Legalizing Social Norms: How State Environmental Laws Reduce Facility Pollution

Dimitris Andriosopoulos[1], Kyung Yoon Kwon[1], Tanjina Shahjahan[1, *]

[1]University of Strathclyde, Accounting and Finance Department, Glasgow G1 1XQ, United Kingdom

Abstract

Every state enacts 12 new environmental laws per year on average, with substantial heterogeneity across states; yet the efficacy of these laws has remained unexplored. Corporate behavior in a given state is shaped by its laws, which are crafted to address regional needs and reflect social norms. We find that a 1% rise in state-level environmental legislation reduces facility pollution by 0.073%. The reduction in pollution is similar for both punitive and non-punitive legislation, indicating that this decline results not only from penalties but also from public pressure and changing social norms as represented in the legal framework. Environmental laws demonstrate greater effectiveness in Democratic-leaning states, as well as in states with weak enforcement, suggesting that strong social norms may foster compliance among firms. To establish causality, we employ instrumental variables, such as news coverage of state climate issues and public climate opinion. Such instruments capture public concern and societal pressure regarding environmental issues, and the results further validate that societal norms influence the formation of environmental laws, which in turn shape firm behavior.

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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. Hence, the involvement of state governments becomes increasingly important in serving as a safeguard for environmental conservation (NCEL, 2024). Amid rising concern over environmental pollution, more states in the US are passing environmental laws aimed at reducing pollution (Scarlett, 2019). Given the significant role that state-level legislation plays, this study investigates how the growing number of state-level environmental laws affects corporate environmental pollution.

With the growing public concern about environmental pollution, state legislatures have increasingly enacted environmental laws aimed at controlling polluters' behavior. In this paper, we conjecture that the regulatory action by a state – state-level environmental laws – reflects the social norms and regional needs on environmental matters and thus affects corporate polluting behavior. In specific, we expect that a higher number of the state-level environmental laws reflecting a high public awareness and public pressure on environmental matters will reduce corporate environmental pollution.

There is ample evidence about the influence of federal legislation on corporate environmental behavior. However, limited evidence exists concerning state-level environmental laws. While federal laws play an important role, state-level laws can be equally important because they reflect local social norms (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 standards echoes the influence of California's stringent auto pollution laws 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). Additionally, states function as "policy laboratories," where policymakers customize and implement effective methods by learning from the outcomes of policies elsewhere (Volden, 2006).

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 asses their impact on corporate pollution. With a total of 9,987 environmental laws from 2000 to 2022, our findings indicate that environmental laws reduce facility-level pollution. Specifically, a one-standard deviation increase in environmental legislation (0.869) leads to a 6.3% decrease in pollution. We also find that private facilities[1] 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

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

heighten 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.

[Insert Figure 1 here]

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 seek to foster awareness, transparency, or voluntary enhancement. We posit that both categories will be effective as they embody societal demand for environmental accountability. Our findings confirm that both punitive and non-punitive laws are equally effective in reducing pollution. This reinforces the perspective that companies respond to environmental legislation driven by societal norms, rather than only by the threat of penalties. We find that a one-standard deviation rise in punitive (non-punitive) laws is associated with a 6.4% (6.5%) reduction in pollution at 1% significance level. The findings regarding punitive environmental laws in mitigating pollution align with *Deterrence Theory*, which posits that more environmental laws in form of punishments may deter undesirable behaviors (Leung, 1995)However, the similar efficacy of both punitive and non-punitive laws indicates that *Deterrence Theory* alone cannot completely determine compliance behavior, instead underscoring the significance of social norms and public pressure in motivating firms to conform to environmental expectations. It points to a broader mechanism aligned with *Institutional Theory*, which posits that firms modify their conduct in reaction to an evolving social expectation, in the form of regulatory framework.

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 supervised machine learning algorithms, such as Support Vector Machines (SVM). The results suggest that a one-standard deviation increase in industry-relevant laws results in a 10.9% 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).

To address the potential endogeneity between environmental legislation and pollution, we examine two instrumental variable (IV) techniques: 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 become more environmentally aware due to public expectations (Dyck et al., 2008; Heese et al., 2022). Hence, resulting in 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 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.

Lastly, to determine that environmental laws reflect prevailing social norms, we look at how their effectiveness varies across institutional and political context. 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 and even in states with lax enforcement, 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, with effects being more pronounced under Democratic-leaning legislatures than under governors. Further study reveals that in states with heightened enforcement, the efficacy of environmental laws is more pronounced in mitigating pollution. Nonetheless, even in jurisdictions with minimal enforcement, additional environmental laws still result in a decrease in pollution. The evidence suggests that legislation alone is sufficient to regulate polluters' behavior, as it embodies societal expectations and public pressure, which are essential for promoting compliance, regardless of the level of formal enforcement.

A key contribution to our research is highlighting how a nation's normative environment impacts environmental outcomes, with environmental legislation acting as a vehicle for public pressure and societal norms to influence corporate behavior. Most studies related to environmental laws concentrate on its deterrent effect—how enforcement and sanctions influence compliance (Becker, 1968). By shifting the focus to norms, our study shows legislation, including non-punitive laws reflecting public expectations and societal norms, influences corporations' behavior in curbing pollution. Furthermore, our findings also indicate that environmental legislation successfully governs corporate practices, even in jurisdictions with inadequate enforcement. Therefore, it challenges the conventional perspective of law as only a "stick," a mechanism for deterring misconduct(De Geest and Dari-Mattiacci, 2013), and validates that laws mirror social norms and serve as instruments for shaping business conduct.

Our research also contributes to the ongoing debate regarding the influence of environmental legislation on corporate pollution. Some studies highlight the beneficial aspects of legislation, such as the NOx Budget Trading Program aimed at Eastern and Midwestern U.S. states, which encourages firms to implement cleaner technologies (Shapiro and Walker, 2018). Bartram et al. (2022) find that California's carbon cap-and-trade legislation results in a reduction in pollution within the regulated (home) state, while also causing ripple effects in non-regulated (host) states. Dai et al. (2021a) also reveal the unintended consequences of the stringent greenhouse gas (GHG) targets that lead to the outsourcing of GHG emissions. In contrast to studies that concentrate on specific federal or state environmental statutes, our study examines the comprehensive impacts of newly enacted state-level environmental legislation.

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., 2021b). 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, 2019, 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 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 issue. 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. Therefore, we propose the following hypothesis:

H2: ***Punitive environmental laws are equally effective as non-punitive laws in mitigating pollution.***

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 analysis encompasses all states with annual legislative patterns, with the exception of Arkansas, Montana, Nevada, North Dakota, and Texas, which pass legislation every two years. This ensures that the time frame of the dataset is consistent. As a result, our dataset covers 9,987 environmental laws enacted in 45 states between 2000 and 2022.

Furthermore, we classify the legislation into punitive (4,887 bills) and non-punitive (5,100 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,[2] such as "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”[3] 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

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[2] 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', '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

[3] “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.

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 1,923 industry-specific laws which are around 19.3% of total environmental laws. The model is trained in balanced articles consisting of 30,379 relevant and 29,906 irrelevant industries. In this process we gather 1,923 industry-relevant environmental laws.

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 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[4], 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 (2019), 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 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[5] 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

[4] 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.

[5] 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.

