Freedom of Information and Corporate Pollution

Adriana S. Cordis[**] Po-Hsuan Hsu[†] Hunghua Pan[*] Jin Zhang[‡]

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Abstract

We document a significant reduction in facility-level toxic emissions when state-level Freedom of Information Act (FOIA) laws are enacted and strengthened. Such laws reduce the costs of obtaining quasi-private information. Strengthened FOIA laws are associated with more FOIA requests to state-level environmental protection agencies, which are negatively related to local toxic emissions. Tests using paired facilities across state borders support a causal interpretation of our findings. Notably, the negative association between the strength of FOIA laws and pollution emissions is concentrated in states with higher preexisting pollution abatement costs, higher preexisting levels of public corruption, and more lenient environmental policies. Our empirical evidence suggests that reducing the costs of accessing information on governmental activities, especially those related to the regulation and monitoring of corporate emissions, mitigates polluting behavior.

Keywords: freedom of information; open records; transparency; pollution; environmental awareness.

JEL: D80, H40, Q50

1. Introduction

Industrial pollution has garnered significant attention among environmental, social, and governance (ESG) issues due to its potentially catastrophic risks (Thomas et al., 2022; Xu and Kim, 2022; Dechow, 2023; Tsang et al., 2023). Although prior research suggests that public disclosures, such as mandatory reporting of CSR activities or toxic emissions, may influence toxic pollution levels (Delmas et al. 2010; Chen et al., 2018; She, 2022), there is limited evidence on the role of private (or quasi-private) information, in part because tracking the flow of such information is empirically challenging.

In this study, we propose to use the provisions of state-level Freedom of Information Act (FOIA) laws as indicators of the availability and acquisition costs of quasi-private information.[1] FOIA laws allow individuals and organizations to submit requests for critical data on pollution levels, regulatory investigation and enforcement, and corporate environmental practices, which enhances the public's ability to hold both government entities and businesses accountable for their actions. Information requested through FOIA laws is quasi-private (Gargano et al., 2017) in the following sense: on the one hand, it is not fully public, as only those who submit a FOIA request can obtain the information and there are non-trivial implicit costs (Blankespoor et al., 2020; Glaeser et al., 2023); on the other hand, it is also not fully private, as anyone can submit such a request. In states with stronger FOIA provisions, such requests are processed more effectively and generate more quasi-private information at lower costs to the requestors.[2] By examining how corporate pollution varies with changes in state-level FOIA laws, we may be able to shed light on the importance of quasi-private information and its acquisition costs in promoting firms' environmentally responsible actions.

We propose that FOIA laws can mitigate corporate pollution through the following mechanisms. First, enhanced FOIA laws encourage citizens and advocacy groups to request information on state environmental agency activities, and such quasi-private information facilitates

[1] The basic rationale of FOIA laws is that all government records are presumed open unless they fall under specific exceptions serving a clear public purpose, which are subject to rigorous scrutiny from transparency advocates. Thus, firms are unlikely to successfully lobby for pollution-specific exemptions.

[2] In the five decades since the federal FOIA's passage in 1966, all 50 states have enacted or updated their own FOIA laws. For example, South Carolina adopted its FOIA in 1974 and made significant revisions in 1978, 1987, and 2017 to expand exemptions, address electronic records, and adjust response time limits. Many states similarly revised their laws in response to pressure from advocacy groups like the National Freedom of Information Coalition. We analyze each state's FOIA provisions over time, developing a measure of law strength, which we detail in Figure 2, Table IA 2.1, and Appendix A.

their monitoring of government efforts, which ensures that environmental regulations are enforced and that policy priorities reflect public interests. Second, under weak FOIA laws, firms may rationally choose to pollute more due to high pollution abatement costs and low expected violation penalties; however, such a choice may change under higher monitoring and pressure due to strengthened FOIA laws. Third, by reducing the costs of acquiring information, FOIA laws prevent collusion between polluting firms and local officials (Cordis and Warren, 2014), making it harder to hide environmental violations.[3] Finally, lower costs to access regulatory data and activities mitigate state governments' or officers' tolerance or leniency to particular types of industries and firms, promoting fairer and more efficient monitoring and enforcement of environmental regulations.

Our proposition is supported by real-world examples that illustrate how FOIA laws improve data accessibility and hold public agencies accountable. In 2004, Mike and Linda Raymond from Woburn, Massachusetts, used their state's FOIA law to uncover information about a planned landfill expansion.[4] Their discovery of the city's unpublicized plan, which lacked any environmental or health impact assessments, led to public outcry and the cancellation of the expansion. Similarly, in Michigan, the American Civil Liberties Union (ACLU) and researchers from Virginia Tech utilized FOIA requests to expose critical documents revealing that the Michigan Department of Environmental Quality (MDEQ) had ceased corrosion control treatment for Flint's water supply, leading to the infamous water crisis. These documents also uncovered a cover-up by government officials. The role of FOIA in revealing these harmful decisions was widely covered by the media in 2016. These examples demonstrate how FOIA laws facilitate public access to vital environmental information, enabling citizens to uncover hidden risks and prompting corrective actions.

In our empirical analysis, we begin by collecting emissions data from the US Environmental Protection Agency's (EPA) Toxic Release Inventory (TRI) database, which provides annual, pollutant-level emissions data for all manufacturing facilities (see Section 3 for more details).[5]

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[3] Worthy et al. (2017) and Grimmelikhuijsen et al. (2018) implement field experiments and find significantly higher responsiveness to requests for information that were framed as official FOIA requests in the U.K. and the Netherlands, respectively.

[4] See https://sgp.fas.org/congress/2004/s020604.html.

[5] The origins of this database can be traced to 1986, the year in which the US Congress passed the Emergency Planning and Community Right-to-Know Act (EPCRA) in response to public concerns over the release of toxic chemicals from several environmental accidents. The EPCRA entitles residents in their respective neighborhoods to know the source of detrimental chemicals, especially for their potential impacts on human health from routes of exposure. In response

Consistent with previous studies (e.g., Greenstone, 2003; Akey and Appel, 2021; Hsu et al., 2023), we use the TRI data to track toxic emissions from publicly traded US firms. We then merge this dataset with the National Establishment Time-Series (NETS) and Compustat databases to build a comprehensive dataset covering pollution, employment, and revenue for publicly listed firms' facilities from 1991 to 2020, allowing for a detailed analysis of local pollution. Next, we construct a firm-state-year panel dataset by summing each firm's total toxic emissions by state and year. We then use Cordis and Warren's (2014) methodology to measure the strength of state-level FOIA laws on a scale of 1 to 9, based on provisions such as disclosure presumptions, exemptions, fee and time limits, denial procedures, and penalties for noncompliance.

We design a difference-in-differences analysis around changes in state FOIA scores. For each firm-state combination, we treat a change in the FOIA score as an "event" and focus on an event window in which there is no change in a FOIA score in both pre-event three years and post-event three years. As we discuss further in Section 2 and document in validation tests, such changes in state-level FOIA laws are likely exogenous events to firms. We find a significant reduction in emissions of firm-state observations across the event relative to those of firm-state observations without FOIA law changes (as the control group) in the event window. In particular, a one-unit increase in a state's FOIA score reduces a firm's toxic emissions by about 5%. Moreover, a causal interpretation for our difference-in-differences analysis is supported by the following empirical evidence: (i) we find no differences in the emissions of treated and control groups before events; (ii) we find that state-level emissions do not predict the strength of the state's FOIA law, which mitigates the reverse causality concern; and (iii) we find consistent results when we adopt a conventional approach, in which we use the level of FOIA scores as the explanatory variable and include all firm-state-year observations in the regression sample.

More importantly, we strengthen our identification by using paired facilities near state borders with similar local conditions but different state FOIA laws (Holmes, 1998; Heider and Ljungqvist, 2015). We find that facilities in states with stronger FOIA laws produce lower emissions, suggesting that the reduction is driven by changes in the law rather than local economic factors.

