federal action and generate a "domino effect" (Engel, 2005).

3 California's authority to implement stricter vehicle emission standards originates from Section 209 of the Clean Air Act of 1970 (42 U.S.C. § 7543). While this section preempts most state laws, Section 209(b) allows California to obtain a waiver from the EPA. California used this provision in the 1970s to set the first meaningful tailpipe emission limits, which not only shaped subsequent federal standards but also led to the 1977 Clean Air Act Amendments. This precedent contributed to the broader "California Effect," influencing other U.S. states and international policy reforms.
See Congressional Research Service, *Clean Air Act Issues in the 118th Congress, R48168 (May 2, 2023)*, https://www.congress.gov/crs-product/R48168.

Additionally, states function as "policy laboratories," where policymakers customize and implement effective methods by learning from the outcomes of policies elsewhere (Volden, 2006).

[Insert Figure 1 here]

The wide variation in state-level laws across the US shown in Figure 1, provides a favorable empirical setting to compare the different regulatory approaches of various legal frameworks and evaluate their impact on corporate pollution. With a total of 11,249 environmental laws from 2000-2022, our findings indicate that environmental laws reduce facility-level pollution. Specifically, a one-standard deviation increase in environmental legislation (0.814) leads to a 7.9% decrease in pollution. We also find that private facilities[4] are more reactive to these laws in mitigating pollution than public parent facilities, as they are subject to less scrutiny and oversight by stakeholders (Peek et al., 2010). As these firms encounter more laws implying heightened societal pressure, adherence to environmental legislation transforms into both a legal obligation and a societal responsibility. This is consistent with the *Public Interest Theory* (Demsetz, 1974, Pigou, 2017), which posits that environmental laws rectify market inefficiencies by compelling corporations to bear the societal costs associated with pollution.

To better understand the mechanisms via which the environmental laws collectively reduce pollution, we distinguish laws between punitive and non-punitive. Punitive legislation ensures compliance with laws by utilizing the deterrent effect of punishments to prevent violations (Leung, 1995, Bentham, 1879). Whereas non-punitive laws aim to promote awareness, transparency, or voluntary enhancement. These laws arise from public demands and evolving societal norms, consistent with *Institutional Theory*, which emphasizes the importance of social

[4] Firms, excluding those held by the government, are categorized as private if they are not publicly traded in a specific year.

legitimacy, public interest, and external forces in determining policy (DiMaggio and Powell, 1983). Our findings show that both punitive and non-punitive laws help lower pollution, meaning that government actions, no matter how strict, respond to what the public wants and can improve the environment. However, punitive laws, in contrast to non-punitive ones, have a far more noticeable and substantial impact. This is in line with *Deterrence Theory*, which posits that more environmental laws in the form of punishments may deter undesirable behaviors (Leung, 1995). We find that a one-standard deviation rise in punitive (non-punitive) laws is associated with a 6.1% (3.5%) reduction in pollution at a 1% significance level. This distinction underscores that while social expectations may drive legal reform, regulations achieve greater efficacy when they incorporate deterrent mechanisms.

Companies in certain industries may face increased public scrutiny due to their environmental footprint. Hence, such industries are more impacted by laws than others (Al-Ubaydli and McLaughlin, 2017). This can be captured by classifying environmental laws by their industry relevance. We classify laws according to their relevance to industries utilizing a supervised machine learning approach, specifically, a Support Vector Machine (SVM) algorithm. The results suggest that a one-standard-deviation increase in industry-relevant laws results in a 8.3% decrease in total pollution across all facilities. This finding is consistent with the argument that facilities are likely to respond more effectively to laws relevant to their specific industries than to general legislation (Kalmenovitz, 2023). Such laws may be particularly impactful because they often target high-polluting industries that operate under greater public scrutiny. In this context, societal norms exert public pressure through industry-relevant laws, compelling firms to comply and mitigate pollution.

To address the potential endogeneity between environmental legislation and pollution, we use two alternative instrumental variables (IVs): state news coverage and state-level public climate opinion. In our first IV test, we utilize state-level environmental news coverage as an instrument for the implementation of environmental legislation. The findings indicate that heightened media attention to climate matters results in a greater enactment of environmental legislation, which subsequently decreases pollution at the facility level. This finding highlights the significance of public knowledge dissemination in influencing regulatory outcomes. Consequently, facilities have become more environmentally aware due to public expectations (Dyck et al., 2008; Heese et al., 2022) and leading to a reduction in pollution. In our second investigation, we utilize public climate opinion scores as instruments that reflect climate risk perception and policy support (Bromley-Trujillo and Poe, 2020, Marlon et al., 2022). The findings suggest that heightened public concern regarding climate change causes the implementation of more environmental legislation, which subsequently results in a decrease in facility pollution. This provides further evidence that public expectations influence legislation and have a concrete effect on firms' environmental conduct. These IV results highlight the critical role of social norms and public pressure in influencing the enactment of laws, whether driven by increased media scrutiny or shifting climate opinions as viable approaches to lowering corporate pollution.

To determine whether environmental laws reflect prevailing social norms, we look at how their effectiveness varies across institutional and political contexts. If laws serve not merely as deterrents but also as expressions of societal expectations, then we can expect them to be more effective in Democratic-leaning states where public support for environmental protection may exert its own regulatory pressure. We find that the influence of environmental legislation on pollution is substantial in facilities in states with a Democratic preference. Interestingly, we find that this effect is mainly driven by Democratic-leaning legislatures, with no significant impact observed under Democratic governors. This indicates that the institutional strength of environmental legislation relies more on collective legislative intent than on executive signaling.

Although we conceptualize punitive and non-punitive laws as distinct mechanisms for lowering pollution, the precise techniques by which businesses adhere to these laws remain an open question. To explore this, we examine whether facilities respond to environmental laws by engaging in source abatement activities, which may serve as potential channels through which legal compliance translates into reduced pollution. We find that the stringent regulatory framework characterized by an increased number of environmental laws compels facilities to undertake additional abatement measures to mitigate harmful pollutants (Jing et al., 2024, Akey and Appel, 2019a, Akey and Appel, 2021).

Finally, we examine whether these environmental laws, while effective in cutting pollution, impose significant costs on businesses. If these laws are actually influenced by societal norms and public pressure, they may accomplish environmental objectives without jeopardizing fundamental economic operations. In alignment with this perspective, we observe no significant impact on facility-level sales or employment, suggesting that firms do not encounter declines in market activity or labor adjustments due to regulatory exposure. However, we notice a slight decline in the facility's credit scores, indicating a reduction in short-term payment behavior. This may indicate temporary liquidity challenges resulting from pollution abatement costs, without any significant consequences for facilities. The absence of any significant impact on facility sales growth indicates that the noted reductions in pollution are not a result of decreased economic activity; instead, they are likely due to the direct influence of environmental legislation, reinforcing the hypothesis that these laws accomplish environmental objectives without hindering firm performance.

This research presents a new behavioral lens to assess facility responsiveness to environmental legislation. Most research on environmental legislation focuses on its deterrent effect—how enforcement and penalties affect compliance (Becker, 1968)—we argue that laws also function as codified expressions of public norms and expectations. We show that both punitive and non-punitive laws reduce pollution, highlighting that firms respond not only to the threat of sanctions but also to the legitimacy and public pressure embedded in legal frameworks. Importantly, punitive laws demonstrate approximately double the efficacy of non-punitive laws in mitigating pollution, indicating the enduring significance of enforcement design. This reframing helps explain why firms comply even when enforcement is weak, and why states pass laws. This reframing helps explain why firms comply even when enforcement is weak, and why states pass laws even in politically constrained environments. This indicates that successful environmental legislation involves both "the stick" (De Geest and Dari-Mattiacci, 2013) and normative influence, offering evidence-based guidance to the policymakers on how to design regulations strategies the balance with legitimacy.

Our research enhances the literature on environmental legislation by transitioning the focus from isolated laws or clusters of laws to the overarching legal framework encountered by enterprises, which encompasses a cumulative array of new regulations. While previous studies investigate flagship initiatives such as the NOx Budget Trading Program (Shapiro and Walker, 2018), carbon cap-and-trade (Bartram et al., 2022), and stringent greenhouse gas (GHG) targets (Bartram et al., 2022; Dai et al., 2021), we construct a novel dataset comprising 11,249 state-level environmental laws across all 44 states and show how the cumulative volume of laws—reflecting sustained legal and normative pressure—significantly reduces facility-level pollution. Together, these contributions offer a novel theoretical framework connecting law and social norms, a replicable empirical methodology for assessing legal intensity, and policy-relevant evidence demonstrating that decentralized state action can reduce pollution without compromising facility performance.

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2. Theoretical Framework

Laws are enacted to establish standards and communicate societal values, shaping expected behavior. Social norms are crucial as they symbolize shared beliefs within a sociocultural system (Campbell, 1975), encouraging societal good and discouraging detrimental behaviors. These norms shape community behaviors and expectations, motivating firms to engage in Corporate Social Responsibility (CSR) initiatives that reflect local values (Adler and Kwon, 2002). Although they are not often strictly enforced, they cultivate a sense of communal duty and deter non-compliance (Sunstein, 1996). Within the institutional framework, the political system exerts the most significant influence on corporate social performance, followed by the labor and education systems, and the cultural system (Ioannou and Serafeim, 2023). Environmental laws enforce specific behavior and prompt a collective commitment to safeguarding our environment. Government regulation functions as a dynamic, collaborative mechanism that interacts with market forces, environmental advocacy, and corporate culture to promote socially responsible corporate behavior, challenging the notion of rigidly imposed rules (Kagan et al., 2003).

Two principal theories – *Public Interest Theory* and *Public Choice Theory* – illustrate the presence of laws and their divergent viewpoints serve as a helpful foundation for assessing the influence of environmental laws on corporate behaviors. *Public Interest Theory* posits that laws are designed to address market failures, such as monopoly power and asymmetric information, thereby enhancing social welfare (Demsetz, 2013, Pigou, 2017). According to this view, environmental laws are enacted by regulators with the goal of correcting market failures like the negative externalities of pollution, aiming to make the world a better place. In contrast, *Public Choice Theory* suggests that legislation is designed to promote the interests of regulators rather than to address market failures (Stigler, 2021, Posner, 1974). The proponents of this idea contend that regulators use laws to further their own financial interests rather than promoting market efficiency as a whole. From this viewpoint, environmental legislation may be influenced by the industries that it seeks to regulate, creating laws that poorly tackle environmental degradation and perhaps reinforce market failures to benefit entrenched industry stakeholders. This raises questions about whether environmental laws genuinely prompt firms to change their behavior due to heightened public scrutiny or if they merely create a facade of compliance without substantial environmental improvements.

Public Interest Theory and *Public Choice Theory* provide fundamental justifications for the presence of laws, whereas *Institutional Theory* delves deeper by examining how these laws construct a complex framework of formal and informal norms and thus affect corporate decision-making within this framework (Campbell, 2007). DiMaggio and Powell (1983) assert that a company's decision-making is shaped by not only the basic regulatory requirements but also by a broader array of influences, including regulatory frameworks, societal norms, and cognitive factors. Government laws, stakeholder pressures, financial incentives, and ethical concerns influence a firm's environmental decision-making (Bansal and Roth, 2000) compelling firms to publicly disclose sophisticated environmental policies (Delmas and Toffel, 2010). These legal statutes establish relationships by enabling the firm's interaction with the government and other stakeholders (Roe, 1996, Campbell, 2007). The motivations behind this company's commitment to following the law can be categorized as sanctions, peer pressure, and psychological factors, with peer pressure and psychological motivations are more important in encouraging law-abiding conduct (Friedman, 2016). State legislation is influenced by local social standards, economic conditions, and industry objectives (Chircop et al., 2023, Bromley-Trujillo and Poe, 2020), jointly constructing a resilient legal structure. This framework codifies existing public expectations and generates regulatory pressure that corporations have to cope with. Hence, companies may formulate strategic measures in response to the regulatory framework influenced by existing societal norms, with one possible action being the decrease of pollutants emitted by the firms.

Public Interest Theory and *Institutional Theory* promote voluntary and structural alignment with environmental objectives, however punitive legislation under *Deterrence Theory* serves as vital to guarantee compliance. *Deterrence Theory* (Hobbes, 1894, Bentham, 1879, Beccaria, 2009) posits that the likelihood of illegal conduct can be reduced by enforcing punishment that is harsh, certain, and prompt. Echoing to this, Polinsky and Shavell (1997) assert that punitive damages influence legal dispute outcomes through advocating higher settlements and deterring firms from misconduct. Thus, punitive environmental laws, including fines and penalties, may act as a deterrent to ensure corporate compliance, thereby reducing pollution.

3. Literature Review and Hypothesis

Several factors contribute to the preservation of legality, including formal legal frameworks, administrative authority, and societal norms and perspectives. (Ewick and Silbey, 1998). Local social norms significantly influence company conduct, highlighting the important role of location in decision-making (Hilary and Hui, 2009, York et al., 2018). Social norms spread like wildfire because people tend to often follow the behavior of those they encounter regularly (Kedia and Rajgopal, 2009) and are not fixed; rather, they emerge and evolve in response to social and political factors (Acemoglu and Jackson, 2017). Therefore, legislation that both reflects and reinforces societal values plays a crucial role in influencing corporate behavior.

Legislation exerts a diverse influence on firms by increasing operational expenses (Kalmenovitz, 2023), adversely affecting capital structure (Wald and Long, 2007, Qiu and Yu, 2009), thus limiting profit-maximizing capacity (Hsu et al., 2023), which ultimately reduces firm value (Cain et al., 2017) and thus hinders overall industry growth (Cohen et al., 2013). Research into environmental laws at the federal level (Rassier and Earnhart, 2015) or state level

(Shapiro and Walker, 2018, Bartram et al., 2022), shows how these laws influence firm behavior. Bartram et al. (2022) find that firms under financial stress in California reduce their emissions within the state to comply with California's cap and trade law. Shapiro and Walker (2018) show that the implementation of the NOx Budget Trading Program, a cap-and-trade mechanism for nitrogen oxides, significantly increases the cost of pollution per production unit. This motivates firms to implement cleaner technologies, hence decreasing pollution. This demonstrates that environmental legislation serves as a corrective tool for market inefficiencies, consistent with *Public Interest Theory* (Pigou, 2017).