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)[6], 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 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 **Error! Reference source not found.**presents summary statistics for a full sample consisting of both public and private facilities. The mean facility level Total_Pollution is 29,531 pounds, with a standard deviation of 1.35 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 32,160 pounds and for private parents release an average of 29,784 pounds of toxic pollutants where the difference between them is statistically significant at a 1% level. This 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 full sample.

[6] 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.

Regarding the state-level variables, we find that 12 new environmental laws are enacted per state per year on average. Both punitive and non-punitive legislation average 6 per year while non-punitive legislation shows a higher standard deviation, indicating greater heterogeneity in states' approaches. 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**Error! Reference source not found.** 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 (7.74) than all Compustat firms (5.38) 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 (25%) on average. With respect to innovation, our firms invest less in R&D, averaging 1.74 compared to 4.24 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 ($Per\_Capita\_Tax_{(t-1)}$), per capita environmental expenditures ($Per\_Capita\_Env\_Exp_{(t-1)}$), per capita corruption ($Corruption_{(t-1)}$), 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 ($Sales\_Facility_{(t-1)}$), employees ($Emp\_Facility_{(t-1)}$), and minimum PayDex index ($PayDexMin_{(t-1)}$). 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[7] 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[8], enables the

[7] 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.

[8] 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.

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]

5.1. Baseline results

Table 3 displays the baseline results demonstrating the impact of heightened state-level environmental legislation on facility toxic pollution. Panel A shows that an increased number of environmental laws results 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, $Env\_Laws_{(t-1)}$ (-0.073), indicates that a one-standard deviation increase in environmental legislation (0.869) leads to a 6.3% decrease in pollution level. 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 ($\beta = -0.081$) and non-punitive laws ($\beta = -0.073$) in columns 6 of Panels A and B, respectively, are statistically (1%) and economically significant. A one-standard deviation rise in punitive laws (non-punitive laws) results in a 6.3% (6.4%) reduction in pollution, indicating that both categories of regulations contribute to pollution reduction. Our result on punitive laws indicates that these laws help to deter pollution consistent with *Deterrence theory*. On the other hand, non-punitive laws foster normative behavior that aligns with societal goals of reducing pollution and reflect principles of *Public Interest Theory.* Together, these punitive and non-punitive laws create a strong legal framework that forces firms to use eco-friendly methods to reduce pollution, which is in line with *Institutional Theory*. Laws are embraced not alone due to sanctions or civic responsibility, but because they represent institutionalized reflections of social norms, with corporations pursuing legitimacy through 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. In further analysis (Column 2) we find that privately owned facilities exhibit a greater response to punitive laws. Punitive laws institutionalize social norms in a similar manner to non-punitive laws by reflecting societal expectations. However, they are especially powerful for private enterprises, which, owing to financial limitations (Pagano et al., 1998) and less public oversight (Peek et al., 2010), thereby require stronger legal signals to conform such laws.

[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 (0.784) in the industry-relevant environmental laws results in a 10.9% (0.784 x 0.140) 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:

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

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

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

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 **Error! Reference source not found.**, 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 **Error! Reference source not found.**. 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)[9] 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. 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:

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

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

[9] 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.

$$log(1 + Total\_Pollution)_{f,i,s,t}$$

$$= \lambda\left(\overline{log(1 + Env\_Laws_{s,t-1})}\right) + \delta StateControls_{s,t-1}$$

$$+ \alpha FacilityControls_{s,i,f,t-1} + FEs + \epsilon_{f,i,s,t}$$

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 increase in instrumented environmental laws (0.456) leads to 8.7% (0.456*0.191) 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

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. In column 2, the impact of environmental legislation on corporate environmental conduct is significantly pronounced when the governor is Democratic-leaning, at a 1% significance level (β=-0.071). Column 3 represents the impact of environmental laws on pollution in facilities situated within democratically leaning legislatures. The impact of environmental legislation is larger (β = -0.164) at a 1% significance level than that of a governor with democratic leaning. The findings indicate that local regulatory agencies and legislative frameworks, rather than the governor, are accountable for the enforcement and efficacy of environmental laws, despite Democratic governors possibly backing these laws.

[Insert Table 10 here]

5.4. State Enforcement, Environmental Legislation, and Facility Pollution

Our central argument is that environmental laws are institutional reflections of public pressure. To verify this, we examine the effectiveness of these laws in states where enforcement is lax. If laws are reflections of societal norms, then they ought to shape behavior even in the absence of strict enforcement. We measure enforcement by following Konisky (2007) from the political science literature by utilizing the total number of enforcement activities. Previous research shows that states with robust enforcement mechanisms achieve greater reductions in pollution (Seltzer et al., 2022). In Column 1 of Table 10, we find that the influence of higher number of laws on reducing pollution is more pronounced in states with stringent enforcement compared to those with lax enforcement. Nonetheless, in a distinct analysis in column 3 of Table 10 focusing on states with lax enforcement, we observe a substantial decrease in facility pollution linked with an increased number of environmental laws. This suggests that, while legislation with rigorous enforcement is more effective, such laws alone significantly aid in diminishing pollution even in jurisdictions with lax enforcement, indicating that their legitimacy may derive from the public norms they represent.

6. Conclusion

Using pollution as a proxy for environmental behavior, our study examines the impact of state-level environmental legislation in influencing corporate pollution. We show that the increase in the number of environmental laws significantly reduces pollution from both public and private facilities. We demonstrate that both punitive and non-punitive laws are almost equally effective in curbing pollution. Furthermore, categorizing environmental legislation based on their 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 andstate 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 and those in stringent enforcement states experience larger reductions in pollution when more environmental laws are enacted. Nevertheless, these laws can mitigate pollution even in states with lax enforcement.

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 equally 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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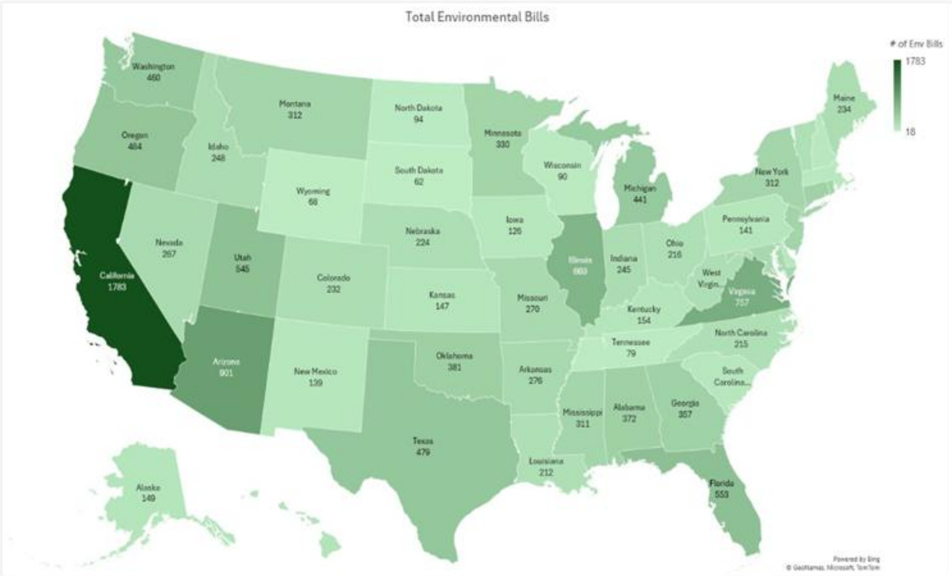