To explore the mechanisms behind the FOIA laws-emissions relationship, we conduct the

to the EPCRA, the EPA established the TRI program that requires all manufacturers to report their chemical emissions that endanger human health and the environment.

following tests. First, the public pressure from transparency increases public-initiated monitoring. We rely on FOIA laws to submit an inquiry to each state's environmental agency to obtain data on state-level FOIA requests received by the agency each year. We find that more FOIA requests on environmental issues were made in states with stronger FOIA provisions, where such requests are processed more effectively. We also find a negative association between the volume of such requests and state-level pollution, indicating that reduced information costs correlates with lower corporate emission levels. Second, public scrutiny from easier and more timely data access forces companies with higher pollution abatement costs and thus emitting more in the past to adjust their choices. We examine cross-sectional variation in preexisting pollution abatement costs, finding that the negative FOIA-emissions relationship is concentrated in states with higher abatement costs, further linking FOIA laws to pollution reduction. Third, the mechanism of reduced governmental corruption is supported by our finding that the negative relation is more pronounced in states with higher corruption levels. Finally, we observe stronger effects in states that had more lenient environmental policies in the past, suggesting that FOIA laws can mitigate the impact of state governments' tolerance of polluting industries. These mechanism test results also strengthen the argument that the FOIA laws-emissions relation is driven by the reduced costs of acquiring quasi-private information rather than by omitted variables.

Our study contributes to the literature on information acquisition costs. According to the review by Blankespoor et al. (2020), information acquisition costs play a key role in informed decision-making. Prior studies on private information acquisition costs mainly focus on selective access to management or explore the use of technology (Chen et al., 2010; Bushee et al., 2018; Blankespoor, 2019; Goldstein et al., 2023). We build on these studies by exploring a setting where there is substantial time-series and cross-sectional variation in information acquisition costs. The staggered changes in FOIA laws offer us richer cross-sectional heterogeneity and mitigate the concern that our treatment coincides with other economic or political factors that may confound our results.

This paper also relates to the literature on the role of information transparency in shaping corporate behavior. Publicly disclosure information enables the public to exert social and regulatory pressure on firms. Prior research shows that mandated disclosure rules and the existence of news agencies help mitigate irresponsible or unethical corporate practices, such as predatory lending, risky securitization, workplace safety negligence, and environmental pollution

(Christensen et al., 2017; Heese et al., 2022; Jiang and Kong, 2023; Kielty et al., 2023; Hsu et al., 2023; Nicoletti and Zhu, 2024). However, there remains limited exploration of how the public gathers and leverages non-disclosed data to influence corporate decisions. This gap underscores the need for our study on the implications of quasi-private information acquisition and related costs in shaping corporate behavior.

More broadly, we offer new evidence on the benefits of promoting "open government" (Yu and Robinson, 2012). Our analysis shows that facilitating timely access to information about government activities, particularly those related to regulating and monitoring industrial pollution, is crucial for achieving emission reductions, highlighting the effectiveness of FOIA laws as a policy tool for environmental improvement.[6] We thus add to the prior literature on the real effects of public disclosure in accounting.[7]

The structure of our study is as follows: Section 2 presents the hypothesis, informed by a review of institutional details and relevant prior research. Section 3 outlines the data and sample selection. Section 4 analyzes the impact of FOIA law strength on toxic emissions. Section 5 explores the underlying mechanisms driving these effects. Finally, Section 6 concludes the study.

2. Institutional Background and Literature Review

2.1 Freedom of Information Act

The federal FOIA, enacted in 1966, marked a significant milestone in the development of transparency laws in the United States. Over the five decades since its passage, all 50 states have adopted or revised their own state-level FOIA or open records laws, many of which were introduced in the wake of the Watergate scandal and are modeled after the federal FOIA. These laws grant possible access to government records, fostering greater awareness of government decision-making and promoting accountability and oversight. The foundation of these laws is the principle that all records are presumed open unless they fall under specific exemptions, such as

[6] The value of quasi-private information related to FOIA laws has been shown in prior studies. Based on the federal-level FOIA laws, Gargano et al. (2017) document that sophisticated institutional investors use the FOIA law to acquire previously undisclosed data from the FDA and generate abnormal returns. Klein et al. (2020) demonstrate that sell-side healthcare analysts who use FOIA requests based on federal laws to obtain FDA records generate stock recommendations with significant returns. On the other hand, Cordis and Warren (2014) highlight how state-level FOIA provisions enhance transparency and influence corporate and governmental actions. Gu et al. (2024) show that FOIA provisions affect corporate tax avoidance.

[7] See Kanodia and Sapra (2016), Hoopes et al. (2018), She (2022), Gibbons (2023), Lee et al. (2023), and Dambra et al. (2024).

those protecting national security or personal privacy. Many states have revised or amended their FOIA laws over time to strengthen them and adapt to technological changes, often due to pressure from nonprofit journalism associations and open government advocacy groups.[8] Such public pressure helped drive these legislative revisions, reflecting the critical role of advocacy groups in strengthening transparency laws.[9]

These examples suggest that firms are *unlikely* to successfully lobby for pollution-specific exemptions in states with strong FOIA laws, such as Florida.[10] FOIA laws generally require that exemptions serve a clear public purpose, and due to rigorous scrutiny from transparency advocates, it is difficult for firms or industry groups to undermine the presumption of disclosure through lobbying efforts. This makes changes to FOIA requirements an exogenous event, enabling us to conduct a difference-in-differences design. In addition, we will design an event window in which there is no change in a state's FOIA law in pre- and post-event years, which mitigates the concern that firms *expect* upcoming changes in transparency. Moreover, our validation test suggests that a state's pollution level does not predict the change in FOIA laws.

Several studies investigate how FOIA requests are used by capital market participants. Gargano et al. (2017) document that sophisticated institutional investors, particularly hedge funds, use the FOIA to acquire information. By requesting information from the Food and Drug Administration, these investors gain access to previously undisclosed data, which helps them target specific firms and generate abnormal returns. Klein et al. (2020) document that sell-side healthcare analysts use FOIA requests to obtain non-public FDA records, such as factory inspections and drug applications, gaining insights beyond management's purview. They find that analysts' buy (sell) recommendations based on this data lead to higher (lower) stock returns. Some other studies

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[8] For example, Georgia's open records movement began in 1956 with lobbying efforts by the Georgia Press Association, which advocated for broad public access to government records. This led to the passage of Georgia's open records law in 1959, before the federal FOIA, with significant revisions in 1988 and 2012. Similarly, South Carolina passed its first FOIA law in 1974 and revised it in 1987 after the South Carolina Press Association pushed for changes following a public controversy over the lack of oversight in the University of South Carolina's fund spending.

[9] See the Open Government Guide prepared by the Reporters Committee for Freedom of the Press available at https://www.rcfp.org/open-government-guide/.

[10] Florida provides a notable example of comprehensive open records legislation. The Florida Sunshine Law, enacted in 1967 and added to the state constitution in 1992, has been widely praised for its breadth. To address concerns over the growing number of exemptions, the legislature passed the Open Government Sunset Review Act in 1995, requiring a review of each exemption every five years. Exemptions are either repealed or reenacted, provided the legislature demonstrates a compelling public interest. In 2002, an amendment to the Florida Constitution further strengthened transparency by requiring a two-thirds legislative majority to pass or renew any exemption.

focus on how FOIA requests affect companies. Coleman et al. (2021) find that the SEC denies FOIA requests when there are ongoing enforcement proceedings, and such denials are public signals that can be used by sophisticated investors to earn future abnormal returns. Down et al. (2024) suggest that the lead arrangers of loan syndicates use the information obtained through FDA FOIA requests to determine their loan share.

Other researchers have started to look at FOIA requests initiated by organizations which are not capital market participants. Kwoka (2016) finds that most requests to the EPA came from commercial entities, such as consulting firms that resell information to real estate stakeholders, followed by media, watchdog groups, and other uncategorized requestors. Glaeser et al. (2023) show that many organizations, such as law firms and intellectual property firms, that submitted FOIA requests to the SEC do so for purposes other than equity-trading. He et al. (2024) show that companies' willingness to contract with the federal government is affected by their concern that competitors may obtain proprietary information through FOIA requests.

Taken together, our review of the institutional background and the literature highlight that (i) FOIA requests serve as a valuable source of information that might otherwise remain unknown, inaccessible, or difficult-to-access to the public; and (ii) FOIA laws and requests have real effects on economic activities.