Dasgupta et al. (2023) demonstrate that investment funds prioritizing social responsibility, particularly those situated within a 100-mile radius of a plant, significantly contribute to pollution mitigation, especially following legal actions by the EPA against neighboring facilities. This is consistent with Friedman (2016) who observes that peer pressure and psychological motivations play a significant role in influencing a firm's compliance with the law. Nonattainment status indicates a failure to meet the National Ambient Air Quality Standards and significantly influences corporate behavior by enforcing stricter environmental regulations. Firms relocate emissions to regions with less stringent regulations to avoid higher regulatory costs with stringent standards (Becker and Henderson, 2000). However, competitive marketplaces in non-attainment regions necessitate that firms engage in green innovations (Dai et al., 2021). A state with strict environmental enforcement mandates that banks include environmental covenants in loan agreements to improve corporate oversight, thereby reducing pollution (Choy et al., 2023). This is consistent with *Institutional Theory* (Campbell (2007), indicating that firms are deeply influenced by the regulatory environments in which they operate.

Factors such as financial constraints (Xu and Kim, 2022, Bartram et al., 2022), stakeholders (Akey and Appel, 2019b, Dyck et al., 2019, Naaraayanan et al., 2021), political connections

(Heitz et al., 2023) and specific laws (Bartram et al., 2022, Shapiro and Walker, 2018), significantly influence a firm's pollution. It is crucial to acknowledge that business operations are localized and regulated by the specific environmental laws of each state. State legislation seeks to tackle specific environmental issues within their jurisdictions, enabling governments to regulate business conduct through this tailored regulatory framework. The legal system of each state is interconnected with its prevailing social norms and regulates the behavior of corporations. A greater number of newly enacted state laws creates a strong regulatory framework that significantly influences corporate pollution management. Drawing from *Public Interest Theory* and *Institutional Theory*, we propose the following hypotheses:

H1: ***More state level environmental laws are negatively related to facility-level pollution.***

The deterrent effect of punitive actions ensures compliance with legislation through adherence. (Leung, 1995). Especially punitive measures are necessary when individual activities have substantial societal impacts, such as causing environmental damage (Karpoff et al., 2005). These legal sanctions function as the principal regulatory mechanism, as the number of penalties for environmental violations is closely associated with losses in a firm's market value (Karpoff et al., 2005). This indicates that punitive legislation might improve deterrence by directly influencing a firm's economic viability, reinforcing compliance, and ensuring responsibility, as reputational sanctions alone are insufficient in resolving environmental offenses. In contrast, Cialdini and Jacobson (2021) note that individuals internalize social norms and adapt to them to avoid social disapproval, which may vary from subtle indications to exclusion. This shame-driven internalization ensures adherence to the law even when violations remain undetected. Although punitive measures are crucial for reducing pollution and preventing wrongdoing, environmental legislation also includes non-punitive measures that avoid fines and penalties, seeking to modify behavior using non-coercive approaches such as guidance, transparency, and incentives. When punitive legislation alone is inadequate to address climate challenges, *Deterrence Theory* may not sufficiently explain the situation. As law reflects current social norms, both punitive and non-punitive legislation can articulate existing social values and public demands based on the urgency of perceived climate issues. This dual response of the regulatory framework aligns with *Institutional Theory*, which asserts that institutions are shaped by normative demands and public expectations. Based on this discussion, both punitive and non-punitive environmental legislation can influence pollution reduction, since firms may comply with either to prevent substantial financial and reputational damage. However, as punitive laws embed formal enforcements mechanisms, they exert a stronger effect on pollution reduction relative to non-punitive laws. Therefore, we propose the following hypothesis:

H2: ***Punitive environmental laws have a stronger pollution-reduction effect than non-punitive laws.***

4. Sample Construction

4.1. State environmental laws

We collect US state-level environmental laws from 2000 to 2022 from LexisNexis. From 20,230 environmental bills that are classified as “environmental laws” by LexisNexis, following Cohen et al. (2013), we exclude laws that contain terminology such as "Budget" or "Appropriation" to focus on substantive environmental policy changes. This ensures the analysis reflects direct legislative efforts on environmental laws without the distortion of general funding allocation. This cleaning process yields a total of 18,230 environmental bills.

In LexisNexis, laws designated as “environmental laws”, often highlight other economic concerns rather than issues directly related to the environment. Therefore, we employ textual analysis to extract bills with a stronger environmental focus by utilizing bag-of-words as outlined by Li et al. (2024), Sautner et al. (2023). This research includes all states with yearly legislative cycles, except for Montana, Nevada, North Dakota, and Texas, which implement legislation biennially. We also exclude Arkansas and Oregon which transitioned from biennial to annual sessions during the sample period (Oregon in 2011 and Arkansas in 2009), potentially causing inconsistencies in annual comparisons of legislative activity. As a result, our data set covers 11,249 environmental laws enacted in 44 states between 2000 and 2022[5].

Furthermore, we classify the legislation into punitive (6,850 bills) and non-punitive (4,399 bills) categories. Each state's legal code on official state legislative websites, we extract frequently used keywords associated with punitive language to find environmental legislation that encompass enforcement or fines. By doing so, we offer insights into gauging the severity of legislation through the introduction of punitive environmental laws. Mulligan and Shleifer (2005) employ the dimensions of computerized version of state-level statutes as a proxy for actual state-level regulation. Dawson and Seater (2013) measure stringency of regulations by counting the pages in the Code of Federal Regulations (CFR), while Coffey et al. (2020) measure by tallying the number of pages in the federal register. Using page counts might be challenging because of the fluctuation in content significance and alterations in page formatting standards over time. Titles in the CFR, such as Title 50 on Wildlife and Fisheries, frequently incorporate visual aids, which contrast with the rich textual content (Al-Ubaydli and McLaughlin, 2017). Our methodology, which emphasizes a list of keywords,[6] such as

5 In a robustness check, we incorporate all 50 states, encompassing those with biennial legislative sessions. The results are consistent, indicating that our findings are unaffected by variations in legislative frequency across states.

[6] In identifying punitive laws, we analyze state legislature websites, such as the California Legislature’s website (https://leginfo.legislature.ca.gov/faces/codesTextSearch.xhtml), by reviewing penal code sections. We filter out key terms include 'Penalty(ies)?', 'Sanction(s)?', 'Punishment(s)?', 'Retribution', 'Sentenc(e|ing)', 'Incarceration', 'Fine(s)?', 'Forfeiture', 'Imprisonment', 'Probation', 'Parole', 'Detention', 'Restitution', 'Mandatory minimum sentence(s)?', 'Compliance Order(s)?', 'Enforcement Action(s)?', 'Remediation Order(s)?', 'Permit Revocation(s)?', 'Mandatory Measure(s)?', 'Punitive Damage(s)?', 'Retributive',

"Penalties," "Punishment," "Fines," "Imprisonment", "Felonies", etc., provides a more transparent and nuanced way to measure the stringency of laws.

We utilize a Support Vector Machine (SVM) to classify bills according to their relevance to various industries to analyze the differential impact of environmental legislation across these various industries. Not every industry is affected by environmental laws in the same way. For instance, a manufacturing firm is typically more responsive to EPA regulations, whereas a bank holding company is more subject to laws enforced by the Federal Deposit Insurance corporation (Kalmenovitz, 2023). To train the model for SVM, we download articles classified based on NAICS 6-digit codes from the "Business Insights: Essentials"[7] database. We consider nine machine-learning classifiers: naïve Bayes, k-nearest neighbors, random forest, decision tree, gradient boost, linear support vector classification (SVC), Gaussian SVC, logistic regression, and a "voting" classifier that aggregates predictions from the decision tree, gradient boost, and linear SVC models. Each model fits the training sample, and their out-of-sample performance is evaluated based on standard metrics. Table IA1 reports the results, showing that the Gaussian SVC with default settings performed the best, achieving 83.5% precision, 82.4% recall, and 82.3% accuracy. We fit the Gaussian SVC model to the training sample and then distinguish 702 industry-specific laws which are around 6.5% of total environmental laws. The model is trained in balanced articles consisting of 30,379 relevant and 29,906 irrelevant industries.

'Punitive Measure(s)?', 'Exemplary Measure(s)?', and 'Restitution'. These keywords are then applied to legislative texts gathered from LexisNexis, allowing for the systematic identification and classification of laws with punitive provisions across various states

[7] "Business Insights: Essentials" includes one or two industry overview essays, articles from "Academic Journals," "News," and "Trade Journals." Each article is pre-classified by the data vendor to a 6-digit NAICS industry. Since our dependent variable is toxic release emissions reported by the EPA, we define relevant industries as those covered by EPA-designated industries under 6-digit NAICS codes, while irrelevant industries fall under other NAICS codes.

4.2. Pollution data

To obtain facility level pollution of US public and private companies, we collect facility level toxic pollution data from the Toxic Release Inventory (TRI) database, which is maintained by the EPA. The TRI database contains annual information on all U.S. chemical pollution at the facility level. Specifically, the TRI data includes the report year, level of chemical pollutants in pounds, chemical category names, location of Federal Information Processing Standards (FIPS) codes, and company names. All firms, both public and private, are required to report pollution data. TRI data is self-reported, but evidence indicates firms seldom misreport emissions. Unlike civil and misreporting offenses that may incur criminal consequences, high emissions do not cause any punishment (Greenstone, 2003). Regular audits conducted by the EPA guarantee the accuracy and completeness of the data. As the TRI data are provided at the chemical-facility-year level, we aggregate chemical-facility level pollution to the facility-year level. The total toxic pollution of a firm is defined as the aggregate of all pollution, including on-site and off-site, as per Delmas and Toffel (2010), Jing et al. (2024). Our main measure for facility-level pollution is Total_Pollution[8], estimated as a natural logarithm of total pollution to adjust for the skewness of the nominal total toxic pollution. We eliminate observations with zero total pollution (i.e., in our main outcome variable-Total_Pollution) at the facility-year level following Akey and Appel (2019b), Akey and Appel (2021).

Since there is no uniform and shared identity in the TRI and Compustat databases, we match the distinct parent company names of each plant with the public company names in Compustat using a fuzzy string-matching approach. For each facility, we identify the parent company, defined as the corporation that owns at least 50% of voting shares (Akey and Appel, 2021). We

[8] We additionally use toxic pollution scaled by employees and toxic pollution intensity scaled by facility sales as alternative outcome variables and find similar results. Detailed results are provided in the online appendix Table IA3 and Table IA4.

manually verify our sample companies using several identifiers, like DUNS numbers, company websites, and headquarters locations, to guarantee the match is accurate following Xu and Kim (2022), Jing et al. (2024). Our sample comprises a total of 28,054 facilities, encompassing both publicly and privately owned facilities. After matching these facilities to Compustat, we identify 1,580 firms associated with 9,964 public parent facilities.

4.3. Control Variables

We gather state-level demographic data from the US Census and Bureau of Economic Analysis (BEA). We also control for social capital[9] by using the Northeast Regional Center for Rural Development (NERCRD). A firm's decision-making in a specific region is systematically related to the region's social capital, as indicated by the density of social networks and the strength of civic norms present in the area (Hasan et al., 2017). We also account for state-level corruption per capita, as states with higher corruption exhibit lower CSR commitments (Qian et al., 2023) and increased pollution (Cole, 2007). We measure this variable by utilizing data from the US Department of Justice Public Integrity Section (PIN)[10], which maintains records of public corruption convictions. Following Smith (2016), we standardize the number of convictions in each state with population estimates from the US Census. We account for state-level enforcement, quantified by the number of EPA enforcement actions per state from the U.S. Environmental Protection Agency's Integrated Compliance Information System (ICIS),

[9] Social capital is quantified as the primary principal component derived from a principal component analysis of Pvote, Respn, Nccs, and Assn, in accordance with Rupasingha, Goetz, and Freshwater (2006). Data are sourced from the NRCRD datasets (OLD: 1990, 1997, 2005; NEW: 1997, 2005, 2009), with omissions addressed by utilizing the latest available estimates prior to the gaps. The measure incorporates indicators of voter participation, response rates, nonprofit density, and association membership to evaluate social cohesion and community engagement.

[10] The DOJ annually publishes conviction statistics for the 94 US district court districts in its Report to Congress on the Activities and Operations of the Public Integrity Section. Corruption investigations reported to and conducted by PIN encompass bribery, extortion, election offenses, and criminal conflicts of interest.

as higher enforcement reduces firm pollution (Seltzer et al., 2022, Konisky, 2007). We collect state-level temperature data from the National Oceanic and Atmospheric Administration (NOAA).

to account for climatic factors that may affect pollution levels and industrial operations. We obtain financial data on facilities from the National Establishment Time-Series (NETS) database. We utilize Compustat data to construct firm-level control variables.

4.4.Summary Statistics

Panel A of Table 2 presents summary statistics for a full sample consisting of both public and private facilities. The mean facility level Total_Pollution is 29,690 pounds, with a standard deviation of 1.36 million pounds. Panel B of Table 2 reports the descriptive statistics separately for all public parent facilities and private parent facilities, respectively. The average Total_Pollution per facility in the public parent sample reaches 32,290 pounds, and private parents release an average of 29,920 pounds of toxic pollutants, where the difference between them is statistically significant at a 1% level. This evidence suggests that public facilities generally release higher quantities of pollutants compared to private facilities, consistent with Shive and Forster (2020). The predominant source of pollution is Onsite_Pollution, comprising roughly 82% of Total_Pollution, whereas Offsite_Pollution accounts for around 18% based on the statistics of the full sample.

In terms of state-level variables, we observe an average of 12 new environmental laws enacted per state annually. Punitive laws average 7 per year, and non-punitive legislation averages 4 per year. The standard deviations of both punitive and non-punitive environmental laws are high relative to their means.This is especially true for non-punitive laws, where the coeffficient of variation exceeds 1, indicating high relative heterogeneity across states and time. Furthermore, states implement industry-specific environmental laws, averaging 2 per year. To address the skewness of both dependent and independent variables, we employ the natural logarithm of these variables.

[Insert Table 2 here]

Panel C of Table 2 provides summary statistics for the firm-level observations within our sample and compares them with all Compustat non-financial firms, excluding the parents of the TRI-matched facilities. The summary statistics show that our sample has a significantly larger firm size (7.75) than all Compustat firms (5.20) on average. This is consistent with the notion that larger firms are strongly associated with higher levels of pollution (Aswani et al., 2024). Our firms also have more tangible assets (30%) than Compustat firm's tangible ratio (27%) on average. With respect to innovation, our firms invest less in R&D, averaging 1.84 compared to 4.55 for all Compustat firms, perhaps due to their emphasis on compliance and operational efficiency rather than innovation. The primary reason for the differences might be that our sample outweighs the manufacturing sector.