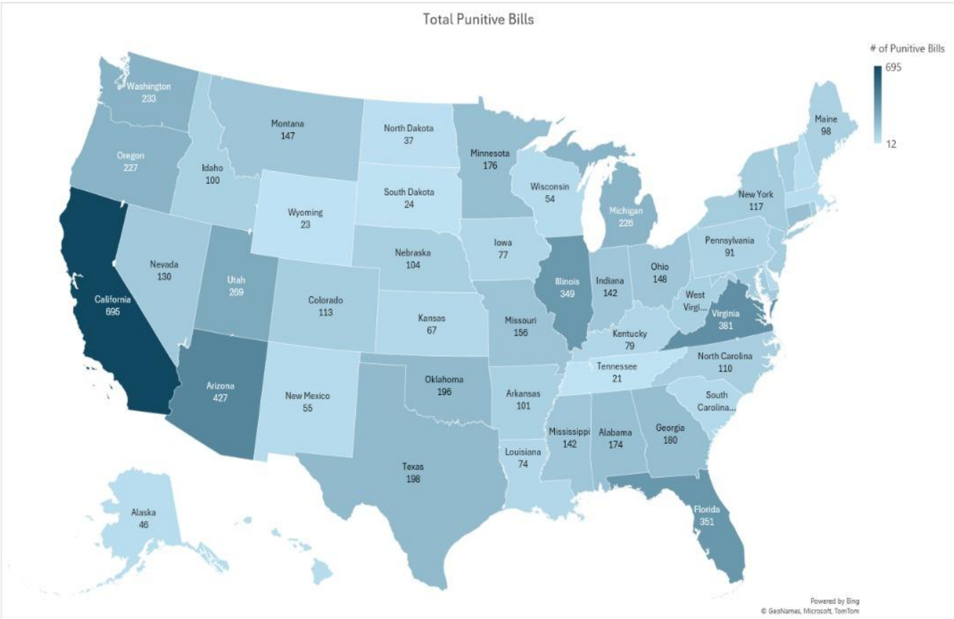


Figure 1: The first map shows the total number of environmental legislations enacted by each state, with California, Arizona, Illinois, Florida, Utah, and Virginia in the forefront. States like South Dakota and Wyoming pass less environmental legislation. The second map shows a comparable trend, depicting 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 5,580 laws as punitive laws which is about 48.9% of total environmental laws.

Table 1: Variable Definition

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
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. 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 Variables

	Full Sample					
Variables	**Obs**	**Mean**	**Med**	**SD**	**25th**	**75th**
Total_Pollution	273,691	29.53	0.48	1,355.52	0.01	5.62
Onsite_Pollution	273,691	24.45	0.08	135.21	0.00	2.20
Offsite_Pollution	273,691	5.08	0.00	93.67	0.00	0.06
Air_Pollution	273,691	10.38	0.03	91.70	0.00	1.46
Water_Pollution	273,691	2.39	0.00	62.05	0.00	0.00
Ground_Pollution	273,691	11.03	0.00	1,325.80	0.00	0.00
Production_Waste	273,691	232.53	5.96	6,977.62	0.30	33.77
Log_Total_Pollution	273,691	5.86	6.18	3.43	2.83	8.63
Log_Onsite_Pollution	273,691	4.59	4.36	3.75	0.78	7.69
Log_Offsite_Pollution	273,691	2.16	0.00	3.27	0.00	4.25
Log_Air_Pollution	273,691	4.23	0.35	3.71	0.35	7.28
Log_Water_Pollution	273,691	0.37	0.00	1.50	0.00	0.00
Log_Ground_Pollution	273,691	0.35	0.00	1.68	0.00	0.00
Log_Production_Waste	273,691	7.78	5.71	3.62	5.72	10.42
Sales_Facility	273,691	16.57	15.53	1.71	15.53	17.69
Emp_Facility	273,415	4.42	3.52	1.42	3.52	5.39
PayDexMin	247,508	67.89	69	9.51	63	75
PayDexMax	247,472	74.37	76	6.49	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	74,390	32.16	0.49	339.32	0.02	6.90	178,939	29.78	0.46	1,662.92	0.01	4.66
Onsite_Pollution	74,390	25.29	0.86	309.42	0.00	2.57	178,939	25.47	0.07	1,661,46	0.00	2.10
Offsite_Pollution	74,390	6.86	0.00	136.78	0.00	0.10	178,939	4.31	0.00	69.87	0.00	0.05
Air_Pollution	74,390	14.60	0.04	126.86	0.00	1.33	178,939	8.81	0.03	75.73	0.00	1.50
Water_Pollution	74,390	2.85	0.00	69.61	0.00	0.00	178,939	2.32	0.00	61.26	0.00	0.00
Ground_Pollution	74,390	7.50	0.00	271.74	0.00	0.00	178,939	13.50	0.00	1,631.53	0.00	0.00
Production_Waste	74,390	253.28	8.74	5,178.41	0.04	43.98	178,939	228.56	5.02	7,875.85	0.25	29.71
Log_Total_Pollution	74,390	6.02	6.21	3.49	3.04	8.84	178,939	5.78	6.14	3.42	2.71	8.56
Log_Onsite_Pollution	74,390	4.69	4.46	3.86	0.77	8.84	178,939	4.54	4.26	3.72	0.74	7.65
Log_Offsite_Pollution	74,390	2.34	0.00	3.34	0.00	4.46	178,939	2.08	0.00	3.68	0.00	4.00
Log_Air_Pollution	74,390	4.24	3.71	3.75	0.33	7.14	178,939	4.21	3.61	3.68	0.33	7.31
Log_Water_Pollution	74,390	0.49	0.00	1.71	0.00	0.00	178,939	0.32	0.00	1.40	0.00	0.00
Log_Ground_Pollution	74,390	0.47	0.00	1.99	0.00	0.00	178,939	0.31	0.00	1.56	0.00	0.00
Log_Production_Waste	74,390	8.22	9.07	3.55	6.12	10.69	178,939	7.78	8.52	3.65	5.52	10.29
Sales_Facility	74,390	17.23	17.34	1.71	17.34	18.31	176,477	16.25	16.34	1.62	15.29	17.32
Emp_Facility	74,317	4.77	4.89	1.51	3.93	5.78	176,315	4.25	4.33	1.34	3.43	5.17
PayDexMin	67,072	66.39	68	9.68	62	73	161,925	68.67	70	9.35	64	76
PayDexMax	67,058	73.59	75	6.64	70	78	161,909	74.78	77	6.38	72	79