2.2 Information and Sustainability-related Decision-making

In recent years, policymakers worldwide have increasingly mandated companies to disclose sustainability-related information. This regulatory push has opened new avenues for researchers to explore whether such mandatory disclosures drive changes in firms' sustainability-related decision-making. For example, Patten (1998) shows that the EPA's mandatory disclosure of toxic releases leads to more resources being allocated to environmental and resource programs in states with more severe pollution problems. Christensen et al. (2017) find that mandating mine-safety disclosures in financial reports under the Dodd-Frank Act leads to a reduction in mine-site injuries, as shifting the information to a more widely disseminated channel enhances accountability. Chen et al. (2018) examine the impact of mandatory CSR disclosures in China, where large firms were required to disclose sustainability information. Although firms were not mandated to increase sustainability investments, the pressure from governments and interest groups decreased industrial wastewater and SO_2 emissions, indicating that the disclosure altered firm behavior and generated positive social outcomes. Similarly, Downar et al. (2021) show that a requirement for UK firms to report greenhouse gas (GHG) emissions at the parent-company level resulted in emissions reductions. Tomar (2023) shows that the US Greenhouse Gas Reporting Program, which mandates facilities to report emissions, leads to a 7.9% reduction in GHG emissions, driven by benchmarking among peers and concerns over future regulations. These studies illustrate how mandatory transparency can drive meaningful environmental and safety improvements.

However, not all enhanced transparency programs achieve their desired outcomes. For example, healthcare report cards, which publicly disclose physician and hospital performance, may correct information asymmetries but also incentivize providers to avoid treating more severely ill patients. Dranove et al. (2003) use cardiac surgery report cards in New York and Pennsylvania and find that while they improved patient-hospital matching, they also lead to increased resource use and worse outcomes for sicker patients, ultimately reducing patient and social welfare in the short term. Doshi et al. (2013) find that mandatory information disclosure regulations create institutional pressure to improve performance, with responses varying based on organizational characteristics. Establishments near their headquarters or industry siblings show faster improvements, while large establishments in sparse regions are slower to respond, but private firms outperform public ones.

2.3 Hypothesis Development

Unlike the public information resulting from mandatory disclosures, information transmitted through FOIA requests is quasi-private. It is not fully public, as only those who submit a FOIA request can obtain the information. Although the explicit costs of obtaining information through FOIA requests are low, the implicit costs could be quite high (Glaeser et al., 2023). In the framework of Blankespoor et al. (2020), the implicit costs include learning about the existence of FOIA laws (awareness costs), requesting information from the environmental agencies (acquisition costs), and interpreting the information (integration costs). On the other hand, it is also not fully private, as anyone can submit such a request (Gargano et al., 2017). Sometimes, the media may request information and then disseminate to the public. Different from mandatory sustainability disclosures that are subject to firms’ selection in the information they provide, FOIA laws provide legal access to a wide range of government-held information, including data on government regulatory actions, which allows the public, media, and NGOs to scrutinize corporate environmental and social practices.

We propose that state-level FOIA laws can reduce toxic emissions through multiple mechanisms. First, many states have their own environmental agencies tasked with managing environmental issues and enforcing federal laws.[11] FOIA laws reduce quasi-private information acquisition costs, and therefore encourage citizens and advocacy groups to request information on state environmental agency activities. Such FOIA requests facilitate the monitoring and analysis of both state and federal efforts, ensuring that environmental regulations are enforced and that policy priorities reflect public interests.[12]

Second, under weak FOIA laws, firms may choose their optimal level of toxic emissions by weighing in all factors (especially pollution abatement costs and expected violation penalties); however, after such laws being strengthened, these firms expect greater scrutiny and public pressure and may rationally reduce their emissions. Third, FOIA laws help reduce corruption by creating a "paper trail" that can expose regulatory leniency or unethical actions benefiting firms at the expense of environmental protection (Cordis and Warren, 2014). Finally, stronger FOIA laws limit the ability of state officials to implement more lenient environmental policies, thus fostering stricter enforcement of regulations. As a result, firms in states with stronger FOIA laws tend to have lower pollution levels due to greater public oversight and reduced opportunities for regulatory evasion. This leads to our hypothesis, expressed in alternate form as follows:

H: Companies reduce their state-level pollutant emissions in response to legislative actions that strengthen state-level FOIA laws.

3. Research design

3.1 Baseline Model

We adopt a difference-in-differences approach to examine the relation between corporate pollution and FOIA laws. We focus on firm-state level pollution instead of facility-level pollution

[11] The Pollution Prevention Act (PPA) of 1990 requires the EPA to establish a program aimed at reducing pollutants at the source by modifying production processes, using less toxic materials, and promoting conservation. The EPA is also tasked with providing grants to states and maintaining a source reduction database. Similar federal environmental laws, such as the Clean Water Act, Clean Air Act, and Resource Conservation and Recovery Act (RCRA), are implemented at the state level, where the EPA allocates funds and provides grants to support state programs for pollution control and hazardous waste management. State legislatures have the authority to direct state agencies on how to implement these programs.

[12] For example, the Missouri Coalition for the Environment (MCE) spent two decades advocating for the relocation of radioactive materials that contaminated the St. Louis, Missouri region. These efforts resulted in a 2018 EPA decision to relocate 70% of the radioactive material to a licensed out-of-state facility.

for two reasons. First, firms may shift their production and employees across facilities. Such a relocation, however, is more likely to occur within the same state due to geographic distance and legal issues (such as facility registration). Second, we can compare how a firm's emissions react to changes in FOIA laws ($\Delta FOIA$) in a treated state to how the same firm's emissions vary in an unaffected state. We then estimate the following model with a firm-state-year panel (denoted by *i*, *s*, and *t*, respectively):

$$Pollutants_{ist} = \alpha_0 + \alpha_1 \Delta FOIA_{st} + \alpha_2 Control\ variables_{ist} + \theta Year\ FE_t + \gamma Firm * State\ FE_{is} + \varepsilon_{ist}\ , \quad (1)$$

The basic idea is as follows. For each firm-state combination, we treat a change in the state FOIA score as an "event" and collect information for the six years surrounding the change (three years before and three years after the change).[13] The details of how to compute FOIA scores are provided in Section 3.2. For each firm that experiences a change in a given state in year *t*, we compare the observations for that firm's facilities in *affected* states with its and other firms' facilities in all other *unaffected* states. Unaffected states are those that do not experience any change in the FOIA score during the six-year window. Note that focusing on firms' emissions in different states around FOIA change events highlights the relation between firms' emissions and FOIA laws (if such a relation indeed exists) while minimizing the influence of other economic and political factors. $\Delta FOIA_{st}$ is the change of FOIA scores in the event. For the treatment group, we assign the value of 0 in the three pre-event years and the value of the change in all the three post-event years. For the control group, $\Delta FOIA_{st}$ is set to zero for every year in the event window. For example, if a company A has operation in state B and state C and if the FOIA score for state B increases from 5 to 7 in year *t*. Then for firm A-state B combination, $\Delta FOIA_{st}$ is set to 2 for year *t*, year *t*+1, and year *t*+2, and is set to 0 for year *t-3*, year *t-2*, and year *t-1*. For firm A-state C combination, $\Delta FOIA_{st}$ is set to 0 for all the six years.

$Pollutants_{ist}$ denotes the two firm-state pollution measures: $Ln(Toxicity)_{ist}$ and $Ln(Toxicity/Emp)_{ist}$. Because the amount of emissions is highly skewed, we take the natural logarithm of 1 plus the value of each measure. $Ln(Toxicity)_{ist}$ is the natural logarithm of 1 plus the amount of toxic release by firm i in state s in year t. $Ln(Toxicity/Emp)_{ist}$ is the natural

[13] We require that there is no change in the state FOIA score for the three-year pre-event window. If a firm-state combination experiences two successive FOIA score changes that overlap in their six-year windows, we drop facility-year observations in overlapping years.

logarithm of 1 plus the amount of toxic release by firm *i* in state s in year *t* divided by the number of employees working for firm *i* in state s in year *t*.

$Control\ variables_{ist}$ denotes a group of firm characteristics and state variables. *Firm size* denotes the natural logarithm of the firm's market value of equity; *Firm Tobin's Q* is defined as total assets plus market value of equity minus book value of equity minus deferred tax liability, divided by total assets; *Firm ROA* denotes firms' return on assets, defined as income before extraordinary items divided by total assets; *Firm leverage* is defined as total debt divided by total assets; *Ln(State emp)* denotes the logarithm of the number of a firm's employees in a state in a year; and *Ln(State GDP)* denotes the logarithm of the GDP of a state in a year. The detailed definitions of these variables are provided in Appendix B. More importantly, we control for year fixed effects ($Year\ FE_t$) and firm-state fixed effects ($Firm * State\ FE_{is}$) that absorb all trends in pollution and the heterogeneity at the firm-state level. We cluster standard errors by state because our main explanatory variable is state-specific (Acharya et al., 2014; Png, 2017).