5. Empirical Results

In this section, we introduce our ordinary least squares (OLS) regression model that relates state environmental laws to facility pollution. The baseline regression is as follows:

$$
\begin{aligned}
log(1 + Total\_Pollution)_{f,i,s,t} \\
&= \beta \log\left(1 + EnvLaws_{s,t-1}\right) + \delta StateControls_{s,t-1} + \theta FirmControls_{i,t-1} \\
&+ \sigma FacilityControls_{i,t-1} + FEs + \epsilon_{f,i,s,t}
\end{aligned}
$$

where *f* denotes facility in state *s* and affiliated with parent firm *i* at time *t*. State controls include the rate of population change (Pop_Change_Rate$_{(t-1)}$), social capital (Social_Capital$_{(t-1)}$), unemployment rate (Unemp_Rate$_{(t-1)}$), per capita taxes (Per_Capita_Tax$_{(t-1)}$), average state-level temperature(Temp$_{(t-1)}$), per capita corruption (Corruption$_{(t-1)}$), state level enforcements

($Enforcement_{(t-1)}$) and neighbouring states environmental laws ($Neighbouring\_Laws_{(t-1)}$). We also include parent company controls in our analysis of public firms, including firm size ($Firm\_Size_{(t-1)}$), firm age ($Firm\_Age_{(t-1)}$), and long-term debt ($Long\_Term\_Debt_{(t-1)}$). The fundamental features of the parent firms are crucial for comprehending the broader business context in which the facilities operate.Facility-level controls include sales ($Sales\_Facility_{(t-1)}$) and employees ($Emp\_Facility_{(t-1)}$). We incorporate industry-fixed effects determined by the primary 6-digit NAICS code for each plant to account for time-invariant heterogeneity at the industry level, allowing for comparisons of results within each industry. Year-fixed effects address time-varying elements that uniformly influence all states and industries, including general economic conditions, technological improvements, and changes in public awareness of environmental issues. Standard errors are clustered at the industry-year[11] level to accommodate variation within an industry in a given year.

To account for facility-level heterogeneity, we implement fixed effects derived from facility groups, classifying facilities into five separate categories based on their chemical release profiles. This classification, termed Facility_Group_by_Chem fixed effects[12], enables the comparison of pollution reduction across facilities with similar harmful discharge profiles. To alleviate the impact of outliers, all continuous variables are winsorized at the 1st and 99th percentiles.

[Insert Table 3 here]

[11] As a robustness check, we also run our baseline analysis with standard errors clustered at the state-year level to account for variations within states in a given year in our online appendix Table IA5.

[12] We do not include facility fixed effects because each facility is unique in each state, rendering facility-level fixed effects unnecessary when considering state-level variation. In addition, the main focus of our study is state-level environmental laws. Hence, adding a facility fixed effect would not provide enough variation to draw any conclusions about how these laws affect pollution.

5.1. Baseline results

Table 3 displays the baseline results demonstrating the impact of heightened state-level environmental legislation on toxic pollution. Panel A shows that an increased number of environmental laws result in a substantial reduction in facility pollution. This effect is consistent across all specifications and is statistically significant at the 1% level. In Column 6, the coefficient for laws, $Env\_Laws_{(t-1)}$ (-0.097), indicates that a one-standard deviation increase in environmental legislation (0.818) leads to a 7.9% decrease in pollution level[13]. This translates to about 2,881 pounds less pollution per facility on average. In Panel B, we analyze public and private parent facilities separately. Laws play a crucial role in regulating both public and private entities while the impact of environmental legislation on pollution is higher for private parent facilities than for public parent facilities. Our findings support both the *Public Interest Theory* and *Institutional Theory*, indicating that corporations modify their pollution levels in reaction to strong regulatory structures driven by an increased number of laws.

[Insert Table 4 here]

Panels A and B of Table 4 present the results for punitive and non-punitive environmental laws, respectively. The negative coefficients for punitive laws ($\beta = -0.104$) and non-punitive laws ($\beta = -0.081$) in columns 6 of Panels A and B, respectively, are statistically (1%) and economically significant. When we include both laws in a combined model, we find consistent results: both types of laws are associated with significant reductions in pollution, though with differing magnitudes. A one-standard deviation increase in punitive laws (as opposed to non-punitive laws) leads to a 6.1% (3.5%) decrease in pollution, indicating that punitive laws are

[13] As a robustness check, we normalize total pollution by sales and by employment to account for firm size. The results remain negative and statistically significant (Appendix Table IA4 and Table IA3), indicating that the main findings are not driven by firm scale

nearly twice as effective, highlighting the significance of punitive components in regulatory design. The strong effect of punitive laws aligns with *Deterrence Theory*, which emphasizes the role of enforcement in influencing corporate behavior. However, the finding that both punitive and non-punitive laws diminish pollution corresponds with *Institutional Theory*, which posits that corporations respond to rules as manifestations of social norms and seek legislative compliance.

[Insert Table 5 here]

In Table 5, we further analyze whether the impacts of the environmental legislation along with their subcategories—punitive and non-punitive laws—vary according to the ownership type of firms: public vs. private, considering their differing levels of exposure to public scrutiny. The influence of environmental laws is more pronounced for private parent facilities compared to public parent facilities in all specifications. The increased reaction from private facilities may arise from their lower levels of public and shareholder scrutiny compared to publicly traded companies (Peek et al., 2010), making them more susceptible to direct regulatory influence. Hence, our findings suggest that social norms, conveyed through public pressure, are most effectively communicated through formal legal mechanisms in contexts where informal monitoring is less robust. In contrast, publicly traded companies are accountable to public and investor expectations, which likely motivates them to actively reduce pollution. The additional pressure from environmental laws is less pronounced for public firms than for private firms.

[Insert Table 6 here]

Next, in Table 6 we classify the environmental laws based on the industries they impact, as certain industries undergo more public scrutiny than others. Our findings show that industry-relevant laws have a significantly stronger impact on pollution reduction. Specifically, in

Column 6, a one-standard deviation increase (0.697) in the industry-relevant environmental laws results in an 8.4% (0.697 x 0.121) decrease in total pollution across all facilities. Facilities in the most polluting industries are more likely to adopt measures to reduce pollution due to heightened regulations resulting from rising public awareness and demand. Thus, emphasizing the necessity of tailored regulatory frameworks to tackle the unique environmental challenges of each industry (Kalmenovitz, 2023).

[Insert Table 7 here]

5.2. Identification Strategy

Our baseline results indicate a negative relationship between state-level environmental legislation and facility pollution levels. Identifying the causal impact of these legislation on pollution remains challenging. The primary issue pertains to reverse causality: increased pollution may prompt the legislatures to enact more environmental laws to address these issues (Carson, 2010). On the other hand, there may be another concern related to omitted variable bias. Unobserved variables may influence facility pollution, potentially biasing the OLS coefficients. To establish causality, it is necessary to introduce an exogenous source of variation in state-level environmental laws, such as instrumental variables that is correlated with the environmental laws while ensuring independent of facility pollution. In this section, we utilize two IV-techniques which encompass state newspaper coverage of environmental issues and state public climate opinions. These two variables serve as proxies for public pressure and societal norms, which subsequently influence environmental legislation. As public pressure escalates, legislators are increasingly inclined to enact more environmental laws to alleviate pollution. In all cases public pressure is thus used as an instructional variable to reduce the possibility of endogeneity problems in the relationship between environmental laws and facility pollution.

5.2.1. Newspaper Coverage

The media plays a vital role in communicating the public about climate change (Anderson, 2009). Mass media coverage constitutes a social link among scientists, policy makers, and the public, mediated through news packages (Boykoff and Boykoff, 2007). Prior studies indicate that media coverage enhances public awareness and scrutiny (Campa, 2018, Sampei and Aoyagi-Usui, 2009), climate risk perception, and climate policy support (Anderson, 2009). As a result, public awareness about environmental preservation are strengthened, and lawmakers are prompted to respond by enacting more environmental laws to protect the environment (Carson, 2010). Building on this, we employ Dow Jones Factiva data on local newspaper coverage of environmental issues in U.S. states as an instrumental variable to determine the causal impact of public pressure, indicated by media salience, on environmental legislation and, subsequently, on pollution at the facility level. News coverage is believed to influence facility-level pollution indirectly by enhancing public pressure, which in turn amplifies political pressure on lawmakers to enact additional legislation, rather than directly affecting facility emissions.

The first-stage specification is as follows:

$$
\begin{aligned}
&log\ (1 + Env\_Laws_{s,t-1}) \\
&\qquad = +\ \tau.\ log\ (News\_Coverage_{s,t-2}) + \delta StateControls_{s,t-1} \\
&\qquad + \alpha FacilityControls_{s,i,f,t-1} + FEs + \epsilon_{f,i,s,t}
\end{aligned}
$$

In the second stage, we run the following regression specification:

$$
\begin{aligned}
&log(1 + Total\_Pollution)_{f,i,s,t} \\
&\qquad = \ \lambda \left(\overline{log(1 + Env\_Laws)_{s,t-1}} \right) + \ \delta StateControls_{s,t-1} \\
&\qquad + \ \alpha FacilityControls_{s,i,f,t-1} + FEs + \epsilon_{f,i,s,t}
\end{aligned}
$$

where *f* denotes facilities situated in state *s* at time *t*. We apply the same control variables as in our baseline regression and maintain the same fixed effects to ensure consistency in the analysis.

We present the first-stage regression results in column 1 of Table 7 where we regress environmental laws on local news coverage. We find that an increase in climate related news coverage is associated with the higher number of environmental laws, confirming that exogenous shifts in environmental saliences translate into greater policy outcome via the public pressure channel. We then examine the effects of environmental laws on firms' pollution in column 2 of Table 7. The coefficient estimates reported in column 2 show that, for a one-standard deviation (0.475) increase in the instrumented environmental laws (*EnvLaws_IV*), total facility pollution drops by approximately 51% (0.475*1.064) based on the log-linear specification.

5.2.2. Public Climate Opinion

In our second IV test, we utilize public opinion on global warming as an instrumental variable to examine the causal relationship between environmental legislation and facility pollution. We use climate opinion poll data collected by the Yale Program on Climate Change Communication (YPCCC)[14] which tracks state-level variations in Americans' climate opinion such as climate beliefs, risk perceptions, and policy support (Howe et al., 2015). Based on prior studies, states where climate change is perceived to be a serious issue, and where attention to climate change is high, are more likely to pass legislation addressing environmental issues (Bromley-Trujillo and Poe, 2020). This instrument is unlikely to violate exclusion restrictions.

[14] Using YPCCC data, we derive an overall climate score for each state by calculating the average of the subcategories: belief in climate change, risk perceptions, and support for climate-related legislation. This climate score, together with other subcategories, enables us to determine the level of public awareness and its potential impact on environmental consequences.

Public sentiment greatly influences the political process, as elected officials are answerable to the electorate and frequently consider public opinion in their policy decisions. Public concern regarding environmental issues exerts indirect pressure on companies by influencing the regulatory framework within which they function. Nevertheless, companies typically do not directly react to individual public sentiment; rather, they respond to the legal and institutional frameworks established by policymakers. Hence, public opinion influences corporate behavior mainly by shaping legislation, rather than exerting a direct effect on corporate decision-making.

This forms the basis of our first-stage regression, which investigates the impact of public climate opinion on the number of environmental laws:

$$
\begin{aligned}
& log\,(1 + Env\_Laws_{s,t-1}) \\
& \qquad = +\,\tau .\, log\,(Climate\_Opinion_{s,t-2}) + \delta StateControls_{s,t-1} \\
& \qquad + \ \alpha FacilityControls_{s,i,f,t-1} + FEs + \epsilon_{f,i,s,t}
\end{aligned}
$$

In the second stage, we assess the causal impact of instrumented environmental laws on pollution levels using the following specification:

$$
\begin{aligned}
& log(1 + Total\_Pollution)_{f,i,s,t} \\
& \qquad = \ \lambda\left(\overline{log(1 + Env\_Laws_{s,t-1})}\right) + \ \delta StateControls_{s,t-1} \\
& \qquad + \ \alpha FacilityControls_{s,i,f,t-1} + FEs + \epsilon_{f,i,s,t}
\end{aligned}
$$

where *f* denotes facilities situated in state *s* at time *t*. We apply the same control variables as in our baseline regression and maintain the same fixed effects to ensure consistency in the analysis.

[Insert Table 8 here]

Column 1 of Table 8 presents the findings from our first stage regression, indicating that stronger public opinion on climate issues correlates with an increased number of environmental laws, with results significant at the 1% level. In the subsequent stage of our regression analysis in column 2, we observe that a one-standard deviation increases in instrumented environmental laws (0.431) leads to 6.3% (0.431*0.148) decrease in pollution, indicating a significant causal relationship between legislation and pollution reduction.

[Insert Table 9 here]

5.3. Political Leaning, Environmental Legislation, and Facility Pollution

Environmental laws, as reflections of prevailing social norms, should exhibit greater efficacy in mitigating pollution in contexts where those norms are firmly established. A recent survey performed by Stanford University in 2024 indicates that 37% of Democrats regard global warming as very or extremely essential, compared to 18% of independents and 5% of Republicans who share this perspective (Stanford, 2024). This indicates that Democrats are generally more environmentally aware than Republicans. Hence, we investigate whether the influence of environmental legislation on pollution is more pronounced in Democratic-leaning states, where public endorsement for environmental protection is typically stronger. Column 1 of Table 9 illustrates the effect of a fully Democratic state government, characterized by a Democratic governor and legislature, on pollution reduction via environmental legislation. The findings indicate that environmental legislation exerts a more pronounced adverse impact on pollution in Democratic states. This further supports our hypothesis that public pressure reflected in regional social norms plays a crucial role in shaping both stringency and effectiveness of climate policy. However, as shown in Column (3), this effect is predominantly driven by Democratic legislatures, whereas Column (2) shows that the effect under Democratic governors is not statistically significant. The impact of environmental legislation is more substantial (β = -0.201) at a 1% significance level compared to that of a governor with democratic inclinations. The findings suggest that the institutional provenance of legislation—

particularly from domestically elected legislatures—plays a more pivotal role in influencing environmental outcomes, despite Democratic governors possibly backing these laws.

[Insert Table 10 here]

5.4. Channel Analysis: Investment in Abatement Activities

Our analysis thus far points to the relationship between environmental laws (Punitive and Non-Punitive) and firm pollution. This section examines how these laws work. Table 10 examines one such channel—investment in pollution abatement at facility level—indicates that heightened environmental laws result in reduced corporate pollution through increasing abatement activities. According to prior research, companies engage in pollution-reduction technology to lessen harmful pollutants (Jing et al., 2024, Akey and Appel, 2019, Akey and Appel, 2021). These investments help firms reduce pollution related expenses, including penalties for legal violations and cleanup costs. By implementing such initiatives, firms not only complying with environmental legislation can also alleviate the financial obligations linked to pollution. We utilize the EPA's P2 database to track source reduction initiatives at the facility level as a measure of abatement activities. For the past decade, manufacturers have concentrated on source reduction initiatives to reduce the quantity of chemical waste necessitating recycling, treatment, or disposal. From 1991 to 2021, the Toxic Release Inventory (TRI) documented 470,000 source reduction actions across more than 23,000 sites, resulting in a consistent decrease in chemical emissions during this timeframe (EPA,2024). While firms do not report the exact dollar amounts spent, they disclose the types of source reduction actions taken. We measure the abatement activities by using the logarithm of one plus the count of abatement actions reported per facility year, as many firms fail to submit abatement activities for each facility-year. The findings indicate that a rise in environmental law noticeably increases abatement activities, specifically one standard deviation increase in legislation to increase source reduction activities by 1.4%. In Panel B, we further substantiate this finding by illustrating that the higher number of environmental laws require facilities to adopt abatement methods, which consequently lead to a reduction in pollution.