Panel C-State Level Variables						
Variables	**Obs**	**Mean**	**Med**	**SD**	**25th**	**75th**
Env_Laws$_{(t-1)}$	273,691	11.79	8.00	12.81	4.00	13.00
Punitive_Laws$_{(t-1)}$	273,691	5.82	4.00	5.66	2.00	7.00
Non_Punitive_Laws$_{(t-1)}$	273,691	5.98	3.00	7.88	1.00	7.00
Industry_Relevant$_{(t-1)}$	273,691	2.20	1.00	3.00	0.00	3.23
Neighbouring_Laws$_{(t-1)}$	273,691	39.08	35	21.42	24	50
Pop_Change_Rate$_{(t-1)}$	273,691	0.65	0.55	0.60	0.60	0.22
Social_Capital$_{(t-1)}$	273,691	0.62	0.75	1.26	1.26	-0.01
Temp_Anomaly$_{(t-2)}$	273,691	1.47	1.425	1.28	0.59	2.37
Unemp_Rate$_{(t-1)}$	273,691	5.78	5.35	2.00	4.40	6.75
Per_Capita_Tax$_{(t-1)}$	272,965	0.06	0.03	0.12	.01	0.07
Per_Capita_Env_Exp$_{(t-1)}$	272,965	2.20	1.11	3.86	.59	2.26
Corruption$_{(t-1)}$	272,965	0.31	0.16	0.77	0.06	0.32

Panel D-Firm Level Variables

	All Compustat Firms				Sample Firms				Mean Difference	
Variables	**Obs**	**Mean**	**Med**	**SD**	**Obs**	**Mean**	**Med**	**SD**	**Mean Difference**	**P-Value**
$ROA_{(t-1)}$	141,066	-4.50	0.01	383.89	16,227	-0.22	0.04	15.10	-4.83	0.13
$Tobinq_{(t-1)}$	123,034	68.92	1.60	2851.13	15,145	2.86	1.42	71.54	75.33***	0.00
$Firm\_Size_{(t-1)}$	142,800	5.38	5.45	2.79	16,243	7.71	7.74	2.05	-2.62***	0.00
$Payout\_Ratio_{(t-1)}$	129,681	0.25	0.00	49.72	15,369	0.75	0.30	19.72	-0.56	0.18
$Capex\_to\_ppe_{(t-1)}$	131,999	0.55	0.19	42.01	16,159	0.16	0.14	0.12	0.46	0.20
$Long\_Term\_Debt_{(t-1)}$	139,093	0.09	0.00	5.47	16,037	0.01	0.01	0.03	0.08*	0.07
$Tangibility_{(t-1)}$	140,528	0.25	0.14	0.26	16,238	0.30	0.25	0.19	-0.05***	0.00
$Age_{(t-1)}$	154,495	15.04	10.00	14.76	16,331	30.17	26.00	20.46	-16.91***	0.000
$Book\_Leverage_{(t-1)}$	141,364	2.00	0.21	63.94	16,208	0.34	0.27	3.71	1.88***	0.00
$Cashflow_{(t-1)}$	139,437	-2.12	0.06	90.12	16,206	0.01	0.11	8.45	-2.41***	0.00
$R\&D_{(t-1)}$	130,230	4.24	0.00	163.13	16,188	1.74	0.01	202.43	2.85***	0.03

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 273,691 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)
$Env\_Laws_{(t-1)}$	-0.090***	-0.064***	-0.107***	-0.044***	-0.063***	-0.073***
	(-12.187)	(-8.712)	(-10.091)	(-5.569)	(-7.647)	(-9.020)
$Corruption_{(t-1)}$			0.146***	0.274***	0.168***	0.172***
			(5.788)	(13.413)	(8.354)	(8.777)
$Pop\_Change\_Rate_{(t-1)}$			0.150***	0.092***	0.044***	0.038***
			(6.057)	(7.117)	(3.183)	(2.749)
$Unemp\_Rate_{(t-1)}$			-0.049	-0.345***	-0.018	-0.107***
			(-0.816)	(-14.880)	(-0.454)	(-2.647)
$Per\_Capita\_Tax_{(t-1)}$			-0.011*	-0.016***	0.001	-0.001
			(-1.953)	(-4.059)	(0.357)	(-0.337)
$Per\_Capita\_Env\_Exp_{(t-1)}$			-0.518**	-1.493***	-0.845***	-0.938***
			(-2.172)	(-7.664)	(-4.506)	(-5.078)
$Social\_Capital_{(t-1)}$			0.176***	0.074***	0.115***	0.114***
			(22.707)	(12.567)	(19.458)	(19.419)
$Neighbouring\_Laws_{(t-1)}$			-0.086***	0.024**	-0.014	-0.002
			(-5.242)	(2.078)	(-1.174)	(-0.180)
$Sales\_Facility_{(t-1)}$			0.160***	-0.054***	-0.015	0.010
			(5.748)	(-5.462)	(-1.539)	(1.055)
$Emp\_Facility_{(t-1)}$			0.030	0.251***	0.194***	0.190***
			(1.017)	(20.731)	(16.279)	(16.210)
$Paydexmin_{(t-1)}$			0.009***	-0.002**	0.000	-0.000
			(7.629)	(-2.175)	(0.172)	(-0.195)
Constant	6.053***	5.997***	2.955***	6.330***	5.396***	5.161***
	(349.691)	(352.968)	(7.898)	(43.569)	(35.210)	(34.317)
Observations	273,691	272,742	239,907	239,878	239,878	239,869
Adj. R-squared	0.001	0.303	0.026	0.260	0.265	0.294
Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	No	Yes	Yes	Yes
Facility_Group_by_Che	No	Yes	No	No	No	Yes

Panel B	**Public Owned Facilities**			**Private Owned Facilities**		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
$Env\_Laws_{(t-1)}$	-0.025*	-0.032**	-0.038**	-0.083***	-0.086***	-0.098***
	(-1.826)	(-2.105)	(-2.525)	(-9.028)	(-8.368)	(-9.706)
$Corruption_{(t-1)}$		0.251***	0.228***		0.137***	0.154***
		(6.259)	(5.792)		(5.624)	(6.499)
$Pop\_Change\_Rate_{(t-1)}$		0.018	0.015		0.051***	0.038**
		(0.707)	(0.606)		(3.016)	(2.342)
$Unemp\_Rate_{(t-1)}$		-0.125	-0.222***		0.063	-0.019
		(-1.559)	(-2.770)		(1.297)	(-0.397)
$Per\_Capita\_Tax_{(t-1)}$		-0.013	-0.016*		0.010**	0.009*
		(-1.583)	(-1.933)		(2.054)	(1.939)
$Per\_Capita\_Env\_Exp_{(t-1)}$		-0.638*	-0.618*		-1.029***	-1.250***
		(-1.726)	(-1.697)		(-4.498)	(-5.546)
$Social\_Capital_{(t-1)}$		0.097***	0.094***		0.129***	0.132***
		(7.590)	(7.455)		(17.881)	(18.561)
$Neighbouring\_Laws_{(t-1)}$		0.047*	0.046*		-0.039***	-0.025*
		(1.921)	(1.906)		(-2.723)	(-1.749)
$Paydexmin_{(t-1)}$		0.003*	0.003*		-0.001	-0.001
		(1.853)	(1.807)		(-0.655)	(-0.866)
$Sales\_Facility_{(t-1)}$		-0.083***	-0.082***		0.009	0.033***
		(-3.916)	(-3.971)		(0.811)	(2.888)
$Emp\_Facility_{(t-1)}$		0.235***	0.246***		0.174***	0.175***
		(9.530)	(10.170)		(12.272)	(12.467)
$Firm\_Size_{(t-1)}$		0.066***	0.073***			
		(6.622)	(7.510)			
$Firm\_Age_{(t-1)}$		-0.004***	-0.004***			
		(-5.480)	(-4.769)			
$Long\_Term\_Debt_{(t-1)}$		0.248	0.035			
		(0.370)	(0.053)			
Observations	74,189	62,845	62,842	178,200	157,104	157,098
Adj. R-squared	0.283	0.273	0.291	0.336	0.288	0.323
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: Variable Definition.