3.2 FOIA Scores

We obtain data on FOIA laws and provisions from the Open Government Guide published by the Reporters Committee for Freedom of the Press,[14] which compiles information on each state's open records law (we also examine the state law or statute where necessary). We provide two examples of these laws in Appendix A.

We use the information on FOIA laws and provisions to determine a FOIA score for each state in each year that measures the strength of the state's open records law over time. Similar to Cordis and Warren (2014), we calculate the FOIA score by giving one point each if the law meets the following criteria: (1) creates a presumption in favor of disclosure and exempts specific records from public access, (2) does not contain a generic public interest exemption, (3) limits the fees charged for processing requests, (4) prohibits charging fees for the time spent searching and collecting records, (5) waives the cost of searching or copying records if disclosure is in the public interest, (6) establishes criminal penalties for an agency's noncompliance, (7) establishes civil penalties for an agency's noncompliance, (8) provides for the award of attorneys' fees and costs to a successful plaintiff in a public records case, (9) provides that the time to respond to a request for records is 15 days or less, and (10) provides for administrative appeal of an agency's decision

[14] Available at www.rcfp.org.

to deny a request for public records. The FOIA score for the sample period ranges from 1 to 9.[15]

In Panel A of Figure 2, we present the average FOIA score of each state to illustrate the geographic variation in freedom of information. CT, IN, and LA are the three states with the highest FOIA scores in our sample period. In Panel B of Figure 2, we calculate the average annual changes of the FOIA score of each state to illustrate the time trend in each state.[16] PA appears to be the state with the largest FOIA increase during our sample period.

In addition, we plot the time series of the average annual FOIA scores across all states in Figure 3, which shows a steady growth over our sample period. We further tabulate the time series of each state's annual FOIA scores in Table IA 2.1 in the Internet Appendix, which shows a reasonable time-series variation in most states. In particular, we find substantial increases in FOIA scores in MN, NV, NJ, NM, ND, PA, or SD. On the other hand, the FOIA scores appear stable in other states, such as AK, KS, LA, OH, TN, or VA.

4. Sample Formation and Descriptive Statistics

4.1 Data Sources

We obtain facility-level pollution data from the US EPA's Toxic Release Inventory (TRI) database to identify the facility locations and emissions of US firms. The TRI database was established in response to the 1986 Emergency Planning and Community Right-to-Know Act (EPCRA), which requires firms in manufacturing industries with Standard Industrial Classification (SIC) codes between 2000 and 3999 to report all of their factory locations as well as their releases of hazardous substances.[17] Consequently, the TRI database is often regarded as the most comprehensive and reliable data source on the industrial pollution generated by firms and their facilities (Patten, 1998; Greenstone, 2003; Akey and Appel, 2021; Hsu et al., 2023).[18]

We collect facility-level employee data from the National Establishment Time-Series (NETS)

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[15] Our FOIA scores calculation with respect to response time differs slightly from Cordis and Warren (2014). By counting only the "15 days or less" response time we give equal weight to all criteria considered.

[16] For each state in each year, the change of FOIA denotes the state's FOIA in a year minus its FOIA in the prior year.

[17] The EPCRA requires any facility that uses TRI-listed chemicals above specified thresholds and has ten or more full-time equivalent employees to report its emissions of each TRI-listed toxic chemical. Although companies self-report their toxic emissions, the EPA conducts audits to verify their reporting quality. EPA's penalties are related only to misreporting, not to the level of toxic emissions. Therefore, companies do not need to hide their pollution data (Greenstone 2003). Brehm and Hamilton (1996) find that most violations in reporting concentrate on facilities that only release a small amount of toxic emissions, suggesting that most misreporting is unintentional.

[18] For the limitation of the TRI database, please refer to Chen et al. (2024).

database, firm-level financial data from the Compustat database, and firm historical headquarters location data from financial statements in the SEC's EDGAR database.[19] We also obtain state-level GDP data from the Bureau of Economic Analysis. Our sample period begins in 1991 because the coverage of TRI before 1991 is sparse.

Following Chen et al. (2024), we use each TRI facility's parent company name or the facility name to link the information from the TRI database to publicly listed firms in the Compustat database.[20] To capture a firm's production scale in each facility location, we match each TRI facility to the facility listed in the NETS database, which ends in 2020. We aggregate the number of employees and the amount of pollution emissions at the firm-state level each year. As a result, we have the emissions and employees of 3,467 unique firm-state combinations of 617 unique public firms in our 1991-2020 sample.

4.2 Descriptive Statistics

Table 1 provides summary statistics. On average, an average firm emits 352,106 pounds of pollutants in each state it operates. Using the number of employees in a state to normalize these amounts reveals that an average firm emits 865 pounds of pollutants per employee. The average FOIA score is 5.53. The median value of firm-level total assets is 26 (5) billion dollars. An average firm has a Tobin's Q of 1.70. The mean value of firm ROA of 5%, and the mean value of firm leverage is 29%. On average, each state has 2 million employees, and a GDP of 393 billion dollars.

Figure 1 shows the average value of TRI emissions per capita in each state during our sample period, which illustrates the geographic variation of pollution. Panel A includes emissions from all facilities covered by the TRI database. Panel B includes emissions from our sample firms.

5. Empirical Results

5.1 Baseline Regressions

We present the baseline regression results in Table 2. In Columns (1) and (2), we do not include any control variables to prevent the "bad control" concern (Angrist and Pischke, 2009).

[19] The data can be obtained from Professor Bill McDonald's webpage: https://sraf.nd.edu/data/augmented-10-x-header-data/.

[20] For each facility's names, we first calculate the similarity scores between these names and firm names in Compustat using the Damerau–Levenshtein distance. We then manually read through all possible matches to decide the final matches.

We find a negative and statistically significant relation between FOIA and pollution. In Column (2), in which the dependent variable is total toxic release per employee, the estimated coefficient on ΔFOIA is -0.035 and is statistically significant at the 5% level, suggesting that a one-unit increase in the state FOIA score is associated with a 3.5% reduction in a firm's toxic release per 1,000 employees in the state. We obtain consistent results when we include all control variables in Columns (3) and (4): the estimated coefficients on ΔFOIA are -0.037 and -0.32 with statistical significance at the 5% level, respectively.

We argue that our difference-in-differences approach using ΔFOI_{st} has a causal interpretation for the following reasons. First, as explained in Section 2, the strength of state-level FOIA laws is plausibly unrelated to firms' decisions because it is unlikely for firms to successfully lobby state legislators to create FOIA laws exemptions that are specifically related to pollution.

Second, we have implemented an extensive list of tests to validate our difference-in-differences approach, which includes checking reverse causality, verifying the parallel trends assumption, and using the level of FOIA scores as the explanatory variable in a regression for all firm-state-year observations. We only briefly explain them here and leave all the details in Section IA.1 in the Internet Appendix. To address concerns about reverse causality, we examine if a state's FOIA laws are influenced by local pollution by regressing its FOIA scores on lagged average firm-state pollution. We find no evidence that the prevailing pollution level in a state affects the future FOIA score in the state.

It is also important to verify that the treated and control groups display no discernable differences in their pre-treatment polluting behavior. We do so by including time indicators for years prior to FOIA changes in Equation (1) to capture any differential pre-treatment pollution trends between these two groups. The estimated coefficients on pre-treatment years are insignificant, suggesting that there are no differential trends in pollution between the treated and control groups before FOIA changes.

We also consider a conventional regression approach in which we estimate a difference-in-differences regression by using state-level FOIA scores as the explanatory variable and including all firm-state-year observations. We find a negative and statistically significant relation between FOIA and pollution; in particular, we find similar economic magnitudes of the difference-in-differences coefficients.

5.2 Further Identification Tests: Paired Facilities across State Borders

To further strengthen a causal interpretation of the relation between FOIA laws and corporate pollution, we use a paired facility sample to implement an identification test that is based on state borders (Holmes, 1998; Heider and Ljungqvist, 2015). State laws end at state borders whereas local conditions (e.g., economic factors and societal activities) prevail across state borders. We therefore construct a paired sample of facilities across state borders because these facilities share similar local conditions but different state laws.