5.5. Do environmental laws affect facility financial health?

Table 11 presents the effect of environmental legislation on three dimensions of facility-level financial performance: sales growth, employment growth, and creditworthiness (PayDex). Columns (1) and (2) indicate that environmental laws do not have a statistically significant impact on facility-level sales or employment growth. This suggests that the enactment of a higher number of environmental laws does not seem to incur real economic burdens in terms of output or labor force reductions at the facility level. These findings indicate that facilities are not reacting to environmental laws by reducing size or scaling back operations.

[Insert Table 10 here]

However, in column (3), we observe a statistically significant negative relationship between environmental laws and PayDex scores, an indicator of creditworthiness. Specifically, a one-standard deviation increase in environmental laws is associated with a 0.15% reduction in PayDex scores. This indicates that heightened regulatory exposure may impose nuanced financial burdens, potentially through compliance costs, investment in abatement technology, or tighter short-term liquidity. Therefore, the lack of negative impacts on sales or employment, along with the slight decrease in Paydex scores, reinforces the hypothesis that pollution reduction is influenced by direct compliance and institutional adaptation rather than economic contraction.

6. Conclusion

Using pollution as a proxy for environmental behavior, our study examines the impact of state-level environmental legislation on influencing corporate pollution. We show that the increase in the number of environmental laws significantly reduces pollution from both public and private facilities. We show that both punitive and non-punitive laws effectively mitigate pollution; however, punitive laws exert a greater influence on pollution reduction. Furthermore, categorizing environmental legislation based on its industry relevance reveals a more significant impact on pollution reduction compared to other categories of environmental laws.

We mitigate the potential endogeneity between environmental laws and facility pollution by using two instrumental variable techniques: state-level news coverage of climate issues and state public climate opinion, which reflect regional social norms. In all specifications we find that the enactment of additional environmental legislation reduces facility-level pollution. We also show that facilities situated in Democratic-leaning states experience larger reductions in pollution when more environmental laws are enacted. We identify facility-level source abatement investment as a key channel through which these laws reduce pollution. Finally, we find that these laws have no effect on sales or employment growth and only a minor impact on creditworthiness, suggesting that pollution reduction is driven by regulatory action rather than economic contraction.

Our research aligns with *Public Interest Theory*, *Institutional Theory*, and *Deterrence Theory*, showing that freshly passed cumulative state environmental laws provide a solid legal basis to tackle market failures by limiting negative corporate behaviors. Different types of legislation serve different purposes: non-punitive laws work to develop norms around climate stewardship, while punitive laws ensure compliance. By showing that both punitive and non-punitive measures are effective in reducing pollution, we emphasize how these laws collectively reflect institutionalized social norms aimed at addressing environmental concerns. Hence, this underscores the necessity of considering their cumulative impact to foster a healthier and more sustainable environment.

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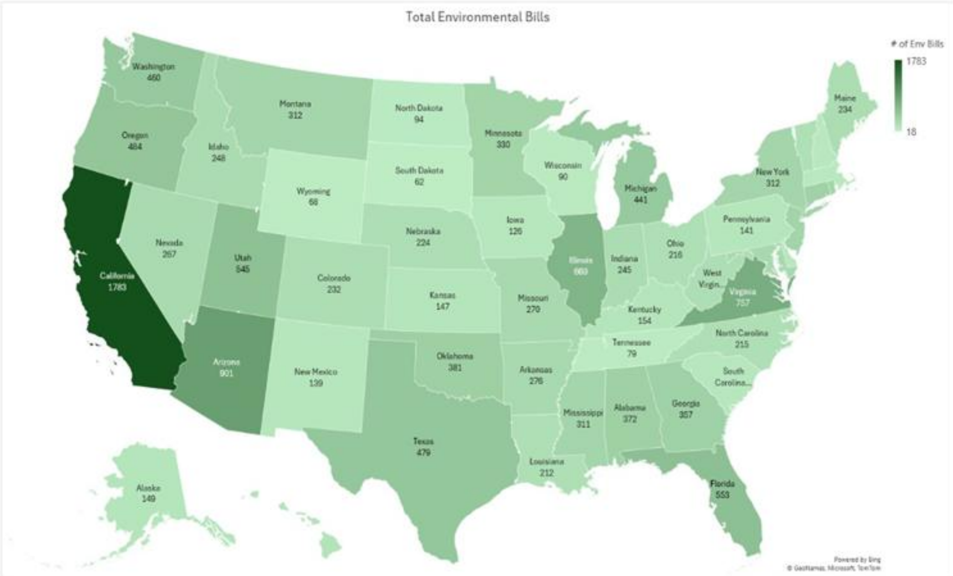


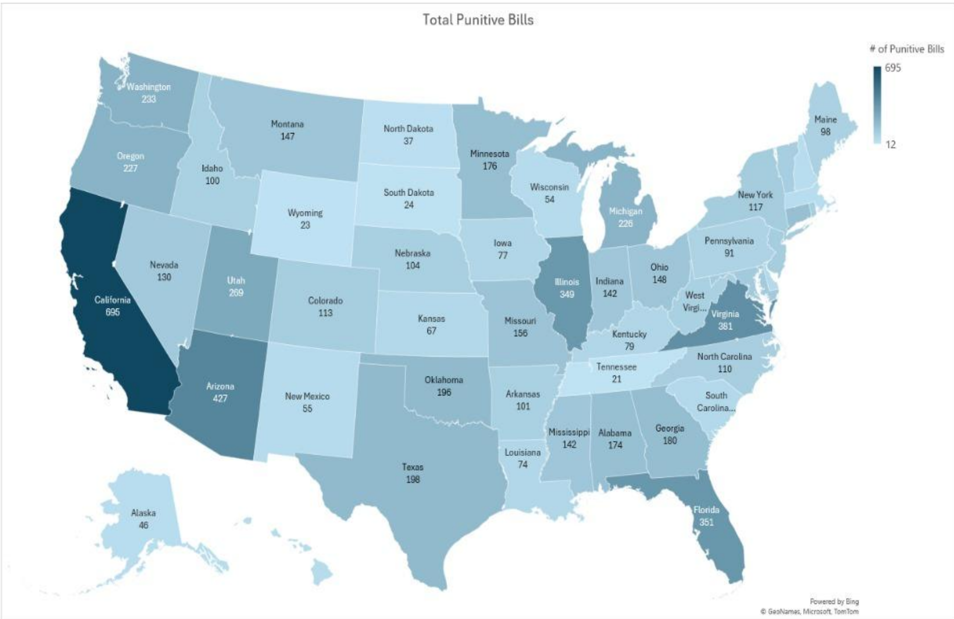


Figure 1: The first map shows the total number of environmental legislations enacted by each state, with California, Arizona, Illinois, Florida, Utah, and Virginia in the forefront. States like South Dakota and Wyoming pass less environmental legislation. The second map shows a comparable trend, depicting punitive environmental laws as a subset of environmental legislation; states with a higher number of environmental bills, such as California, Illinois, Arizona, Florida, Virginia, and Utah, also demonstrate a notable prevalence of punitive measures. This indicates that states that are more aggressive in environmental preservation also prioritize enforcement and fines within their strategy. Our approach specifically reflects the punitive features of the legal landscape by directly considering the consequences of non-compliance, thus capturing the genuine restrictiveness and deterrent effect of regulations. In this procedure, we identify a total of 6,850 laws as punitive laws which is about 59.5% of total environmental laws.

Table 1: Variable Description		
Variable	**Definition**	Data Source
Pollution -Variables		
Total_Pollution	Total quantity of on- and off-site toxic emission at the facility-year level	TRI
Onsite_Pollution	Total quantity of the toxic chemical released to air, water and land on-site at the facility-year level	TRI
Offsite_Pollution	Total quantity of the toxic chemical reported as transferred to off-site locations for release or disposal at the facility-year level	TRI
Air_Pollution	Total quantity of onsite stack emissions and on-site fugitive emissions at the facility-year level	TRI
Water_Pollution	Total quantity of toxic pollution released on-site as surface water discharges at the facility-year level	TRI
Ground_Pollution	Total quantity of toxic pollution released to on-site grounds at the facility-year level	TRI
Production_Waste	Total quantity of production-related waste.	TRI
State Level Variables		
Pop_Change_Rate$_{(t-1)}$	The percentage changes in the population from the previous year to the current year.	US Census
Per_Capita_Taxes$_{(t-1)}$	Total Tax Revenue/Population	US Census
Per_Capita_Env_Exp$_{(t-1)}$	Budget for Natural Resources/Population	BLS
Unemp_Rate$_{(t-1)}$	The percentage of the total labor force in a state that is unemployed	
Social_Capital$_{(t-1)}$	Social capital is calculated using data from the Northeast Regional Center for Rural Development (NRCRD) at Pennsylvania State University, following Hasan et al. (2017).	NRCRD
Corruption$_{(t-1)}$	Defined as state-level conviction data from the Department of Justice Public Integrity Section, scaled for state-level population.	DOJ, US Census
Enforcement$_{(t-1)}$	The natural logarithm of one plus the number of enforcements at state-year level lagged by 1 year	ICIS FE&C
Temp$_{(t-1)}$	State-level average annual temperature (°F), lagged one year	NOAA
Law-Variables		
Env_Laws$_{(t-1)}$	Natural logarithm of (one plus) environmental laws lagged by 1 year	LexisNexis
Punitive_Laws$_{(t-1)}$	Natural logarithm of (one plus) punitive laws lagged by 1 year	LexisNexis
Non_Puntiive_Laws$_{(t-1)}$	Natural logarithm of (one plus) non-punitive laws lagged by 1 year	LexisNexis
Relevant_Laws$_{(t-1)}$	Natural logarithm of (one plus) industry-relevant laws lagged by 1 year	LexisNexis
Facility-Variables		

Sales_Facility$_{(t-1)}$	Logarithm of number of sales dollar amount (inflation adjusted) at the facility year level lagged by 1 year	D&B NETS dataset
Emp_Facility$_{(t-1)}$	Logarithm of number of employees at the facility year level lagged by 1 year	D&B NETS dataset
Paydexmin$_{(t-1)}$	Captures the lowest Paydex score recorded for an establishment during the previous year.	D&B NETS dataset
Firm Level Variables		
Firm_Size$_{(t-1)}$	Natural logarithm of total assets	Compustat
	(Total asset + Common shares outstanding × Closing price (Fiscal year) − Common equity − Deferred taxes)/Asset	Compustat
Firm_Age$_{(t-1)}$	Difference between the current observation year and the year when the firm first appeared in Compustat.	Compustat
Long_Term_Debt$_{(t-1)}$	TLTD=Long-Term Debt (DLTT)+Current Portion of Long-Term Debt (DLC)	Compustat
Variables -Cross-Sectional Analysis		
State_Enforcements_Count$_{(t-1)}$	The natural logarithm of one plus the number of enforcements at state-year level lagged by 1 year	ICIS FE&C
High_Enforcement_State$_{(t-1)}$	Natural logarithm of (one plus) the number of EPA enforcement cases) at the state-year leve	ICIS FE&C
Democratic_State$_{(t-1)}$	Indicator variable that equals 1 if the state is Democratic-leaning states, where both the legislature and governor are Democratic and zero otherwise	NCSL
Democratic_Governor$_{(t-1)}$	Indicator variable that equals 1 if in the state the governor is Democratic-leaning and zero otherwise	NCSL
Democratic_Legislature$_{(t-1)}$	Indicator variable that equals 1 if in the state the legislature is Democratic-leaning and zero otherwise	NCSL
Variable- Instrumental Variables		
Climate_Score$_{(t-1)}$	A composite score representing the mean of belief, risk perception, and policy support scores, reflecting how aware and serious people are about global warming and their support for action lagged by 1 year	YPCCC
High_Climate_Opinion_State$_{(t-1)}$	Indicator variable that equals 1 if the state's Climate_Score_Overall is in the top quartile among states in the same year, and 0 otherwise.	YPCCC
Env_News_Count$_{(t-1)}$	The natural logarithm of one plus the number of environmental news at state-year level.	FACTIVA
State_with_High_News$_{(t-1)}$	Indicator variable that equals 1 if the state falls under the top quartile based on environmental news across states in the year, and 0 otherwise.	FACTIVA

Table 2: Descriptive Statistics

This table presents the summary statistics of facility-level pollution across various categories, state-level variables, and firm-level variables, along with the correlation matrix during 2000 to 2022 period. The analysis is restricted to 44 U.S. states with annual legislative sessions, excluding states with biennial sessions during the sample period (Arkansas, Montana, Nevada, North Dakota, Oregon, and Texas). Panel A provides summary statistics for the full sample of facilities, including those associated with both public and private firms. Panel B presents the summary statistics of subsample restricted to facilities with public parent firms as well as private parent firms while Panel C presents summary statistics at the state level, covering relevant state-level variables. Panel D presents statistics for all nonfinancial firms listed in Compustat, focusing specifically on U.S. public companies during the sample period. It also includes data for our sample firms within the same timeframe for comparison.