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

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

Panel A-Punitive Laws			**Full Sample**			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Punitive_Laws$_{(t-1)}$	-0.094***	-0.055***	-0.118***	-0.057***	-0.071***	-0.081***
	(-11.412)	(-6.959)	(-10.135)	(-6.460)	(-7.914)	(-9.135)
Corruption$_{(t-1)}$			0.151***	0.277***	0.171***	0.175***
			(5.974)	(13.500)	(8.509)	(8.955)
Pop_Change_Rate$_{(t-1)}$			0.145***	0.092***	0.042***	0.034**
			(5.907)	(7.117)	(3.025)	(2.523)
Unemp_Rate$_{(t-1)}$			-0.056	-0.339***	-0.020	-0.111***
			(-0.938)	(-14.610)	(-0.503)	(-2.757)
Per_Capita_Tax$_{(t-1)}$			-0.010*	-0.016***	0.002	-0.001
			(-1.859)	(-4.060)	(0.424)	(-0.240)
Per_Capita_Env_Exp$_{(t-1)}$			-0.622***	-1.526***	-0.906***	-1.010***
			(-2.613)	(-7.847)	(-4.840)	(-5.485)
Social_Capital$_{(t-1)}$			0.179***	0.077***	0.117***	0.117***
			(22.991)	(12.912)	(19.715)	(19.713)
Neighbouring_Laws$_{(t-1)}$			-0.080***	0.025**	-0.011	0.002
			(-4.929)	(2.156)	(-0.909)	(0.164)
Paydexmin$_{(t-1)}$			0.009***	-0.002**	0.000	-0.000
			(7.683)	(-2.165)	(0.209)	(-0.148)
Sales_Facility$_{(t-1)}$			0.159***	-0.054***	-0.015	0.010
			(5.724)	(-5.461)	(-1.550)	(1.042)
Emp_Facility$_{(t-1)}$			0.031	0.251***	0.195***	0.190***
			(1.052)	(20.727)	(16.296)	(16.230)
Observations	273,691	272,742	239,907	239,878	239,878	239,869
Adj. R-squared	0.000	0.303	0.026	0.260	0.265	0.294
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**					
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Non-Punitive_Laws$_{(t-1)}$	-0.102***	-0.078***	-0.110***	-0.040***	-0.063***	-0.073***
	(-13.869)	(-10.799)	(-10.346)	(-5.110)	(-7.774)	(-9.144)
Corruption$_{(t-1)}$			0.138***	0.271***	0.162***	0.166***
			(5.449)	(13.233)	(8.080)	(8.447)
Pop_Change_Rate$_{(t-1)}$			0.154***	0.092***	0.046***	0.040***
			(6.178)	(7.112)	(3.301)	(2.883)
Unemp_Rate$_{(t-1)}$			-0.047	-0.351***	-0.019	-0.107***
			(-0.788)	(-15.146)	(-0.465)	(-2.665)
Per_Capita_Tax$_{(t-1)}$			-0.011*	-0.016***	0.002	-0.001
			(-1.930)	(-3.976)	(0.398)	(-0.287)
Per_Capita_Env_Exp$_{(t-1)}$			-0.404*	-1.465***	-0.783***	-0.866***
			(-1.687)	(-7.477)	(-4.150)	(-4.661)
Social_Capital$_{(t-1)}$			0.172***	0.072***	0.112***	0.111***
			(22.334)	(12.271)	(19.139)	(19.015)
Neighbouring_Laws$_{(t-1)}$			-0.083***	0.026**	-0.013	-0.000
			(-5.150)	(2.243)	(-1.042)	(-0.013)
Paydexmin$_{(t-1)}$			0.009***	-0.002**	0.000	-0.000
			(7.612)	(-2.168)	(0.165)	(-0.203)
Sales_Facility$_{(t-1)}$			0.160***	-0.054***	-0.015	0.010
			(5.756)	(-5.465)	(-1.551)	(1.040)
Emp_Facility$_{(t-1)}$			0.030	0.251***	0.195***	0.190***
			(1.013)	(20.740)	(16.289)	(16.222)
Observations	273,691	272,742	239,907	239,878	239,878	239,869
Adj. R-squared	0.001	0.303	0.026	0.260	0.265	0.294
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 5: Differential impact of 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: Variable Definition.

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

VARIABLES	(1)	(2)	(3)
Private_Dummy	0.040	0.007	-0.006
	(1.018)	(0.199)	(-0.211)
$Env\_Laws_{(t-1)}$*Private_Dummy	-0.068***		
	(-4.050)		
$Punitive\_Laws_{(t-1)}$ *Private_Dummy		-0.070***	
		(-3.791)	
$Non\text{-}Punitive\_Laws_{(t-1)}$ *Private_Dummy			-0.067***
			(-4.032)
Constant	5.202***	5.191***	5.180***
	(32.163)	(31.998)	(32.148)
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: Variable Definition. 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.

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

Panel A

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Relevant_Laws$_{(t-1)}$	-0.140***	-0.088***	-0.125***	-0.046***	-0.072***	-0.083***
	(-16.760)	(-10.996)	(-10.605)	(-5.204)	(-7.886)	(-9.324)
Corruption$_{(t-1)}$			0.123***	0.265***	0.154***	0.156***
			(4.871)	(12.926)	(7.643)	(7.927)
Pop_Change_Rate$_{(t-1)}$			0.142***	0.089***	0.040***	0.032**
			(5.750)	(6.909)	(2.873)	(2.368)
Unemp_Rate$_{(t-1)}$			-0.027	-0.343***	-0.007	-0.094**
			(-0.447)	(-14.569)	(-0.166)	(-2.323)
Per_Capita_Tax$_{(t-1)}$			-0.009*	-0.015***	0.002	-0.000
			(-1.678)	(-3.838)	(0.602)	(-0.045)
Per_Capita_Env_Exp$_{(t-1)}$			-0.307	-1.433***	-0.727***	-0.802***
			(-1.272)	(-7.257)	(-3.837)	(-4.297)
Social_Capital$_{(t-1)}$			0.174***	0.073***	0.114***	0.113***
			(22.633)	(12.457)	(19.451)	(19.394)
Neighbouring_Laws$_{(t-1)}$			-0.076***	0.027**	-0.008	0.005
			(-4.732)	(2.389)	(-0.692)	(0.405)
Paydexmin$_{(t-1)}$			0.009***	-0.002**	0.000	-0.000
			(7.663)	(-2.126)	(0.204)	(-0.156)
Sales_Facility$_{(t-1)}$			0.159***	-0.054***	-0.015	0.010
			(5.722)	(-5.477)	(-1.585)	(1.001)
Emp_Facility$_{(t-1)}$			0.032	0.251***	0.195***	0.191***
			(1.070)	(20.764)	(16.339)	(16.282)
Observations	273,691	272,742	239,907	239,878	239,878	239,869
Adj. R-squared	0.001	0.303	0.026	0.260	0.265	0.294
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 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 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: Variable Definition. 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
$News\_Coverage_{(t-2)}$	0.090***	
	(0.003)	
Env_Laws_IV		-1.064***
		(0.063)
Observations	204,549	204,549
R-squared	0.207	-0.069
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)	705.3	
Weak Identification Test (Kleibergen-Paap F)	1246	
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 Table 1: Variable Definition . 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$_{(t-2)}$	2.993***	
	(0.066)	
Env_Laws_IV		-0.191***
		(0.042)
Observations	105,318	105,318
R-squared	0.249	0.005
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)	721.7	
Weak Identification Test (Kleibergen-Paap F)	2069	
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 Table 1: Variable Definition.