We match each facility that experiences a change in FOIA score in its location state to another facility (without replacement) that satisfies the following conditions: 1) it is located in another state; 2) it does not experience any change in FOIA score in the three-year window before and after the change; 3) it is located within a 100-kilometer radius; and 4) it belongs to the same two-digit SIC industry. For each matched pair, we keep the observations in the three-year window before and after the change in FOIA scores so we can better capture the effect of FOIA laws. If a facility experiences two successive FOIA score changes that produce overlap in the windows, we drop facility-year observations for the overlapping years. This procedure yields 396 unique pairs of matched facilities.

We then estimate the following regression for all facility-year observations of matched pairs that are included in any event window:

$$
\begin{aligned}
&Pollutants\_f_{jst} \\
&\qquad = \alpha_0 + \alpha_1 \Delta FOIA_{jst} \\
&\qquad + \alpha_2 Control\ variables_{ist}\left(+\alpha_3 Pre - change\ \ pollutants\_f_{jst}\right) + \theta Year\ FE_t \\
&\qquad + \gamma Pair\ FE_j \ \text{ or } \gamma Firm * State\ FE_{is} \ + \varepsilon_{jst}, \quad (2)
\end{aligned}
$$

$Pollutants\_f_{jst}$ denotes the two facility-level pollution measures: $Ln(Toxicity\_f)_{jst}$ and $Ln(Toxicity/Emp\_f)_{jst}$. $Ln(Toxicity\_f)_{jst}$ is the natural logarithm of 1 plus the amount of toxic release by firm *i*'s facility *j* in state *s* in year *t*. $Ln(Toxicity/Emp\_f)_{jst}$ is the natural logarithm of 1 plus the amount of toxic release by firm *i*'s facility *j* in state *s* in year *t* divided by the number of employees working for facility *j* in state *s* in year *t*. $\Delta FOIA_{jst}$ is defined as earlier and equals the change in FOIA scores in each event for treated facilities in the post-event three years, equals 0 for treated facilities for the pre-event three years, and always equals 0 for control facilities. For instance, if a treated facility is located in a state where the FOIA score changes from 3 to 5 in 2001, we include all observations for this facility and its matched facility in 1998 to 2003 in the regression, set $\Delta FOIA$ to 2 for the treated facility in 2001-2003, and set $\Delta FOIA$ to 0 for the other observations.

All control variables in the regression are the same as those in Equation (1). It is noteworthy that we control for (i) the average of *Pollutants_f* in the 3-year window before the change in FOIA scores to absorb the level of each facility and (ii) pair fixed effects, to avoid the correlated omitted variable problem related to local conditions (Cram et al., 2009). The estimates produced by Equation (2) allow us to examine how facility pollution in the treated group changes relative to the control group (treatment facilities in the pre-change window and control facilities in both the pre- and post-change windows).

We report the estimation results for Equation (2) in Table 3. We include pair fixed effects and year fixed effects in Columns (1) and (2), and include firm-state fixed effects and year fixed effects in Columns (3) and (4). The coefficients on $\Delta FOIA$ are negative in all columns for different measures of facility-level emissions (which are statistically significant in all cases), suggesting that reduced costs for quasi-private information helps to curb industrial pollution because the only changes to paired facilities are those in FOIA laws.

6. Mechanism Tests

To further investigate the negative relationship between FOIA laws and local emissions and strengthen the causal interpretation, we conduct four mechanism tests. These tests focus on the number of FOIA requests submitted to each state's environmental agency, firms' pollution abatement costs, government corruption levels, and the political alignment of state government officials. Each factor helps clarify how FOIA laws impact emission reductions and strengthen the link between regulatory oversight and environmental outcomes.

6.1 FOIA Requests

One key implication of our baseline results is that enhanced FOIA laws allow the public to request important information about environmental concerns, regulation, and enforcement. To provide direct evidence for this implication, we initiate FOIA requests by contacting each state's environmental department or agency to obtain the number of FOIA requests received each year. We received timely responses from our contacts in each of the 50 states. However, only 42 states provided informative responses. The remaining eight states did not provide the requested information for various reasons. Some of them simply do not maintain this information (AL, SD, TX). The others either do not maintain records that break down requests by year/state agency (HI, OK) or only provide information to requestors who can prove that they officially reside in the state (AR, DE, TN).

Among the 42 states that provided information, many noted that they have switched to web-based systems of tracking FOIA requests in recent years, so data are available only for recent years. In addition, states may have incomplete data on FOIA requests or track the requests in different ways. For example, Louisiana recently introduced a public-facing Electronic Document Management System that allows members of the public to directly access a range of documents, leading to a decrease in the volume of FOIA requests received. Figure 4 plots the annual average of FOIA requests per facility in all states to illustrate the geographic variation in the public's use of FOIA laws to uncover information about environmental issues. To illustrate the time-series patterns, we present the aggregate and state-level number of these requests in Table IA 2.2 in the Internet Appendix. The table presents the numbers of FOIA requests for 368 state-years. Overall, Table IA 2.2 shows steady increases in the number of FOIA requests submitted over time in most states.

We argue that FOIA laws reduce the acquisition costs of quasi-private information. To support this argument, we first examine whether enhanced FOIA laws lead to more FOIA requests per facility. Using a state-year panel, we regress the number of FOIA requests per facility in a state on the state's annual change of FOIA scores, along with an extensive list of state-level control variables, state fixed effects, and year fixed effects.[21] We obtain the data on state population and personal income per capita from the Bureau of Economic Analysis, and the data on state unemployment rate and education level from the IPUMS-CPS database (Flood et al., 2024). Panel A of Table 4 shows that changes in FOIA scores positively explain the intensity of FOIA requests, indicating that strengthened FOIA laws facilitate stakeholders' access to environment-related information from the government by submitting FOIA requests.

If the volume of state-level FOIA requests reflects state residents' concerns about environmental issues, a higher number of requests may pressure state governments and agencies to enhance their monitoring and analysis of local pollution and enforcement of environmental

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[21] Our state-year panel only include those observations that we were able to collect annual FOIA requests from our FOIA requests.

regulations. To test this proposition, we regress reported toxic pollution in a state on the number of FOIA requests per facility in that state, along with state-level control variables, state fixed effects, and year fixed effects. We present the estimation results for high-FOIA states in Panel B of Table 4. We find that the intensity of FOIA requests is negatively associated with toxic emissions produced by facilities located in the state.[22] These findings provide direct evidence of how residents' and stakeholders' requests for environment-related information may change the behavior of governments or firms with respect to environmental issues. If one posits that FOIA laws do not play any role in mitigating local pollution, then it is difficult to rationalize such a nexus among FOIA changes, FOIA requests, and corporate pollution.

6.2 Pollution Abatement Costs

As discussed earlier, firms that may rationally choose to pollute more due to high pollution abatement costs and low expected violation penalties under weak FOIA laws. Once FOIA laws are strengthened, these firms will rationally reduce toxic emissions due to higher monitoring and pressure. Thus, we expect that the impact of FOIA laws is stronger in states with higher preexisting pollution abatement costs. We obtain preexisting state-level pollution abatement capital expenditure data from the *Current Industrial Reports: Pollution Abatement Costs and Expenditures* issued by the U.S. Department of Commerce.[23] *High cost* (*Low cost*) is an indicator variable that equals 1 if the total pollution abatement capital expenditure in a state in 1990 divided by state GDP is above (below) the median of all states, and 0 otherwise. We then modify Equation (1) by replacing $\Delta FOIA$ with two interaction terms: $\Delta FOIA \times$ *High cost* and $\Delta FOIA \times$ *Low cost*.

We present the estimation results in Table 5. We find that across all four columns, the estimated coefficients on $\Delta FOIA \times$ *High cost* are statistically significant and negative, whereas the estimated coefficients on $\Delta FOIA \times$ *Low cost* are not significant. These results support our argument that, as the cost of obtaining quasi-private information decreases, firms that rationally produced more toxic emissions in the past due to high abatement costs now face greater pressure and thus become more likely to reduce their local emissions to avoid potential regulatory risk. More importantly, by showing that the impact of FOIA laws is stronger for firms that face higher

[22] On the other hand, we do not find a significant relation between FOIA requests and pollution in low-FOIA states.
[23] Keller and Levinson (2002) examine the impact of pollution abatement costs on the inflows of foreign direct investment to the U.S. using a state-level panel data set and find that abatement costs have a deterring effect on foreign investment.

preexisting abatement costs, we confirm that our baseline result is related to pollution rather than to other factors, which further supports our identification.