Panel A. Establishment Level			**Full Sample**			
Variables	**Obs**	**Mean**	**Med**	**SD**	**25th**	**75th**
Total_Pollution	269,631	29.69	0.49	1,366.65	0.02	5.63
Onsite_Pollution	269,631	24.62	0.08	136.33	0.00	2.22
Offsite_Pollution	269,631	5.07	0.00	93.34	0.00	0.07
Air_Pollution	269,631	10.46	0.04	91.51	0.00	1.50
Water_Pollution	269,631	2.49	0.00	63.31	0.00	0.00
Ground_Pollution	269,631	10.08	0.00	1,314.19	0.00	0.00
Production_Waste	269,631	232.13	6.06	6,918.11	0.30	34.08
Log_Total_Pollution	269,631	5.86	6.18	3.43	2.83	8.63
Log_Onsite_Pollution	269,631	4.61	4.36	3.75	0.78	7.69
Log_Offsite_Pollution	269,631	2.16	0.00	3.27	0.00	4.25
Log_Air_Pollution	269,631	4.23	0.35	3.71	0.35	7.28
Log_Water_Pollution	269,631	0.37	0.00	1.50	0.00	0.00
Log_Ground_Pollution	269,631	0.35	0.00	1.68	0.00	0.00
Log_Production_Waste	269,631	7.78	5.71	3.62	5.72	10.42
Sales_Facility (in millions)	269,631	61.4	17.3	212	5.6	49.1
Emp_Facility	269,631	208	90	454.30	32	216
PayDexMin	243,943	67.89	69	9.51	63	75
PayDexMax	243,902	74.37	76	6.50	71	79

Panel B: Establishment-Level Variables based on Ownership Structure												
	Public Parent Facilities						**Private Parent Facilities**					
Variables	**Obs.**	**Mean**	**Med**	**SD**	**25th**	**75th**	**Obs.**	**Mean**	**Med**	**SD**	**25th**	**75th**
Total_Pollution	73,185	32.29	0.49	340.86	0.02	6.90	176,001	29.92	0.47	1,676.92	0.01	5.24
Onsite_Pollution	73,185	25.29	0.86	309.42	0.00	2.66	176,001	25.47	0.07	1,661,46	0.00	2.10
Offsite_Pollution	73,185	6.76	0.00	136.78	0.00	0.13	176,001	4.31	0.00	69.87	0.00	0.05
Air_Pollution	73,185	14.74	0.04	126.86	0.00	1.33	176,001	8.81	0.03	75.73	0.00	1.50
Water_Pollution	73,185	2.88	0.00	69.61	0.00	0.00	176,001	2.32	0.00	61.26	0.00	0.00
Ground_Pollution	73,185	7.57	0.00	271.74	0.00	0.00	176,001	13.50	0.00	1,631.53	0.00	0.00
Production_Waste	73,185	256.03	8.74	5,178.41	0.04	44.22	176,001	228.56	5.02	7,875.85	0.25	29.71
Log_Total_Pollution	73,185	6.02	6.21	3.49	3.04	8.84	176,001	5.78	6.14	3.42	2.71	8.56
Log_Onsite_Pollution	73,185	4.69	4.46	3.86	0.77	7.86	176,001	4.54	4.26	3.72	0.74	7.65
Log_Offsite_Pollution	73,185	2.34	0.00	3.34	0.00	4.46	176,001	2.08	0.00	3.68	0.00	4.00
Log_Air_Pollution	73,185	4.24	3.71	3.75	0.33	7.20	176,001	4.21	3.61	3.68	0.33	7.31
Log_Water_Pollution	73,185	0.49	0.00	1.71	0.00	0.00	176,001	0.32	0.00	1.40	0.00	0.00
Log_Ground_Pollution	73,185	0.47	0.00	1.99	0.00	0.00	176,001	0.31	0.00	1.56	0.00	0.00
Log_Production_Waste	73,185	8.22	9.07	3.55	6.12	10.69	176,001	7.78	8.52	3.65	5.52	10.29
Sales_Facility (in millions)	73,185	113.0	34.2	334.0	11.7	90.5	176,001	38.10	12.60	129.00	4.44	33.80
Emp_Facility	73,185	310.04	130	654.29	50	308	176,001	158.33	74.00	312.06	30.00	175.00
PayDexMin	66,043	66.39	68	9.68	62	73	159,366	68.67	70	9.35	64	76
PayDexMax	67,019	73.59	75	6.64	70	78	161,355	74.78	77	6.38	72	79

Panel C-State Level Variables						
Variables	**Obs**	**Mean**	**Med**	**SD**	**25th**	**75th**
Env_Laws	269,631	11.64	8.00	12.48	4.00	13.00
Punitive_Laws	269,631	7.49	5.00	7.29	3.00	9.00
Non_Punitive_Laws	269,631	4.15	2.00	5.89	1.00	5.00
Industry_Relevant_Laws	269,631	1.55	1.00	2.61	0.00	2.00
Industry_Relevant_Punitive_Laws	269,631	0.85	0.00	1.60	0.00	1.00
Neighbouring_Laws	269,631	37.76	35.00	19.86	24.00	48.00
Pop_Change_Rate	269,631	0.64	0.54	0.65	0.22	0.96
Social_Capital	269,631	0.66	0.84	1.26	0.03	1.49
Unemp_Rate	269,631	5.77	5.35	2.00	4.40	6.75
State_Enforcements	269,631	120.00	83.00	114.97	50.00	144.00
Per_Capita_Tax	268,905	2.12	1.09	3.82	0.57	2.22
Corruption	266,337	0.30	0.16	0.77	0.06	0.31
Temperature	269,631	54.83	53.46	7.64	49.03	60.61

Panel D-Firm Level Variables										
	All Compustat Firms				Sample Firms				Mean Difference	
Variables	Obs	Mean	Med	SD	Obs	Mean	Med	SD	Mean Difference (All	P-Value
ROA$_{(t-1)}$	130,609.00	-4.84	-0.00	398.93	15,355.00	- 0.24	0.04	15.53	-4.59***	0.00
Tobinq$_{(t-1)}$	113,194.00	74.64	1.64	2,972.29	14,346.00	2.93	1.43	73.50	71.7133***	0.00
Firm_Size$_{(t-1)}$	132,331.00	5.18	5.20	2.75	15,370.00	7.75	7.79	2.05	-2.57***	0.00
Payout_Ratio$_{(t-1)}$	119,701.00	0.22	0.00	51.33	14,542.00	0.61	0.32	13.31	-0.39	0.03
Capex_to_ppe$_{(t-1)}$	121,552.00	0.59	0.20	43.78	15,289.00	0.17	0.14	0.12	0.42***	0.00
Long_Term_Debt$_{(t-1)}$	128,785.00	0.10	0.00	5.69	15,171.00	0.02	0.01	0.04	0.08***	0.00
Tangibility$_{(t-1)}$	130,060.00	0.25	0.13	0.27	15,365.00	0.30	0.25	0.19	-0.05***	0.00
Age$_{(t-1)}$	143,912.00	13.82	10.00	13.34	15,426.00	30.42	27.00	20.50	-16.91***	0.00
Book_Leverage$_{(t-1)}$	130,916.00	2.14	0.20	66.43	15,337.00	0.35	0.27	3.82	1.79***	0.00
Cashflow$_{(t-1)}$	128,982.00	-2.30	0.06	93.65	15,336.00	0.00	0.12	8.69	-2.30***	0.00
R&D$_{(t-1)}$	119,746.00	4.55	0.00	157.58	15,319.00	1.84	0.01	208.09	2.71	0.12

Table 3: Baseline Results-Environmental Laws and Facility Pollution

The table presents the OLS regression results examining the impact of state-level environmental legislation on facility pollution. The table includes 269,631 facility-year observations for the full sample which consists of both public parent and private parent facilities. The analysis covers the period from 2000 to 2022, with the dependent variable being the natural logarithm of (1+Total_Pollution). Robust standard errors are clustered by industry-year. *t*-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Table 1.

$$Log(1+Total\_Pollution)_{f,i,s,t} = \beta \text{Log}(1+Env\_Laws_{s,t-1}) + \delta StateControls_{s,t-1} + \theta FirmControls_{i,t-1} + \sigma \text{Facility}Controls_{i,t-1} + FEs + \epsilon_{f,i,s,t}$$

Panel A	**Full Sample**					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Env_Laws$_{(t-1)}$	-0.080***	-0.059***	-0.144***	-0.065***	-0.084***	-0.097***
	(-9.912)	(-7.439)	(-11.697)	(-7.480)	(-9.558)	(-11.396)
Corruption$_{(t-1)}$			0.030	0.209***	0.079***	0.083***
			(1.216)	(10.605)	(3.976)	(4.312)
Pop_Change_Rate$_{(t-1)}$			-0.012	0.057***	-0.039***	-0.042***
			(-0.435)	(4.300)	(-2.717)	(-2.923)
Unemp_Rate$_{(t-1)}$			-0.186***	-0.383***	-0.152***	-0.236***
			(-2.662)	(-16.666)	(-3.696)	(-5.777)
Per_Capita_Tax$_{(t-1)}$			-0.016***	-0.037***	-0.011***	-0.015***
			(-4.629)	(-13.617)	(-4.493)	(-5.951)
Social_Capital$_{(t-1)}$			0.263***	0.104***	0.166***	0.168***
			(22.604)	(12.809)	(20.381)	(20.604)
State_Enforcements$_{(t-1)}$			-0.186***	-0.018*	-0.089***	-0.095***
			(-11.489)	(-1.764)	(-7.923)	(-8.651)
Temp$_{(t-1)}$			0.023***	0.013***	0.018***	0.018***
			(8.687)	(10.041)	(13.550)	(14.193)
Neighbouring_Laws$_{(t-1)}$			-0.101***	-0.001	-0.049***	-0.038***
			(-4.757)	(-0.091)	(-3.690)	(-2.925)
Sales_Facility$_{(t-1)}$			0.173***	-0.063***	-0.023**	-0.003
			(5.883)	(-6.719)	(-2.500)	(-0.341)
Emp_Facility$_{(t-1)}$			0.048	0.247***	0.191***	0.188***
			(1.640)	(21.447)	(16.805)	(16.847)
Constant	6.036***	5.991***	3.259***	5.942***	5.384***	5.217***
	(321.855)	(327.125)	(8.222)	(40.921)	(36.294)	(35.640)
Observations	269,631	268,693	261,110	261,076	261,076	261,067
Adj. R-squared	0.000	0.301	0.033	0.276	0.281	0.309
Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	No	Yes	Yes	Yes
Facility_Group_by_Chem FE	No	Yes	No	No	No	Yes

Panel B	Public Owned Facilities			Private Owned Facilities		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
$Env\_Laws_{(t-1)}$	-0.016	-0.061***	-0.067***	-0.080***	-0.107***	-0.123***
	(-1.129)	(-3.774)	(-4.241)	(-8.074)	(-9.668)	(-11.523)
$Corruption_{(t-1)}$		0.194***	0.169***		0.027	0.048**
		(4.830)	(4.312)		(1.149)	(2.092)
$Pop\_Change\_Rate_{(t-1)}$		-0.062**	-0.054**		-0.029	-0.037**
		(-2.259)	(-1.974)		(-1.642)	(-2.150)
$Unemp\_Rate_{(t-1)}$		-0.289***	-0.378***		-0.069	-0.144***
		(-3.490)	(-4.553)		(-1.374)	(-2.965)
$Per\_Capita\_Tax_{(t-1)}$		-0.025***	-0.028***		-0.003	-0.006**
		(-4.968)	(-5.363)		(-0.946)	(-2.071)
$Social\_Capital_{(t-1)}$		0.141***	0.139***		0.185***	0.192***
		(8.180)	(8.127)		(18.710)	(19.616)
$State\_Enforcements_{(t-1)}$		-0.107***	-0.102***		-0.082***	-0.089***
		(-4.871)	(-4.674)		(-5.884)	(-6.548)
$Temp_{(t-1)}$		0.022***	0.021***		0.017***	0.017***
		(9.038)	(8.627)		(10.052)	(10.654)
$Neighbouring\_Laws_{(t-1)}$		-0.023	-0.019		-0.075***	-0.066***
		(-0.940)	(-0.769)		(-4.636)	(-4.194)
$Sales\_Facility_{(t-1)}$		-0.095***	-0.096***		0.019*	0.037***
		(-4.788)	(-4.943)		(1.708)	(3.417)
$Emp\_Facility_{(t-1)}$		0.251***	0.264***		0.146***	0.146***
		(10.668)	(11.435)		(10.887)	(10.995)
$Firm\_Size_{(t-1)}$		0.054***	0.058***			
		(5.599)	(6.175)			
$Firm\_Age_{(t-1)}$		-0.004***	-0.003***			
		(-5.279)	(-4.312)			
$Long\_Term\_Debt_{(t-1)}$		-0.129	-0.294			
		(-0.200)	(-0.464)			
Observations	72,986	68,399	68,396	175,271	170,696	170,690
Adj. R-squared	0.282	0.276	0.294	0.336	0.309	0.343
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Facility_Group_by_Chem FE	Yes	No	Yes	Yes	No	Yes

Table 4: Punitive and Non-Punitive Laws and Facility Toxic Pollution

This table presents OLS regression results examining the impact of state-level punitive and non-punitive environmental legislation on corporate pollution. Panel A reports the results for punitive laws for the full sample consisting of 273,691 facility-year observations. Panel B reports the results for non-punitive laws for the full sample consisting of 273,691 facility-year observations. The analysis covers the period from 2000 to 2022, with the dependent variable being the natural logarithm of (1+Total_Pollution). Robust standard errors are clustered by industry-year. t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Table 1.

$$Log(1 + Total\_Pollution)_{f,i,s,t} = \beta \text{Log}(1 + \text{Punitive\_}Laws_{s,t-1}) + \delta StateControls_{s,t-1} + \sigma \text{Facility}Controls_{i,t-1} + FEs + \epsilon_{f,i,s,t}$$

$$Log(1 + Total_{Pollution})_{f,i,s,t} = \beta \text{Log}\left(1 + \text{Non Punitive\_}Laws_{s,t-1}\right) + \delta StateControls_{s,t-1} + \sigma \text{Facility}Controls_{i,t-1} + FEs + \epsilon_{f,i,s,t}$$

Panel A-Punitive Laws			**Full Sample**			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Punitive_Laws$_{(t-1)}$	-0.071***	-0.052***	-0.156***	-0.071***	-0.093***	-0.104***
	(-8.526)	(-6.476)	(-12.495)	(-7.963)	(-10.245)	(-11.745)
Corruption$_{(t-1)}$			0.032	0.209***	0.080***	0.084***
			(1.283)	(10.611)	(4.043)	(4.375)
Pop_Change_Rate$_{(t-1)}$			-0.006	0.059***	-0.035**	-0.038***
			(-0.206)	(4.457)	(-2.420)	(-2.643)
Unemp_Rate$_{(t-1)}$			-0.170**	-0.382***	-0.141***	-0.226***
			(-2.438)	(-16.585)	(-3.435)	(-5.543)
Per_Capita_Tax$_{(t-1)}$			-0.018***	-0.038***	-0.013***	-0.016***
			(-5.223)	(-13.918)	(-4.986)	(-6.509)
Social_Capital$_{(t-1)}$			0.275***	0.109***	0.174***	0.177***
			(23.194)	(13.320)	(20.956)	(21.247)
State_Enforcements$_{(t-1)}$			-0.186***	-0.018*	-0.089***	-0.096***
			(-11.531)	(-1.783)	(-7.877)	(-8.655)
Temp$_{(t-1)}$			0.021***	0.012***	0.017***	0.017***
			(8.190)	(9.756)	(13.111)	(13.553)
Neighbouring_Laws$_{(t-1)}$			-0.104***	-0.003	-0.052***	-0.040***
			(-4.910)	(-0.229)	(-3.856)	(-3.047)
Sales_Facility$_{(t-1)}$			0.172***	-0.063***	-0.023**	-0.003
			(5.862)	(-6.718)	(-2.490)	(-0.328)
Emp_Facility$_{(t-1)}$			0.049*	0.247***	0.190***	0.188***
			(1.656)	(21.451)	(16.801)	(16.845)
Observations	269,631	268,693	261,110	261,076	261,076	261,067
Adj. R-squared	0.000	0.301	0.033	0.276	0.281	0.309
Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	No	Yes	Yes	Yes
Facility_Group_by_Chem FE	No	Yes	No	No	No	Yes