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

VARIABLES	(1)	(2)	(3)
Env_Laws(t-1)	-0.001	-0.018	0.023*
	(-0.240)	(-1.162)	(1.759)
Democratic_State(t-1)	0.139***		
	(2.522)		
Democratic_State(t-1) ×Env_Laws(t-1)	-0.121***		
	(-5.336)		
Democratic_Governor(t-1)		0.099**	
		(2.114)	
Democratic_Governo(t-1) r×Env_Laws(t-1)		-0.071***	
		(-3.452)	
Democratic_Legislature(t-1)			0.259***
			(5.310)
Democratic_Legislature(t-1) ×Env_Laws(t-1)			-0.164***
			(-7.952)
Constant	4.898***	4.966***	4.774***
	(25.497)	(25.451)	(24.637)
Observations	135,770	135,989	135,770
Adj. R-squared	0.313	0.313	0.313
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Facility_Group_by_Chem FE	Yes	Yes	Yes

Table 10: Cross-Sectional Analysis- The Impact of State Environmental Laws on Facility Pollution in High and Low Enforcement State

Column 1 and Column 2 presents OLS regression results examining the effect of environmental laws on facility pollution in states with high state-level enforcements compare to low-enforcement states. High_Enforce_State$_{(t-1)}$ is a binary variable that takes a value of 1 if a state's enforcement count in the preceding year $_{(t-1)}$ falls within the highest percentile among all states for that year; otherwise, it assumes a value of 0. Column 3 presents the results examining the effect of environmental laws on facility pollution in states with low enforcements only. 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 noted in the table. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level

VARIABLES	**All States**	**All States**	**Low Enforcement States Only**
Env_Laws$_{(t-1)}$	-0.060***	0.023	-0.059***
	(-6.319)	(-1.197)	(-2.04)
High_Enforce_State$_{(t-1)}$	-0.045		
	(-1.156)		
High_Enforce_State×Env_Laws$_{(t-1)}$	-0.032*		
	(-1.943)		
Enforcement_Count_State$_{(t-1)}$		0.071***	
		(-3.118)	
Enforcement_Count_State×Env_Laws$_{(t-1)}$		-0.051***	
		(-5.566)	
Observations	239,834	231,195	22,044
Adj. R-squared	0.292	0.291	0.3413
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Facility_Group_by_Chem 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.

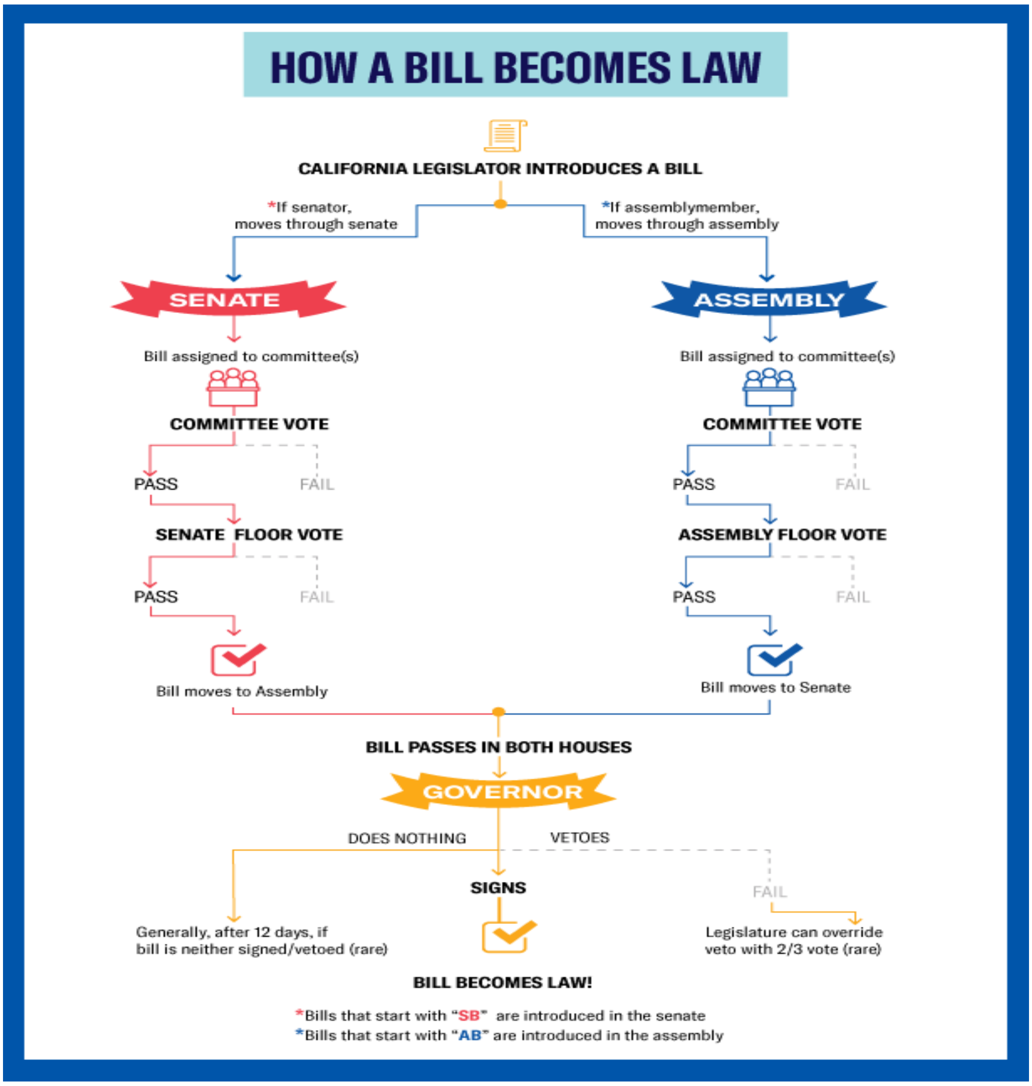


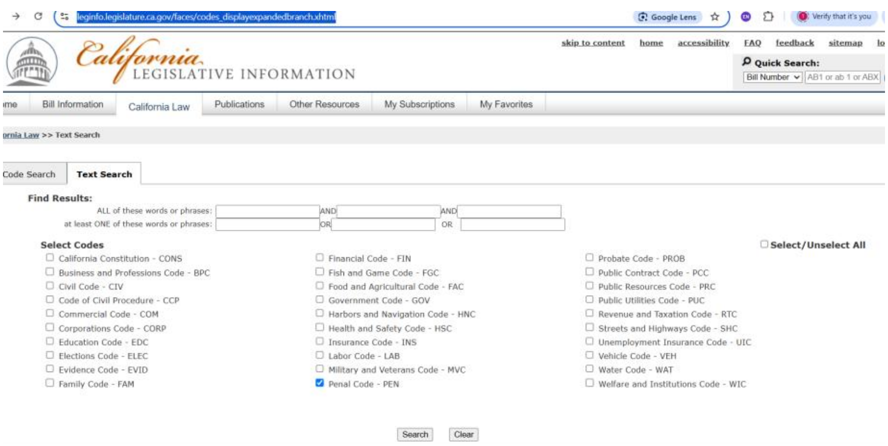
Figure 2 : How a Bill Becomes Law in California. Adapted from the California **State Capitol Museum (2023).**