6.3 Political Corruption

Many federal environmental policies are implemented by states with little federal monitoring of state-level enforcement (Flatt, 1997). Because lax federal oversight allows for considerable variation in the enforcement of federal laws across states, it opens the door for corrupt states and local officials to exert influence.[24] Grooms (2015), for example, looks at the effect of switching from federal to state management of the Clean Water Act on reported violations of the act. She finds that states with a history of high levels of corruption experience a larger decrease in reported facility violation rates than states with lower levels of corruption.

Intuitively, state-level FOIA laws should make it easier to uncover corrupt acts committed by government officials. This argument is consistent with the results of Cordis and Warren (2014), who examine the impact of FOIA laws on convictions of state and local officials for corruption. They find that switching from a weak FOIA law to a strong FOIA law has two key effects: it increases the probability of detecting corrupt acts in the short run and reduces the rate of corruption convictions in the longer run.

The same intuition suggests that state-level FOIA laws should make it easier to uncover weak enforcement of environmental regulations and other actions by state and local officials that are detrimental to the environment. If governmental records are easily accessible to the general public, this should deter government officials from engaging in behavior that the public views unfavorably, even if those actions do not technically qualify as corruption under relevant laws. We expect the effect of FOIA on local pollution to be stronger among states with higher preexisting corruption because they experience a greater change in information availability.

To test our proposition, we construct *High corruption* (*Low corruption*) as an indicator variable that equals 1 if the number of political corruption convictions in a state in 1990 normalized by state population is above (below) the median of all the states, and 0 otherwise. We obtain corruption convictions data from the *Report to Congress on the Activities and Operations of the Public Integrity Section* issued by the US Department of Justice. We then modify Equation (1) by

[24] The literature on the causes and consequences of corruption indicates that corruption can influence policy decisions (Polinsky and Shavell, 2001; Fredriksson and Svensson, 2003; Dincer and Fredriksson, 2018).

replacing $\Delta FOIA$ with two interaction terms: $\Delta FOIA$ × *High corruption* and $\Delta FOIA$ × *Low corruption*.

We report the results in Table 6. Across all four columns, the coefficients on $\Delta FOIA$ × *High corruption* are statistically significant and negative, whereas the coefficients on $\Delta FOIA$ × *Low corruption* are not statistically different from zero. These results support our argument that reducing the costs of obtaining quasi-private information makes it harder for firms located in states with higher preexisting corruption levels to conceal pollution, leading them to reduce local emissions in order to mitigate potential environmental risks.

6.4 Political Alignment of State Government Officials

Naturally, one might suspect that the state-level regulatory environment displays substantial variation across states.[25] Even with the same laws and regulations, the degrees of monitoring and enforcement may vary based on state government officials' beliefs and preferences for specific environmental issues and industries. FOIA laws (and requests based on them) thus ensure that laws and regulations can be implemented more thoroughly and are less likely to be compromised by state government officials' attitudes.

We consider a political alignment index (PAI) that has been used in several prior studies (Kim et al., 2012; Bradley et al., 2016, Gross et al., 2016).[26] Although this index displays substantial variation at the state-level over time, most of this variation is driven by changes in the party of the President. In other respects, the index is quite stable. For example, the set of states that have an above-median value of PAI for the final year of the George H. W. Bush administration (1992) is similar to the group of states that have an above-median value of PAI for the final year of the Donald J. Trump administration (2020). Arguably, states that have high political alignment during Republican administrations are likely to be more laissez-faire in their approach to environmental regulation and enforcement. We therefore propose that the impact of FOIA laws on

[25] For example, lobbying efforts and campaign contributions from politically connected firms may contribute to a more lenient regulatory climate. Several studies support this reasoning. Wu et al. (2016) demonstrate that political connections reduce the frequency of regulatory enforcement actions against corporate fraud, especially in states with weaker legal frameworks. Similarly, Correia (2014) finds that politically connected firms are less likely to face SEC enforcement actions and, if prosecuted, tend to receive lighter penalties.

[26] Note that political alignment, which measures the degree of alignment between the state-level elected officials and the party of the U.S. President, is determined by the location of firms on the geographical map. Unlike lobbying or campaign contributions spending, political alignment is an indirect, plausibly exogenous measure of political connectedness. The description of the index construction closely follows that in Cordis (2024).

emissions is stronger in states that display a high value of PAI during Republican administrations that may be more tolerant of polluting industries.

We construct our Political Alignment Index (PAI) using the methodology pioneered by Kim et al. (2012) as follows:

$$PAI = \tfrac{1}{4} \times Senators + \tfrac{1}{4} \times Representatives + \tfrac{1}{4} \times Governor + \tfrac{1}{4} \times (\tfrac{1}{2} \times State\ senators + \tfrac{1}{2} \times State\ representatives), \tag{3}$$

where *Senators* is the fraction of a state's U.S. Senators that are members of the President's political party, *Representatives* is the fraction of a state's U.S. Representatives that are members of the President's political party, *Governor* is a dummy variable that equals one if the state governor is a member of the President's political party and zero otherwise, *State senators* is a dummy variable that equals one if the fraction of senators in the State Legislature that are members of the President's political party is greater than 0.5 and zero otherwise, and *State representatives* is a dummy variable that equals one if the fraction of representatives in the State Legislature that are members of the President's political party is greater than 0.5 and zero otherwise.[27]

We then construct two indicator variables: *High PAI* (*Low PAI*) equals 1 if the political alignment index in a state in 1990 is above (below) the median of all the states, and 0 otherwise. We then re-estimate Equation (1) by replacing $\Delta FOIA$ with two interaction terms: $\Delta FOIA \times High\ PAI$ and $\Delta FOIA \times Low\ PAI$. We report the results in Table 7. Across all four columns, the coefficients on $\Delta FOIA \times High\ PAI$ are statistically significant and negative, whereas the coefficients on $\Delta FOIA \times Low\ PAI$ are not statistically different from zero. These results support our argument that, as the cost of obtaining quasi-private information decreases, environmental laws and regulations can be fairly and consistently implemented without being influenced by state government officials' attitudes. As a result, firms that operate under more laissez-faire preexisting regulatory regimes face more pressure to reduce local emissions.

7. Conclusion

FOIA laws empower citizens in general and stakeholders specifically to become better informed about public policies and to monitor government actions, promoting accountability among officials. In this study, we demonstrate the significant impact of these laws on the

[27] The data was obtained from the U.S. Congress and the Book of States.

environmental decisions of publicly listed firms. Specifically, we find a strong inverse relation between changes in state-level FOIA laws and various firm-level toxic emission measures. This relation has a causal interpretation based on various validation tests. Moreover, by analyzing paired facilities with similar local conditions but located in different states, we find that facilities in states with strengthened FOIA laws show significantly lower emissions. We thus conclude that FOIA laws have a real effect on mitigating corporate pollution.

We implement several mechanism tests to understand how FOIA laws mitigate corporate pollution. We first show that the number of FOIA requests increases with strengthened FOIA laws and that corporate pollution decreases with FOIA requests. Further, we find that the effect of FOIA laws is stronger in states with higher preexisting pollution abatement costs, higher preexisting levels of corruption, and more lenient environmental policies. These findings suggest that reduced information costs mitigate industrial pollution by increasing public pressure, improving regulatory oversight, and discouraging collusion between polluting firms and local governments.

Our study provides important policy implications by establishing a causal link between stronger FOIA laws and reduced toxic emissions. The US Securities and Exchange Commission (SEC) finalized its long-anticipated Climate-Related Disclosure Rule on March 6, 2024. While this rule advances corporate transparency by focusing on GHG emissions, it may overlook other critical environmental pollutants. The rising focus on clean energy, exemplified by Microsoft's pursuit of nuclear energy, which produces no greenhouse emissions, highlights the need for comprehensive policies that address toxic emissions alongside GHGs.[28] Our study on FOIA laws fills this gap by demonstrating how transparency can drive reductions in industrial pollution, offering valuable insights into the role of regulatory oversight and public accountability in mitigating environmental risks not covered by GHG-centric frameworks. This is especially crucial as companies adopt new energy strategies while still being responsible for their broader environmental impact.