Panel B – Non-Punitive Laws	Full Sample					
	(1)	(2)	(3)	(4)	(5)	(6)
Non-Punitive_Laws$_{(t-1)}$	-0.117***	-0.078***	-0.122***	-0.060***	-0.067***	-0.081***
	(-15.308)	(-10.140)	(-10.372)	(-7.159)	(-7.990)	(-9.895)
Corruption$_{(t-1)}$			0.020	0.203***	0.073***	0.076***
			(0.815)	(10.308)	(3.662)	(3.936)
Pop_Change_Rate$_{(t-1)}$			-0.022	0.053***	-0.046***	-0.049***
			(-0.776)	(4.049)	(-3.139)	(-3.371)
Unemp_Rate$_{(t-1)}$			-0.222***	-0.387***	-0.174***	-0.259***
			(-3.184)	(-16.871)	(-4.241)	(-6.371)
Per_Capita_Tax$_{(t-1)}$			-0.013***	-0.035***	-0.010***	-0.013***
			(-3.706)	(-12.993)	(-3.799)	(-5.091)
Social_Capital$_{(t-1)}$			0.238***	0.093***	0.151***	0.151***
			(21.037)	(11.624)	(18.948)	(18.856)
State_Enforcements$_{(t-1)}$			-0.190***	-0.020**	-0.092***	-0.098***
			(-11.727)	(-1.980)	(-8.183)	(-8.901)
Temp$_{(t-1)}$			0.023***	0.013***	0.018***	0.018***
			(8.901)	(10.171)	(13.561)	(14.293)
Neighbouring_Laws$_{(t-1)}$			-0.082***	0.006	-0.038***	-0.025*
			(-3.995)	(0.466)	(-2.861)	(-1.954)
Sales_Facility$_{(t-1)}$			0.173***	-0.063***	-0.024**	-0.004
			(5.896)	(-6.714)	(-2.541)	(-0.395)
Emp_Facility$_{(t-1)}$			0.049*	0.248***	0.191***	0.189***
			(1.652)	(21.433)	(16.839)	(16.889)
Observations	269,631	268,693	261,110	261,076	261,076	261,067
Adj. R-squared	0.001	0.301	0.033	0.276	0.281	0.309
Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	No	Yes	Yes	Yes
Facility_Group_by_Chem FE	No	Yes	No	No	No	Yes

Panel C: Combined Model Estimating the Impact of Law Types on Toxic Release	
	(1)
Punitive_Laws$_{(t-1)}$	-0.077***
	(-7.061)
Non-Punitive_Laws$_{(t-1)}$	-0.041***
	(-4.047)
Constant	5.173***
	(35.077)
Observations	261,067
Adj. R-squared	0.309
Controls	Yes
Year FE	Yes
Industry FE	Yes
Facility Group FE	Yes

Table 5: Differential impact on environmental laws by ownership type (Private/Public)

The table presents OLS regression results analyzing the differential impact of environmental laws on pollution based on ownership type (Private vs. Public) of parent facilities. The analysis covers the period from 2000 to 2022, with the dependent variable being the natural logarithm of (1+Total_Pollution). Private_Dummy, equals 1 for facilities owned by private parent companies and 0 for those with public ownership. Robust standard errors are clustered at the industry-year level, and t-statistics are reported in parentheses. Statistical significance is denoted by *, **, and ***, representing significance at the 10%, 5%, and 1% levels, respectively. Definitions for all variables are detailed in Table 1 .

$$Log(1+Total\_Pollution)_{f,i,s,t} = \beta Log(1+Env\_Laws_{s,t-1}) * Private\_Dummy + \delta StateControls_{s,t-1} + \theta FirmControls_{i,t-1} + \sigma \text{Facility}Controls_{i,t-1} + FEs + \epsilon_{f,i,s,t}$$

VARIABLES	**(1)**	**(2)**	**(3)**
Private_Dummy	0.059	0.016	-0.001
	(1.461)	(0.446)	(-0.023)
$Env\_Laws_{(t-1)}$*Private_Dummy	-0.069***		
	(-3.996)		
$Env\_Laws_{(t-1)}$	-0.052***		
	(-3.470)		
$Punitive\_Laws_{(t-1)}$ *Private_Dummy		-0.059***	
		(-3.284)	
$Punitive\_Laws_{(t-1)}$		-0.066***	
		(-4.200)	
$NonPunitive\_Laws_{(t-1)}$ *Private_Dummy			-0.075***
			(-4.647)
$NonPunitive\_Laws_{(t-1)}$			-0.031**
			(-2.220)
	5.202***	5.191***	5.180***
Constant	(32.163)	(31.998)	(32.148)
			-0.075***
Observations	221,941	221,941	221,941
Adj. R-squared	0.299	0.299	0.299
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Facility_Group_by_Chem FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 6: Industry Relevant Laws and Facility Toxic Pollution

The following table displays the OLS regression examining the impact of state-level Industry-relevant environmental laws on facility pollution. The dataset comprises 273,691 facility-year observations. The analysis spans the period 2000–2022, with the dependent variable being the natural logarithm of (1+Total_Pollution). Definitions of variable construction are provided in Table 1. Robust standard errors are clustered by industry by year and reported in parentheses, with fixed effects as noted in the table. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

$$Log(1 + Total\_Pollution)_{f,i,s,t} = \beta Log(1 + Relevant\_Laws_{s,t-1}) + \delta StateControls_{s,t-1} + \sigma \text{Facility}Controls_{i,t-1} + FEs + \epsilon_{f,i,s,t}$$

Panel A

VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$Relevant\_Laws_{(t-1)}$	-0.164***	-0.119***	-0.178***	-0.078***	-0.107***	-0.121***
	(-17.279)	(-12.862)	(-12.618)	(-7.656)	(-10.450)	(-12.165)
$Corruption_{(t-1)}$			0.006	0.188***	0.061***	0.064***
			(0.242)	(9.475)	(3.058)	(3.303)
$Pop\_Change\_Rate_{(t-1)}$			-0.007	0.058***	-0.036**	-0.040***
			(-0.261)	(4.334)	(-2.453)	(-2.721)
$Unemp\_Rate_{(t-1)}$			-0.120*	-0.362***	-0.116***	-0.197***
			(-1.697)	(-15.536)	(-2.747)	(-4.696)
$Per\_Capita\_Tax_{(t-1)}$			-0.011***	-0.034***	-0.008***	-0.011***
			(-3.168)	(-12.423)	(-3.245)	(-4.450)
$Social\_Capital_{(t-1)}$			0.252***	0.100***	0.160***	0.162***
			(22.043)	(12.405)	(19.881)	(20.037)
$State\_Enforcements_{(t-1)}$			-0.183***	-0.017	-0.090***	-0.095***
			(-11.171)	(-1.625)	(-7.836)	(-8.500)
$Avg\_Temp_{(t-1)}$			0.020***	0.011***	0.016***	0.017***
			(7.667)	(9.051)	(12.373)	(12.958)
$Neighbouring\_Laws_{(t-1)}$			-0.082***	0.002	-0.039***	-0.026**
			(-3.934)	(0.170)	(-2.911)	(-2.046)
$Sales\_Facility_{(t-1)}$			0.175***	-0.061***	-0.022**	-0.003
			(5.919)	(-6.494)	(-2.383)	(-0.307)
$Emp\_Facility_{(t-1)}$			0.047	0.246***	0.191***	0.189***
			(1.591)	(21.206)	(16.667)	(16.725)
Observations	265,181	264,251	256,723	256,686	256,686	256,677
Adj. R-squared	0.001	0.301	0.032	0.276	0.281	0.309
Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	No	Yes	Yes	Yes
Facility_Group_by_Chem FE	No	Yes	No	No	No	Yes

Table 7: Instrumental Variable Approach: News Paper Coverage

This table presents the results of a two-stage least square (2SLS) regression, illustrating the causal impact of environmental legislation on pollution levels. The time period is 2009 to 2022. Column 1 presents the initial-stage findings where $Env\_Laws_{(t-1)}$ are instrumented by local climate $News\_Coverage_{(t-2)}$. The second-stage instrumental variable results in column 2 indicate that the instrumented environmental legislation significantly reduces total pollution. Definitions of variable construction are provided in Table 1. Robust standard errors are clustered by industry-year and reported in parentheses, with fixed effects as noted in the table. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	First-Stage Results	**Second-Stage (IV) Results**
	Env_Laws	Total_Pollution
$News\_Coverage_{(t-2)}$	0.111***	
	(0.004)	
Env_Laws_IV		-0.803***
		(0.029)
Observations	134,160	134,160
R-squared	0.252	-0.029
Controls	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
Facility_Group_by_Chem FE	Yes	Yes
Instrument Validity Tests:		
Underidentification Test (Kleibergen-Paap LM)	508.3	
Weak Identification Test (Kleibergen-Paap F)	920	
Stock-Yogo Critical Value (10%)	16.38	

Table 8: Instrumental Variable Approach: Public Climate Opinion and Environmental Law

This table presents the results of a two-stage least square (2SLS) regression, illustrating the causal impact of environmental legislation on pollution levels. Column 1 presents the iniial-stage findings where Env_Laws$_{(t-1)}$ are instrumented by local public Climate_Opinion$_{(t-2)}$. The second-stage instrumental variable results in column 2 indicate that instrumented environmental legislation significantly reduce Total_Pollution. Definitions of variable construction are provided in . Robust standard errors are clustered by industry-year and reported in parentheses, with fixed effects as noted in the table. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	First-Stage Results	**Second-Stage (IV) Results**
	Env_Laws	Total_Pollution
Climate_Opinion$_{(t-2)}$	3.069***	
	(0.065)	
Env_Laws_IV		-0.148***
		(0.044)
Observations	114,237	114,237
Adj. R-squared	0.262	0.008
Controls	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
Facility_Group_by_Chem FE	Yes	Yes
Instrument Validity Tests:		
Underidentification Test (Kleibergen-Paap LM)	635.1	
Weak Identification Test (Kleibergen-Paap F)	2258	
Stock-Yogo Critical Value (10%)	16.38	

Table 9: The Impact of Environmental Laws on Facility Toxic Pollution in States with Democratic Leaning Overall

This table presents OLS regression results examining the interaction effect of Democratic-leaning governance and environmental laws on facility pollution. The dataset includes 135,770 facility-year observations. Columns 1 analyzes fully Democratic-leaning states, where both the legislature and governor are Democratic. Columns 2 focuses on states with Democratic-leaning governors, and column 3 examines states with Democratic-leaning legislatures. In the equation, Democratic_Leaning denotes the Democratic_States, Democratic_Governor, and Democratic_Legislatures.The analysis covers the period from 2009 to 2022, with the dependent variable being the natural logarithm of (1+Total_Pollution). Robust standard errors are clustered at the industry-year level, and t-statistics are reported in parentheses. Statistical significance is denoted by *, **, and ***, representing significance at the 10%, 5%, and 1% levels, respectively. Definitions for all variables are detailed in **Error! Reference source not found.**.

$$log(1+Total\_Pollution)_{f.i.s.t} = \beta\log(1+Env\_Laws_{s.t-1}) * Democratic\_Leaning + \delta StateControls_{s.t-1} + \sigma\text{Facility}Controls_{i.t-1} + FEs + \epsilon_{f.i.s.t}$$

VARIABLES	**(1)**	**(2)**	**(3)**
Env_Laws$_{(t-1)}$	-0.011	-0.087***	0.013
	(-0.861)	(-8.269)	(0.997)
Democratic_State$_{(t-1)}$	0.309***		
	(5.161)		
Democratic_State$_{(t-1)}$ ×Env_Laws$_{(t-1)}$	-0.176***		
	(-7.323)		
Democratic_Governor$_{(t-1)}$		0.035	
		(-0.879)	
Democratic_Governo$_{(t-1)}$ r×Env_Laws$_{(t-1)}$		-0.023	
		(-1.317)	
Democratic_Legislature$_{(t-1)}$			0.396***
			(7.733)
Democratic_Legislature$_{(t-1)}$ ×Env_Laws$_{(t-1)}$			-0.201***
			(-9.371)
Observations	147,228	261,067	147,228
Adj. R-squared	0.334	0.309	0.334
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Facility_Group_by_Chem FE	Yes	Yes	Yes

Table 10: Channels Analysis- The Impact of State Environmental Laws on Facility Toxic Pollution Through Abatement Initiatives

This table reports the results of OLS regressions testing the effect of environmental on firm pollution via abatement channels. This table focus on the interaction between environmental and punitive laws and the Abatement_Dummy variable, which equals 1 if a facility reports any abatement activity and 0 otherwise. Variable definitions are detailed in Table 1. Robust standard errors are clustered at the industry-year level and t-statistics are reported in parentheses. Fixed effects, controls, and R-squared values are specified in the table. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

$$log(1 + Total\_Pollution)_{f,i,s,t} = \beta \log(1 + Env\_Laws_{s,t-1}) * Abatement\_Dummy + \delta StateControls_{s,t-1} + \sigma \text{Facility}Controls_{i,t-1} + FEs + \epsilon_{f,i,s,t}$$

VARIABLES	**(1)**	**(2)**
Env_Laws$_{(t-1)}$	-0.024	-0.100***
	(-0.710)	(-11.202)
Abatement_Dummy	0.329***	
	(4.108)	
Abatement_Dummy*Env_Laws$_{(t-1)}$	-0.085**	
	(-2.536)	
Abatement_Count		0.052***
		-4.097
Abatement_Count*Env_Laws		-0.018***
		(-3.365)
Observations	248,776	248,776
Adj. R-squared	0.311	0.311
Controls	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
Facility_group_by_chemical FE	Yes	Yes

Table 11: Effect of Environmental Laws on Firm-Level Financial and Operational Outcomes

This table presents the impact of environmental laws on firm-level financial and operational outcomes. The dependent variables are (i) log difference in facility sales, (ii) log difference in employment, and (iii) Paydex score, which reflects the timeliness of bill payments (higher values indicate better credit behavior). Robust standard errors are clustered at the industry-year level, and t-statistics are reported in parentheses. Statistical significance is denoted by *, **, and ***, representing significance at the 10%, 5%, and 1% levels, respectively. Definitions for all variables are detailed in Table 1.

$$log(Facility\_Financials)_{f,s,t} = \beta \log(1 + Env\_Laws_{s,t-1}) + \delta StateControls_{s,t-1} + \sigma \text{Facility}Controls_{i,t-1} + FEs + \epsilon_{f,i,s,t}$$

	Δ log(Sales)	Δ log(Employment)	Paydex(Creditworthiness)
VARIABLES	**(1)**	**(2)**	**(3)**
$Env\_Laws_{(t-1)}$	-0.001	-0.001	-0.125***
	(-0.767)	(-1.148)	(-4.604)
Constant	0.201***	0.514***	73.321***
	(14.258)	(27.246)	(159.426)
Observations	261,067	261,067	237,923
Adj. R-squared	0.024	0.026	0.064
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Facility Group FE	Yes	Yes	Yes

Appendix

“Legalizing Social Norms: How State Environmental Laws Reduce Pollution”

This Internet Appendix contains supplementary data and figures that support the primary content.