Construction of Environmental Legislation Dataset

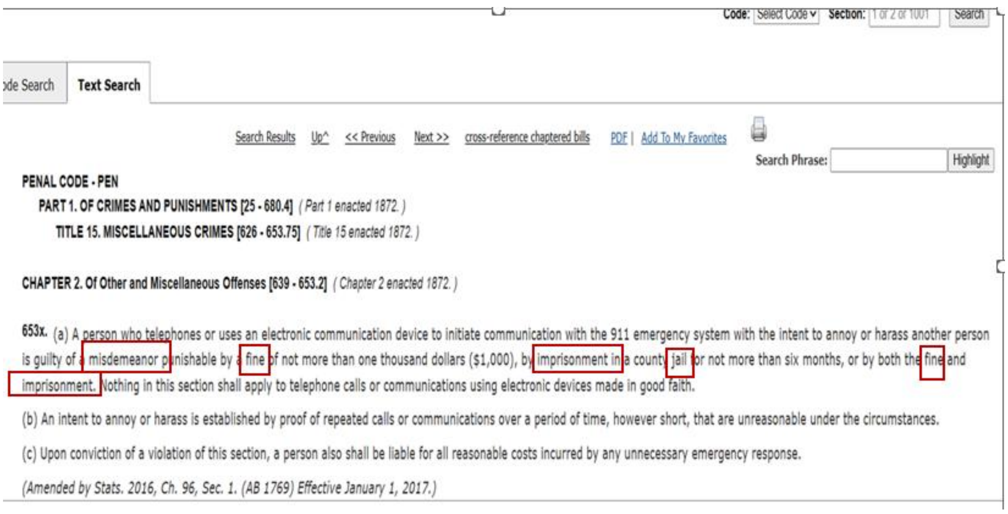
We collect environmental bills by utilizing the LexisNexis legal database from the year 2000 through 2022. Initially, we download 20,230 environmental bills from the website. However, after closer assessment, we identify a few issues. First of all, duplicate environmental bills kept on the website cause 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 45 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.



Code: Select Code Section: 1 or 2 or 1001 Search

Code Search | Text Search

Search Results Up^ << Previous Next >> cross-reference chaptered bills PDF | Add To My Favorites

Search Phrase: Highlight

PENAL CODE - PEN

PART 1. OF CRIMES AND PUNISHMENTS [25 - 680.4] (*Part 1 enacted 1872.*)

TITLE 15. MISCELLANEOUS CRIMES [626 - 653.75] (*Title 15 enacted 1872.*)

CHAPTER 2. Of Other and Miscellaneous Offenses [639 - 653.2] (*Chapter 2 enacted 1872.*)

653x. (a) A person who telephones or uses an electronic communication device to initiate communication with the 911 emergency system with the intent to annoy or harass another person is guilty of a misdemeanor punishable by a fine of not more than one thousand dollars ($1,000), by imprisonment in a county jail for not more than six months, or by both the fine and imprisonment. Nothing in this section shall apply to telephone calls or communications using electronic devices made in good faith.

(b) An intent to annoy or harass is established by proof of repeated calls or communications over a period of time, however short, that are unreasonable under the circumstances.

(c) Upon conviction of a violation of this section, a person also shall be liable for all reasonable costs incurred by any unnecessary emergency response.

(Amended by Stats. 2016, Ch. 96, Sec. 1. (AB 1769) Effective January 1, 2017.)

Next, using the common punitive keywords, we perform another round of textual analysis on our dataset of 9,987 environmental bills to determine the bills that contain punitive elements. Through this process, we identify 4,887 bills as punitive based on the presence of penal-related terminology. The remaining 5,100 bills were classified as non-punitive laws.

Determine industry relevant environmental laws based on the following steps:

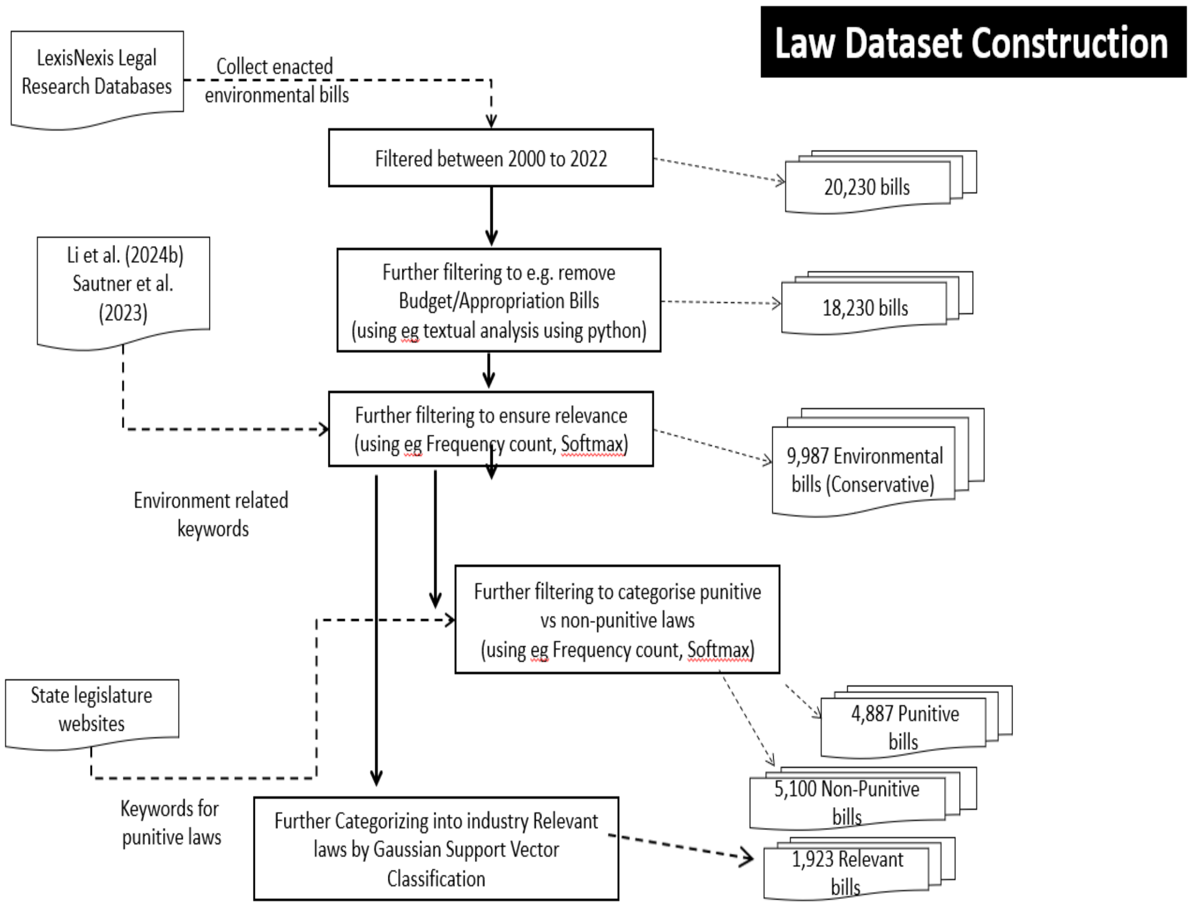
Step 1: Creating dataset for training the model