Overall, our study contributes to the literature on information disclosure, showing that lower information acquisition costs, enabled by FOIA laws, have tangible effects on corporate environmental practices. This research also highlights the importance of public-driven monitoring as a complement to formal regulations in achieving environmental goals. Ultimately, by improving

[28] See the report from this link: https://www.technologyreview.com/2024/09/26/1104516/three-mile-island-microsoft/

data accessibility and encouraging transparency, FOIA laws serve as an effective tool for fostering environmental sustainability and advancing public welfare.

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Appendix A: FOIA Laws Examples

Our methodology for computing the state-level FOIA scores is adapted from Cordis and Warren (2014). We assign one point for each of the following criteria that is met by a state's FOIA law: (1) creates a presumption in favor of disclosure and exempts specific records from public access, (2) does not contain a generic public interest exemption, (3) limits the fees charged for processing requests, (4) prohibits charging fees for the time spent searching and collecting records, (5) waives the cost of searching or copying records if disclosure is in the public interest, (6) establishes criminal penalties for an agency's noncompliance, (7) establishes civil penalties for an agency's noncompliance, (8) provides for the award of attorneys' fees and costs to a successful plaintiff in a public records case, (9) provides that the time to respond to a request for records is 15 days or less, and (10) provides for administrative appeal of an agency's decision to deny a request for public records. To better illustrate the procedure, we provide a couple of detailed examples.

First, consider the state of North Carolina (NC). NC's Public Records Law dates back to 1935. It was amended several times as a result of efforts by the NC Press Association and the NC Association of Broadcasters: in 1975 to expand its scope to records kept in electronic format and other non-traditional formats and in 1995 to clarify issues such as the cost of providing copies of records and the time to respond to requests. The law provides that "no public agency shall charge a fee for an uncertified copy of a public record that exceeds the actual cost to the public agency of making the copy…"actual cost" is limited to direct, chargeable costs related to the reproduction of a public record." Furthermore, the law allows a "special service charge" for search time or information technology resources if the labor costs necessary to produce the records are extensive and does not provide for a fee waiver. There is no provision to limit the response time other than specifying that records should be made available "at reasonable times."

The NC law presumes that public records are "the property of the people" and lists specific records as exempt, such as those involving trade secrets, state and local tax information, and attorney-client privilege. Additional specific exemptions are listed in the NC General Statutes. There is no public interest exemption. The NC's Public Records Law does not provide for civil or criminal sanctions for an agency's noncompliance, nor does it specify an administrative appeal procedure. Attorney's fees may be awarded to requesters who prevail in a civil suit against a public agency who denied access to records. Based on these provisions, NC is awarded one point for items (1) and (2) for the years 1991-2016 and one point for items (3) and (8) for the years 1996-2016. Thus, the FOIA score for NC is 2 for 1991-1995 and 4 for 1996-2016.

Next consider the state of New Mexico (NM), whose FOIA score displays a larger increase than that of NC during our sample period. NM's open records law was passed in 1947, amended in 1973 to add exemptions from disclosure, and then again in 1993 as a result of efforts by the NM Press Association and the NM Foundation for Open Government to improve access to records. The 1993 amendments expanded the definition of public records and created a presumption in favor of disclosure. There is no public interest exemption; specific exemptions are listed in the law and patterned after the federal FOIA.

The law authorizes custodians to charge "reasonable" fees, which are limited to one dollar for copies of documents smaller than eleven by seventeen inches or to actual costs for copies or downloads of electronic records to a storage device. The law does not allow charging a fee for the time spent "determining whether any public record is subject to disclosure." There are no fee waivers in the public interest. An agency must allow inspection of public records as soon as possible, no later than 15 days after receiving a request.

The NM law does not contain a provision for criminal or civil penalties for an agency's noncompliance, but states that the court "shall award damages, costs and reasonable attorneys' fees" to successful plaintiffs. There is no provision for a formal administrative appeal procedure and "exhaustion of administrative remedies shall not be required prior to bringing any action to enforce the procedures of the Inspection of Public Records Act." Based on these provisions, NM is assigned one point for items (2) and (8) for the years 1991-2016 and one point for items (1), (3), (4) and (9) for the years 1994-2016. Thus, the FOIA score for NM is 2 for 1991-1993 and 6 for 1994-2016.

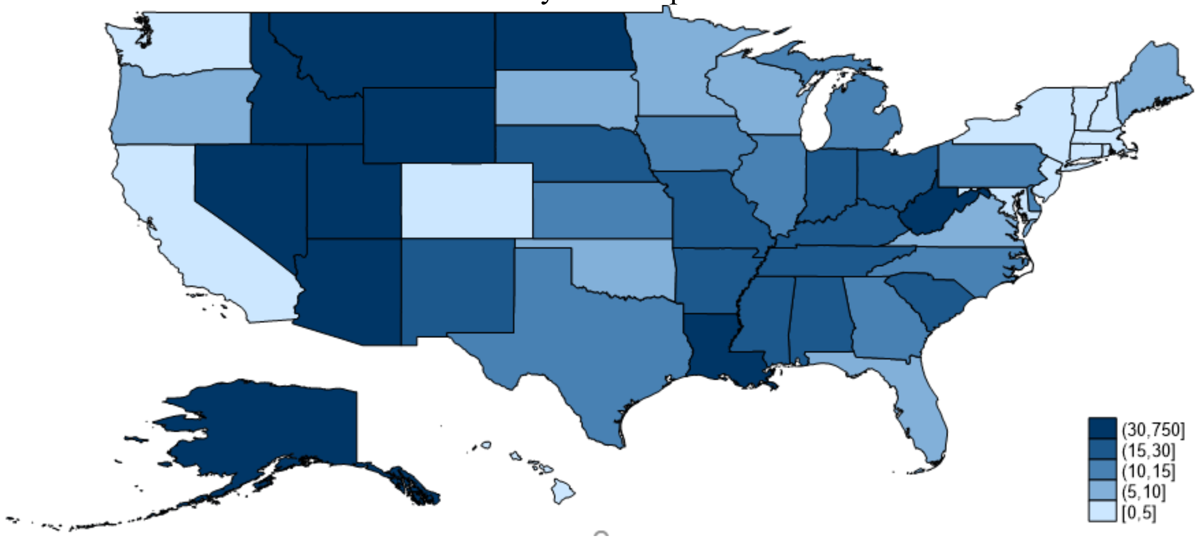
Appendix B: Variable Definitions

Variable	Definition
Ln(Toxicity)	Ln(1+the amount of toxic release by a firm in a state)
Ln(Toxicity/Emp)	Ln(1+the amount of toxic release by a firm in a state divided by the number of employees working for the firm in this state)
Ln(Toxicity_f)	Ln(1+the amount of toxic release by a facility)
Ln(Toxicity/Emp_f)	Ln(1+the amount of toxic release by a facility divided by the number of employees working in the facility)
Pre-change Ln(Toxicity_f)	The average of Ln(*Toxicity_f*) in the 3-year window before the change in FOIA scores
Pre-change Ln(Toxicity/Emp_f)	The average of Ln(*Toxicity/Emp_f*)in the 3-year window before the change in FOIA scores
FOIA	State FOIA score
ΔFOIA	Equals 0 in the three years before the FOIA change, and equals the value of change in the three years after the FOIA change.
FOIA requests per capita	The number of FOIA requests submitted to the state environmental department or agency per 1,000 state population.
Annual change in FOIA	$FOIA_t$ / $FOIA_{t-1}$ -1
Firm size	Ln(Market value of equity)
Firm Tobin's Q	(Total assets + market value of equity - book value of equity - deferred tax liability)/ total assets
Firm ROA	Income before extraordinary items/total assets
Firm leverage	Total debt/total assets
Ln(State emp)	Ln(total number of employees in each state). We aggregate the number of employees in each facility at the state level.
Ln(State GDP)	Natural logarithm of the GDP of a state
Ln(Average Toxicity)	The natural logarithm of one plus the average amount of firm-level toxic release in a state.
Ln(Average Toxicity/Emp)	The natural logarithm of one plus the average amount of firm-level toxic release per employee in a state.
State personal income per capita	Annual personal income per capita in a state
Ln(State population)	Natural logarithm of the population of a state
Ln(State facility #)	Natural logarithm of the number of facilities of a state
Ln(State public firm #)	Natural logarithm of the number of public firms of a state
State unemployment rate	The unemployment rate of a state
State education	Percentage of the labor force who finish 4-years' college
High cost	A dummy variable equals 1 if the pollution abatement cost (state-level pollution abatement capital expenditure divided by state GDP) of the state in 1990 is above median of all the states, and 0 otherwise.
Low cost	1- High cost
High corruption	A dummy variable equals 1 if the corruption level (number of public corruption convictions cases in each state divided by state population) of the state in 1990 is above median of all the states, and 0 otherwise.
Low corruption	Low corruption=1-High corruption
High PAI	A dummy variable equals 1 if the political alignment index of the state in 1990 is above median of all the states, and 0 otherwise.
Low PAI	1-High PAI

Figure 1 TRI Emissions

The figure provides a visual illustration of the average value of TRI emissions level per capita in each state during our sample period. In Panel A, we use the total emissions by all facilities covered by the TRI database scaled by state population. In Panel B, we use the total emissions by our sample firms scaled by state population.