Background of US Legislative process

Each state in the US follows the federal legislative process for proposing and enacting bills that align with the state legal framework. Upon a legislator's introduction of a bill (Figure 2) the clerk assigns it a number, indicating the commencement of its passage through the state's legislative assembly. The designated panel investigates the proposed bills, which may include public hearings, amending the bill's language, or forwarding it to another committee for additional scrutiny. State-level agencies such as the legislative commissioners' office, the office of fiscal analysis, and the office of legislative research assess the measure for constitutional compliance, financial implications, and linguistic clarity. Once approved by the committees, the legislation is subject to debates and voting in the legislative chambers. After being approved by both chambers, the bill is forwarded to the governor, who can choose to sign it into law, veto it, or allow it to become law through inaction within a specified timeframe. This procedure ensures that laws are thoroughly examined and evaluated at the state level, reflecting the thorough examination and adaptability seen in the federal legislative process. We examine all environmental legislation enacted between 2000 and 2022.

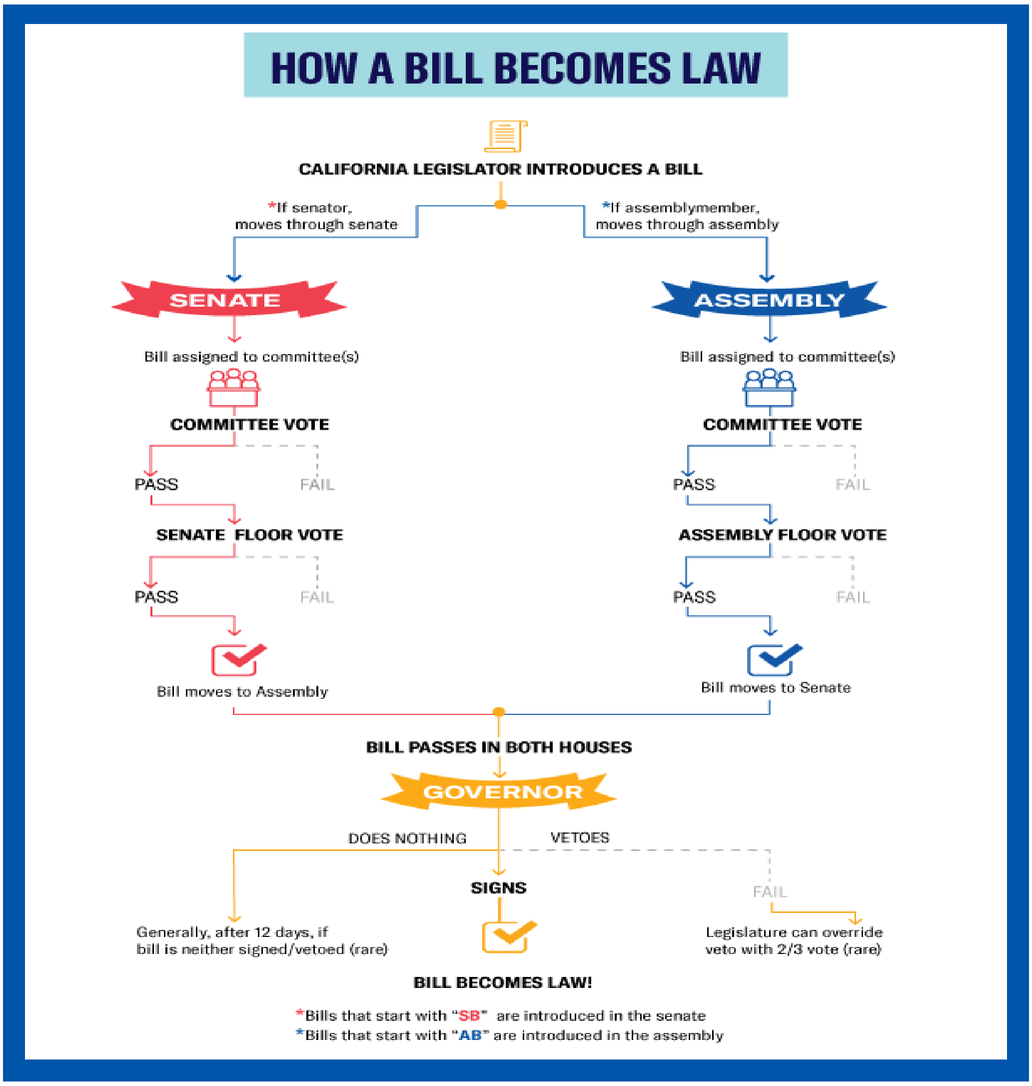


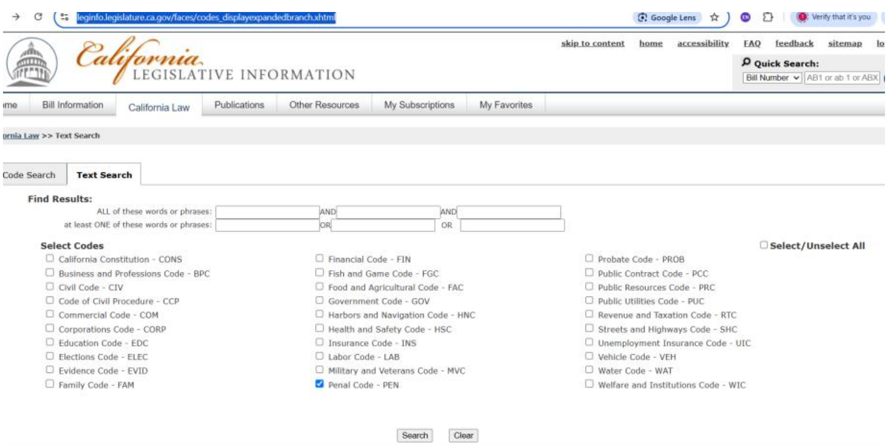
Figure 2 : How a Bill Becomes Law in California. Adapted from the California **State Capitol Museum (2023).**

Construction of Environmental Legislation Dataset

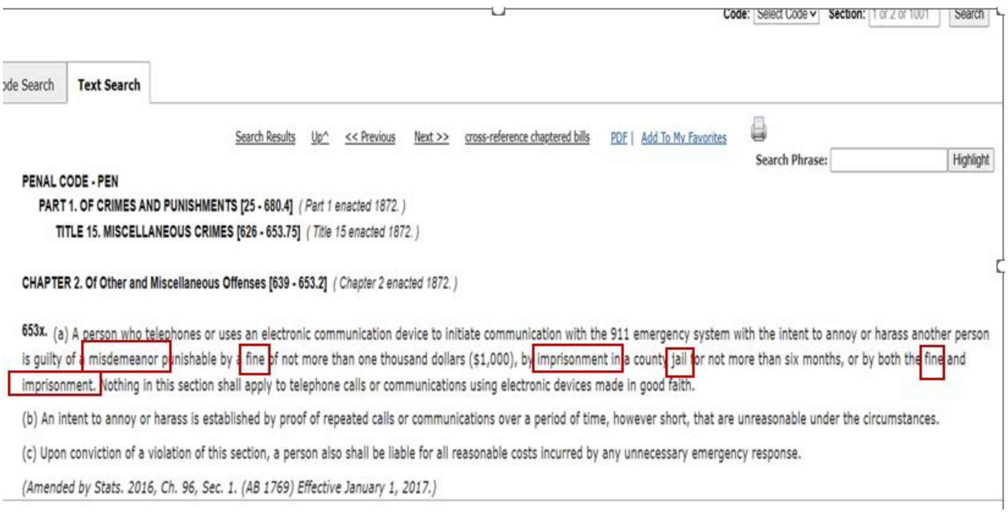
We collect environmental bills by utilizing the LexisNexis legal database from the year 2000 through 2022. Initially, we download 20,230 environmental bills from the website. However, after closer assessment, we identify a few issues. First of all, duplicate environmental bills kept on the website cause double counting. Furthermore, some laws are linked more to budget or appropriations than to direct environmental issues. We then exclude duplicate bills and those linked to budgets or appropriations, resulting in a total of 18,230 bills. Subsequently, as numerous legislations pertain less to environmental issues compared to economic concerns, we conduct textual analysis using the keywords following Sautner et al. (2023), resulting in the identification of 9,987 bills categorized as environmental

Classification: Punitive vs. Non-Punitive Laws

We classify laws using a systematic approach into punitive measure. We explore legal codes pertaining to penalties and punishments using legislative websites of 50 U.S. states. For instance, first we visit the California legislature website and choose penal codes defining legal consequences for violations.



Below is the example of such texts where highlighted keywords are related to penalties. In this process we identify common keywords related to punitive measures.



In our dataset of 11,249 environmental bills, we conducted a two-stage textual analysis to distinguish between punitive and non-punitive environmental laws.

Step 1: Initial Identification of Punitive Bills

We began by scanning the full text of the environmental bills using a curated list of punitive-related keywords (e.g., penalty, fine, imprisonment, sanction). If any of these terms were detected anywhere in the document, the bill was marked as containing punitive elements. However, this approach presented a key limitation: A single bill may address multiple policy areas (e.g., environment, transportation, taxation), and punitive language may pertain to sections unrelated to environmental content.

Step 2: Refinement via Contextual Co-occurrence

To address this concern and improve the precision of our classification, we implemented a co-occurrence-based refinement:

- We examined whether punitive keywords co-occurred within a 50-word window of any environmental-related keywords in the same bill.
- If such a co-occurrence was detected, the bill was assigned a co-occurrence score of 1.

- We then reclassified a bill as a punitive environmental law only if:
    - The bill was previously flagged as punitive (punitive = 1), and
    - It also contained at least one co-occurrence of punitive and environmental terms (co_occurrence = 1).

This stricter criterion ensured that the punitive elements we captured were contextually relevant to environmental content, reducing false positives from multi-topic bills.

Through this process, we identify 6,850 bills as punitive based on the presence of penal-related terminology. The remaining 4,399 bills were classified as non-punitive laws.

Determine industry relevant environmental laws based on the following steps:
Step 1: Creating dataset for training the model

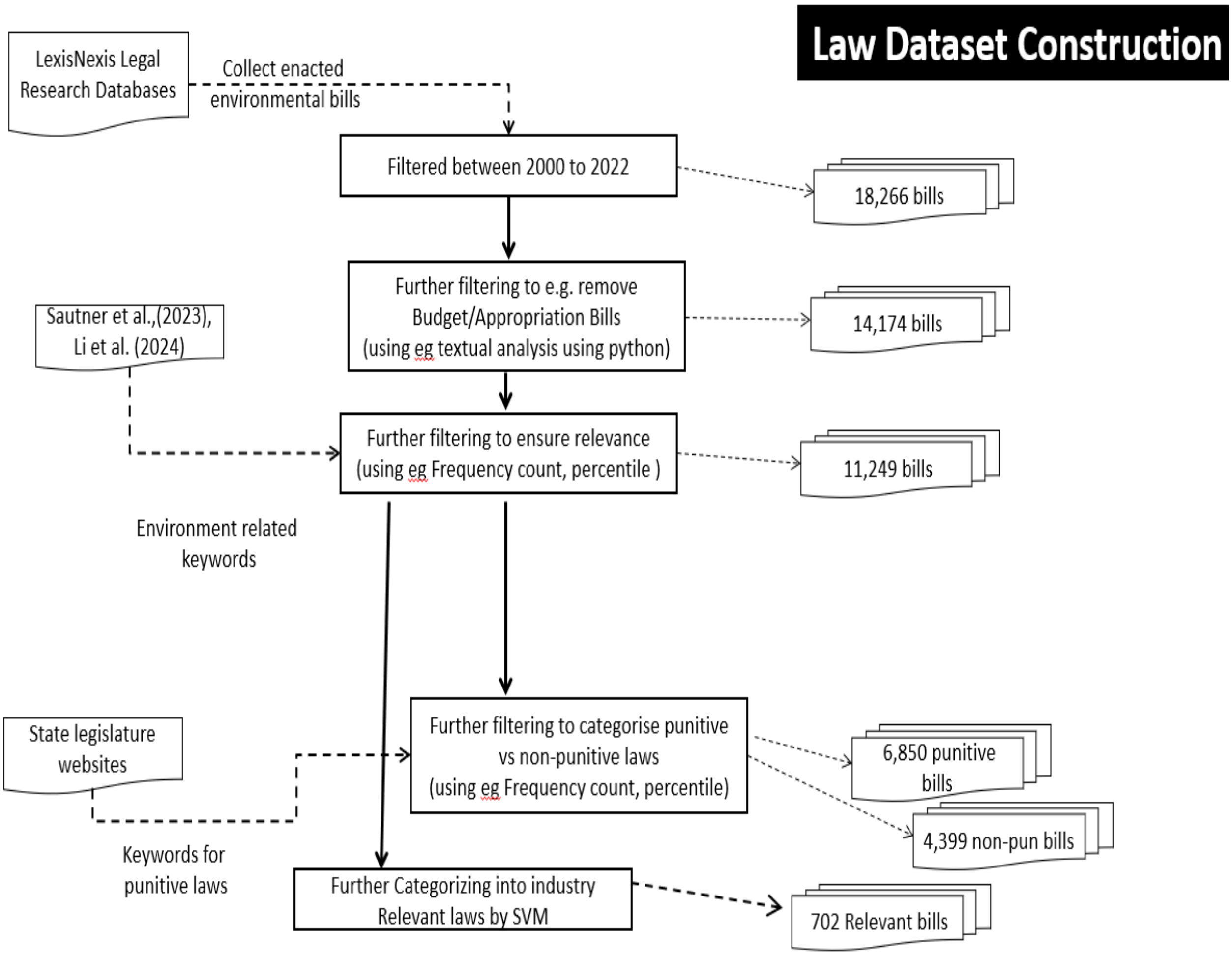
We built a training dataset derived from the "Business Insights Essentials" database in order to create a reliable classification model under supervised machine learning algorithm. The data provider has already allocated these items to six-digit NAICS industries based on their current classification. Each article is allocated to one of the twenty-four two-digit NAICS industries, which enables the model to generalize across categories of sectors that are more comprehensive. Articles in the Training Dataset are collected from the following sources:

- Academic Journals (up to 40 for each industry)
- Articles from the news (up to 40 for each sector)
- Newspapers and magazines (up to 40 for each sector)

The articles are grouped into two categories based on their relevance to TRI-covered industries:

- Relevant Group (30,379 articles): Articles that fall under industries covered by TRI program.