We build 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 1,923 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 273,691 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$_{(t-1)}$	-0.035***	-0.047***	-0.113***	-0.031***	-0.059***	-0.072***
	(-3.999)	(-5.353)	(-9.314)	(-3.370)	(-6.274)	(-7.696)
Corruption$_{(t-1)}$			0.112***	0.314***	0.151***	0.156***
			(3.936)	(12.874)	(6.420)	(6.790)
Pop_Change_Rate$_{(t-1)}$			0.115***	0.116***	0.034**	0.025
			(3.887)	(7.559)	(2.116)	(1.613)
Unemp_Rate$_{(t-1)}$			0.058	-0.411***	0.004	-0.100**
			(0.876)	(-14.665)	(0.078)	(-2.149)
Per_Capita_Tax$_{(t-1)}$			-0.007	-0.025***	0.004	0.000
			(-1.072)	(-5.291)	(0.771)	(0.051)
Per_Capita_Env_Exp$_{(t-1)}$			-0.721***	-1.651***	-0.818***	-0.922***
			(-2.720)	(-7.080)	(-3.687)	(-4.223)
Social_Capital$_{(t-1)}$			0.188***	0.053***	0.116***	0.115***
			(21.677)	(7.615)	(16.582)	(16.615)
Neighbouring_Laws$_{(t-1)}$			-0.070***	0.063***	0.004	0.017
			(-3.643)	(4.657)	(0.299)	(1.249)
Emp_Facility$_{(t-1)}$			-0.750***	-0.793***	-0.817***	-0.789***
			(-43.897)	(-98.590)	(-102.197)	(-103.549)
Paydexmin$_{(t-1)}$			0.012***	-0.002*	0.001	0.001
			(9.351)	(-1.729)	(1.231)	(0.875)
Constant	-10.883***	-10.858***	-8.191***	-6.808***	-7.366***	-7.294***
	(-535.189)	(-522.132)	(-45.279)	(-68.336)	(-62.757)	(-63.699)
Observations	273,625	272,676	239,872	239,843	239,843	239,834
Adj. R-squared	0.000	0.278	0.079	0.291	0.299	0.327
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 Employees

The table presents the OLS regression results examining the impact of state-level environmental legislation on facility pollution. The table includes 273,691 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 /Emp is the natural logarithm of one plus the amount of toxic release by a facility in a state divided by the number of employees working in the facility. 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$_{(t-1)}$	-0.033***	-0.037***	-0.064***	-0.038***	-0.043***	-0.050***
	(-6.292)	(-7.065)	(-8.611)	(-6.934)	(-7.566)	(-8.807)
Corruption$_{(t-1)}$			0.146***	0.174***	0.141***	0.143***
			(8.348)	(12.748)	(10.358)	(10.690)
Pop_Change_Rate$_{(t-1)}$			0.157***	0.068***	0.057***	0.052***
			(9.264)	(7.699)	(5.955)	(5.469)
Unemp_Rate$_{(t-1)}$			-0.160***	-0.193***	-0.036	-0.088***
			(-3.421)	(-13.157)	(-1.270)	(-3.164)
Per_Capita_Tax$_{(t-1)}$			-0.010**	-0.006**	-0.001	-0.003
			(-2.560)	(-2.128)	(-0.269)	(-0.870)
Per_Capita_Env_Exp$_{(t-1)}$			-0.285	-0.922***	-0.629***	-0.673***
			(-1.637)	(-6.926)	(-4.777)	(-5.186)
Social_Capital$_{(t-1)}$			0.117***	0.062***	0.076***	0.076***
			(20.965)	(15.017)	(18.526)	(18.534)
Neighbouring_Laws$_{(t-1)}$			-0.084***	-0.013	-0.025***	-0.018**
			(-7.534)	(-1.604)	(-2.971)	(-2.181)
Sales_Facility$_{(t-1)}$			-0.339***	-0.383***	-0.383***	-0.369***
			(-33.131)	(-75.683)	(-75.839)	(-76.033)
Paydexmin$_{(t-1)}$			0.005***	-0.001*	-0.000	-0.000
			(6.291)	(-1.926)	(-0.391)	(-0.776)
Constant	2.559***	2.567***	8.287***	9.291***	9.006***	8.868***
	(207.918)	(212.315)	(43.122)	(95.990)	(85.345)	(86.402)
Observations	273,415	272,466	239,894	239,865	239,865	239,856
Adj. R-squared	0.000	0.266	0.060	0.294	0.296	0.315
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 IA5: Robustness to Alternative Clustering

The table presents the OLS regression results examining the impact of state-level environmental legislation on facility pollution. The table includes 273,691 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: Variable Definition.

VARIABLES	(1)	(2)	(3)	(4)	(5)
$Env\_Laws_{(t-1)}$	-0.064***	-0.107***	-0.044**	-0.063***	-0.073***
	(-3.858)	(-5.347)	(-2.495)	(-4.061)	(-4.887)
$Corruption_{(t-1)}$		0.145***	0.274***	0.168***	0.172***
		(3.800)	(7.268)	(5.525)	(5.772)
$Pop\_Change\_Rate_{(t-1)}$		0.151***	0.092***	0.044**	0.038**
		(6.166)	(4.129)	(2.374)	(2.042)
$Unemp\_Rate_{(t-1)}$		-0.043	-0.345***	-0.018	-0.107*
		(-0.590)	(-8.346)	(-0.317)	(-1.847)
$Per\_Capita\_Tax_{(t-1)}$		-0.011	-0.016***	0.001	-0.001
		(-1.478)	(-2.602)	(0.243)	(-0.223)
$Per\_Capita\_Env\_Exp_{(t-1)}$		-0.508	-1.493***	-0.845***	-0.938***
		(-1.374)	(-4.358)	(-2.947)	(-3.252)
$Social\_Capital_{(t-1)}$		0.176***	0.074***	0.115***	0.114***
		(18.595)	(7.076)	(14.170)	(13.638)
$Neighbouring\_Laws_{(t-1)}$		-0.085***	0.024	-0.014	-0.002
		(-3.809)	(1.078)	(-0.781)	(-0.122)
$Sales\_Facility_{(t-1)}$		0.160***	-0.054***	-0.015*	0.010
		(14.233)	(-5.815)	(-1.674)	(1.158)
$Emp\_Facility_{(t-1)}$		0.031**	0.251***	0.194***	0.190***
		(2.253)	(20.710)	(16.835)	(17.005)
$Paydexmin_{(t-1)}$		0.009***	-0.002**	0.000	-0.000
		(10.071)	(-2.448)	(0.198)	(-0.224)
Constant	5.997***	2.939***	6.330***	5.396***	5.161***
	(177.911)	(13.635)	(38.779)	(32.531)	(31.045)
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