- Irrelevant Group (29,906 articles): Articles that do not fall under industries covered by TRI program.



Step 2: Training the Model

Once the training data set is created, we build an industry categorization model employing a supervised machine-learning technique. The goal is to train a classifier that could accurately predict the TRI covered industry relevance of any given text, including environmental laws. To ensure robustness, we test nine different classification algorithms using tenfold cross-validation to assess their out-of-sample performance. The algorithms included: Naïve Bayes, K-Nearest Neighbors (KNN), Random Forest Classifier, Decision Tree Classifier, Gradient

Boosting Classifier, Linear Support Vector Classifier (SVC), Gaussian Support Vector Classifier (SVC), Logistic Regression, Voting Classifier (Ensemble Methods). Each algorithm is evaluated based on precision, recall, F1-score, and accuracy. After comparing the results, we identify the Gaussian Support Vector Classifier (SVC) as the most effective model due to its exceptional classification performance.

Step 3: Feeding the Model

We feed the environmental bills to the model which predicts the probability of the law should affect the TRI relevant industries conditional on the text of that bill. Each bill's text is associated with two probabilities: one pertaining to its classification as relevant to the industry and the other as irrelevant. In this process we gather 702 industry relevant environmental laws.

Table IA1: Machine Learning Performance

Each environmental regulation is assigned to one or more sample industries through supervised machine-learning algorithms. A total of nine distinct algorithms are taken into account, and the voting classifier combines the classifications from gradient boosting, decision tree, and linear SVC models. The table provides a comprehensive overview of the Python packages and hyperparameters employed to train each algorithm. Additionally, it includes the out-of-sample performance metrics obtained by a tenfold cross-validation methodology.

Algorithm	Python package	Hyperparameters	Precision	Recall	F1	Accuracy
Naive Bayes	Multinomial NB	Default	71.1%	70.6%	70.4%	70.6%
KNN	K Neighbors Classifier	Default	74.6%	73.6%	73.3%	73.6%
Random Forest	Random Forest Classifier	Default	82.7%	81.4%	81.3%	81.4%
Decision Tree	Decision Tree Classifier	Default	75.6%	75.0%	74.9%	75.0%
Gradient Boost	Gradient Boosting Classifier	Default	82.2%	81.3%	81.2%	81.3%
Linear SVC	LinearSVC	Kernel="linear", C=0.6	81.4%	80.6%	80.5%	80.6%
Gaussian SVC	SVC	Default	83.5%	82.4%	82.3%	82.4%
Logistic Regression	Logistic Regression	Default	81.8%	80.9%	80.8%	80.9%
Voting Classifier all	Voting Classifier	Default	81.7%	81.2%	81.1%	81.2%
Voting Classifier selective	Voting Classifier	Default	81.1%	80.5%	80.4%	80.5%

Table IA 2: Pairwise Correlation

This Table reports the correlation matrix of the key independent variables used in the analysis. Panel B presents the correlation matrix of lagged environmental laws from lag1 to lag 8. Variables are defined in Table 1.

Panel A

	$Env\_Laws_{(t-1)}$	$Pop\_Change\_Rate_{(t-1)}$	$Unemp\_Rate_{(t-1)}$	$Per\_Capita\_Tax_{(t-1)}$	$Per\_Capita\_Env\_Exp_{(t-1)}$	$Neighbouring\_Laws_{(t-1)}$	$Corruption_{(t-1)}$	$Sales\_Facility_{(t-1)}$	$Emp\_Facility_{(t-1)}$
$Env\_Laws_{(t-1)}$	1								
$Pop\_Change\_Rate_{(t-1)}$	0.142***	1							
$Unemp\_Rate_{(t-1)}$	0.129***	-0.102***	1						
$Per\_Capita\_Tax_{(t-1)}$	-0.076***	0.079***	-0.069***	1					
$Per\_Capita\_Env\_Exp_{(t-1)}$	-0.022***	0.028***	-0.009***	0.833***	1				
$Neighbouring\_Laws_{(t-1)}$	-0.045***	0.151***	0.007***	-0.090***	-0.063***	1			
$Corruption_{(t-1)}$	0.015***	0.128***	-0.056***	0.561***	0.531***	-0.138***	1		
$Sales\_Facility_{(t-1)}$	-0.035***	-0.003*	-0.002	-0.008***	0.000	0.006**	0.007***	1	
$Emp\_Facility_{(t-1)}$	-0.023***	-0.005**	0.009***	0.006***	0.011***	0.006***	0.008***	-0.028***	1

Panel B: Pairwise Correlations of Environmental Laws (Lag 1 to Lag 8)								
	$Env\_Laws_{(t-1)}$	$Env\_Laws_{(t-2)}$	$Env\_Laws_{(t-3)}$	$Env\_Laws_{(t-4)}$	$Env\_Laws_{(t-5)}$	$Env\_Laws_{(t-6)}$	$Env\_Laws_{(t-7)}$	$Env\_Laws_{(t-8)}$
$Env\_Laws_{(t-1)}$	1							
$Env\_Laws_{(t-2)}$	0.681^{***}	1						
$Env\_Laws_{(t-3)}$	0.795^{***}	0.668^{***}	1					
$Env\_Laws_{(t-4)}$	0.514^{***}	0.590^{***}	0.563^{***}	1				
$Env\_Laws_{(t-5)}$	0.352^{***}	0.356^{***}	0.340^{***}	0.373^{***}	1			
$Env\_Laws_{(t-6)}$	0.350^{***}	0.347^{***}	0.346^{***}	0.336^{***}	0.377^{***}	1		
$Env\_Laws_{(t-7)}$	0.346^{***}	0.346^{***}	0.337^{***}	0.350^{***}	0.844^{***}	0.376^{***}	1	
$Env\_Laws_{(t-8)}$	0.322^{***}	0.340^{***}	0.336^{***}	0.335^{***}	0.382^{***}	0.841^{***}	0.377^{***}	1

Table IA3: The Effect of Environmental Laws on Facility Toxic Pollution, Scaled by Facility Employees

The table presents the OLS regression results examining the impact of state-level environmental legislation on facility pollution. The table includes 269,631 facility-year observations for the full sample which consists of both public parent and private parent facilities. The analysis covers the period from 2000 to 2022, with the dependent variable Pollution/Sales is the natural logarithm of one plus the amount of toxic release by a facility in a state divided by the facility total sales. Robust standard errors are clustered by industry-year. t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Table 1.

Panel A

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
$Env\_Laws_{(t-1)}$	-0.033***	-0.037***	-0.096***	-0.057***	-0.062***	-0.070***
	(-5.823)	(-6.635)	(-11.138)	(-9.641)	(-10.170)	(-11.714)
$Corruption_{(t-1)}$			0.057***	0.120***	0.068***	0.070***
			(3.254)	(9.106)	(5.025)	(5.326)
$Pop\_Change\_Rate_{(t-1)}$			0.032	0.035***	-0.005	-0.008
			(1.631)	(3.874)	(-0.467)	(-0.786)
$Unemp\_Rate_{(t-1)}$			-0.284***	-0.218***	-0.132***	-0.181***
			(-5.492)	(-15.025)	(-4.625)	(-6.376)
$Per\_Capita\_Tax_{(t-1)}$			-0.012***	-0.021***	-0.011***	-0.013***
			(-5.153)	(-12.060)	(-6.343)	(-7.634)
$Social\_Capital_{(t-1)}$			0.174***	0.090***	0.115***	0.117***
			(20.503)	(16.182)	(20.321)	(20.608)
$State\_Enforcements_{(t-1)}$			-0.125***	-0.047***	-0.075***	-0.079***
			(-10.889)	(-6.591)	(-9.515)	(-10.176)
$Temperature_{(t-1)}$			0.017***	0.011***	0.013***	0.013***
			(9.866)	(12.083)	(13.784)	(14.236)
$Neighbouring\_Laws_{(t-1)}$			-0.098***	-0.035***	-0.053***	-0.046***
			(-6.817)	(-4.041)	(-5.767)	(-5.117)
$Sales\_Facility_{(t-1)}$			-0.333***	-0.399***	-0.400***	-0.387***
			(-26.475)	(-81.634)	(-81.882)	(-83.085)
Constant	2.563***	2.572***	8.554***	9.290***	9.241***	9.131***
	(192.084)	(197.092)	(37.839)	(96.051)	(90.310)	(92.214)
Observations	269,631	268,693	261,217	261,183	261,183	261,174
Adj. R-squared	0.000	0.266	0.063	0.305	0.307	0.325
Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	No	Yes	Yes	Yes
Facility_Group_by_Chem FE	No	Yes	No	No	No	Yes

Table IA4: The Effect of Environmental Laws on Facility Toxic Pollution, Scaled by Facility Sales

The table presents the OLS regression results examining the impact of state-level environmental legislation on facility pollution. The table includes 261,067 facility-year observations for the full sample which consists of both public parent and private parent facilities. The analysis covers the period from 2000 to 2022, with the dependent variable Pollution/Sales is the natural logarithm of one plus the amount of toxic release by a facility in a state divided by the facility total sales. Robust standard errors are clustered by industry-year. t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Table 1.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Env_Laws$_{(t-1)}$	-0.0003***	-0.0002***	-0.0005***	-0.0003***	-0.0003***	-0.0003***[15]
	(-3.673)	(-2.629)	(-6.391)	(-4.070)	(-3.686)	(-3.673)
Corruption$_{(t-1)}$	-0.0002		-0.0001	-0.0001	-0.0002	-0.0002
	(-0.666)		(-0.246)	(-0.237)	(-0.692)	(-0.666)
Pop_Change_Rate$_{(t-1)}$	-0.0000		0.0004***	0.0001	-0.0000	-0.0000
	(-0.198)		(3.050)	(1.081)	(-0.312)	(-0.198)
Unemp_Rate$_{(t-1)}$	-0.0013***		-0.0007*	-0.0008***	-0.0013***	-0.0013***
	(-2.970)		(-1.849)	(-4.950)	(-3.000)	(-2.970)
Per_Capita_Tax$_{(t-1)}$	0.0000		0.0000	0.0000	0.0000	0.0000
	(1.408)		(1.030)	(0.644)	(1.387)	(1.408)
Social_Capital$_{(t-1)}$	0.0004***		0.0007***	0.0003***	0.0004***	0.0004***
	(5.998)		(9.054)	(5.210)	(6.061)	(5.998)
State_Enforcements$_{(t-1)}$	-0.0000		-0.0005***	0.0000	-0.0000	-0.0000
	(-0.004)		(-5.258)	(0.089)	(-0.109)	(-0.004)
Temperature$_{(t-1)}$	0.0000***		0.0000***	0.0000**	0.0000***	0.0000***
	(3.137)		(2.634)	(2.455)	(3.103)	(3.137)
Neighbouring_Laws$_{(t-1)}$	0.0001		-0.0000	0.0001	0.0001	0.0001
	(0.849)		(-0.341)	(1.000)	(0.872)	(0.849)
Emp_Facility$_{(t-1)}$	-0.0042***		-0.0032***	-0.0041***	-0.0041***	-0.0042***
	(-26.234)		(-25.029)	(-26.423)	(-26.415)	(-26.234)
Observations	261,067	268,693	261,110	261,076	261,076	261,067
Adj. R-squared	0.076	0.045	0.022	0.076	0.076	0.076
Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	No	Yes	Yes	Yes
Facility_Group_by_Chem FE	No	Yes	No	No	No	Yes

[15] Coefficients represent the change in log pollution intensity per unit increase in the log of environmental laws. Based on the estimated coefficient in Column (6), and average annual facility sales of $53 million, a 10% increase in state-level environmental laws is associated with a reduction of approximately 1,508 pounds of pollution per facility per year.

Table IA5: Robustness to Alternative Clustering- State by Year

The table presents the OLS regression results examining the impact of state-level environmental legislation on facility pollution. The table includes 272,742 facility-year observations for the full sample which consists of both public parent and private parent facilities. The analysis covers the period from 2000 to 2022, with the dependent variable being the natural logarithm of (1+Total_Pollution). Robust standard errors are clustered by state-year. t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Table 1..

VARIABLES	(1)	(2)	(3)	(4)	(5)
Env_Laws$_{(t-1)}$	-0.059***	-0.143***	-0.065***	-0.084***	-0.097***
	(-3.157)	(-6.957)	(-3.400)	(-5.489)	(-6.352)
Corruption$_{(t-1)}$		0.030	0.209***	0.079***	0.083***
		(0.926)	(6.144)	(3.007)	(3.226)
Pop_Change_Rate$_{(t-1)}$		-0.012	0.057**	-0.039**	-0.042**
		(-0.432)	(2.514)	(-1.995)	(-2.179)
Unemp_Rate$_{(t-1)}$		-0.179***	-0.383***	-0.152***	-0.236***
		(-2.637)	(-9.070)	(-2.755)	(-4.287)
Per_Capita_Tax$_{(t-1)}$		-0.016***	-0.037***	-0.011***	-0.015***
		(-3.282)	(-7.900)	(-2.789)	(-3.615)
Social_Capital$_{(t-1)}$		0.263***	0.104***	0.166***	0.168***
		(19.914)	(7.067)	(15.069)	(14.640)
State_Enforcements$_{(t-1)}$		-0.187***	-0.018	-0.089***	-0.095***
		(-8.494)	(-0.894)	(-5.809)	(-6.352)
Temperature$_{(t-1)}$		0.023***	0.013***	0.018***	0.018***
		(9.232)	(6.244)	(10.454)	(10.943)
Neighbouring_Laws$_{(t-1)}$		-0.100***	-0.001	-0.049***	-0.038**
		(-3.998)	(-0.045)	(-2.600)	(-2.039)
Sales_Facility$_{(t-1)}$		0.173***	-0.063***	-0.023***	-0.003
		(15.047)	(-7.100)	(-2.709)	(-0.381)
Emp_Facility$_{(t-1)}$		0.049***	0.247***	0.191***	0.188***
		(3.703)	(21.800)	(17.677)	(18.270)
Constant	5.991***	3.248***	5.942***	5.384***	5.217***
	(155.573)	(14.836)	(31.008)	(32.626)	(32.131)
Observations	272,742	240,712	239,878	239,878	239,869
Adj. R-squared	0.303	0.026	0.260	0.265	0.294
Year FE	Yes	Yes	No	Yes	Yes
Industry FE	Yes	No	Yes	Yes	Yes
Facility_Group_by_Chem FE	Yes	No	No	No	Yes