Panel A. State Total TRI Emissions Scaled by State Population



Panel B. Sample Firms' Total TRI Emissions Scaled by State Population

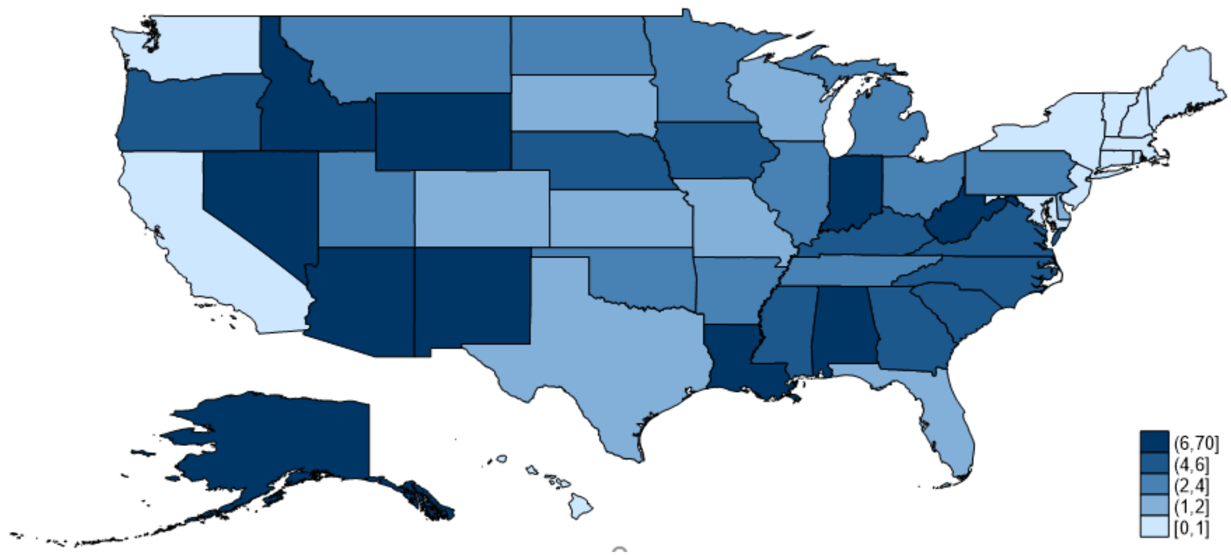
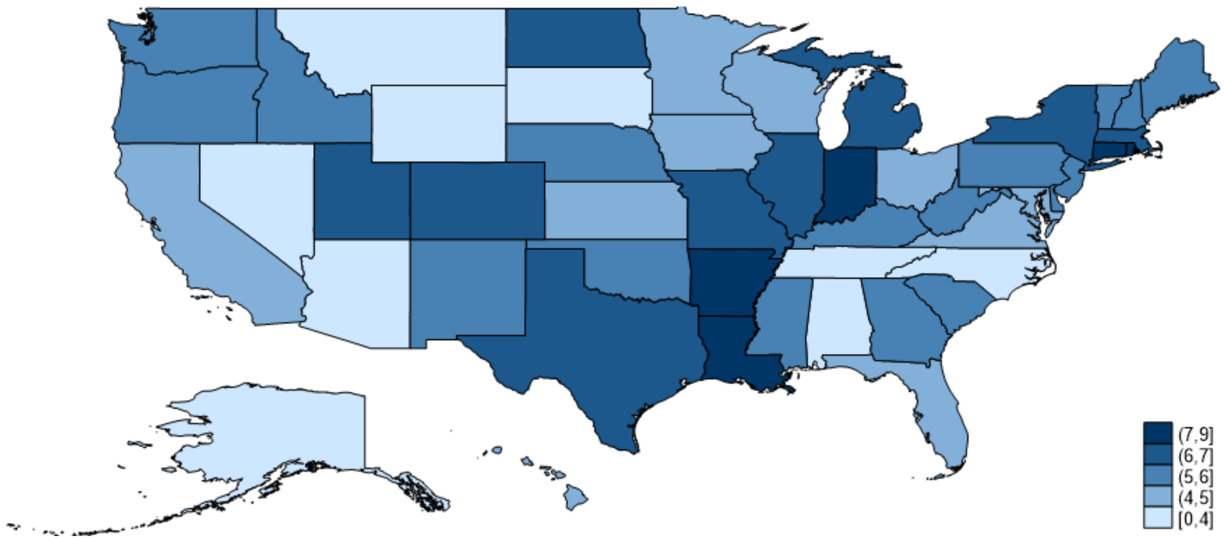


Figure 2 Geographic Variation of FOIA Scores

The figure provides a visual illustration of the FOIA scores in each state. In Panel A, we show the average value of FOIA scores in each state during our sample period. In Panel B, we show the average value of annual FOIA score changes in each state during our sample period.

Panel A. Average FOIA Scores



Panel B. Average Annual FOIA Score Changes

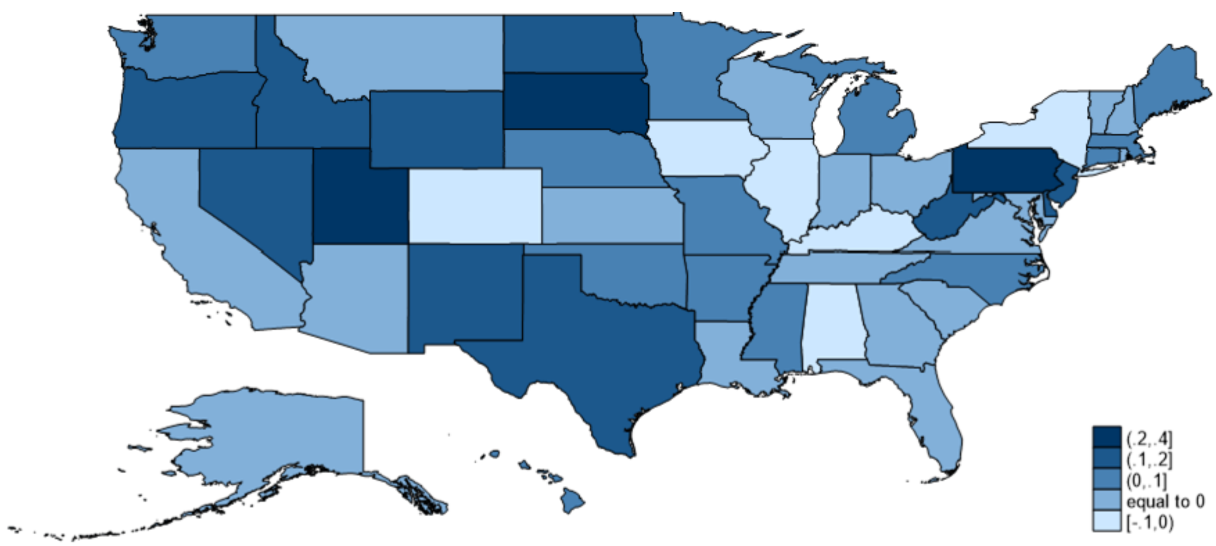


Figure 3 Time-Series Variation in FOIA

The figure plots the average FOIA score of all states in each year.

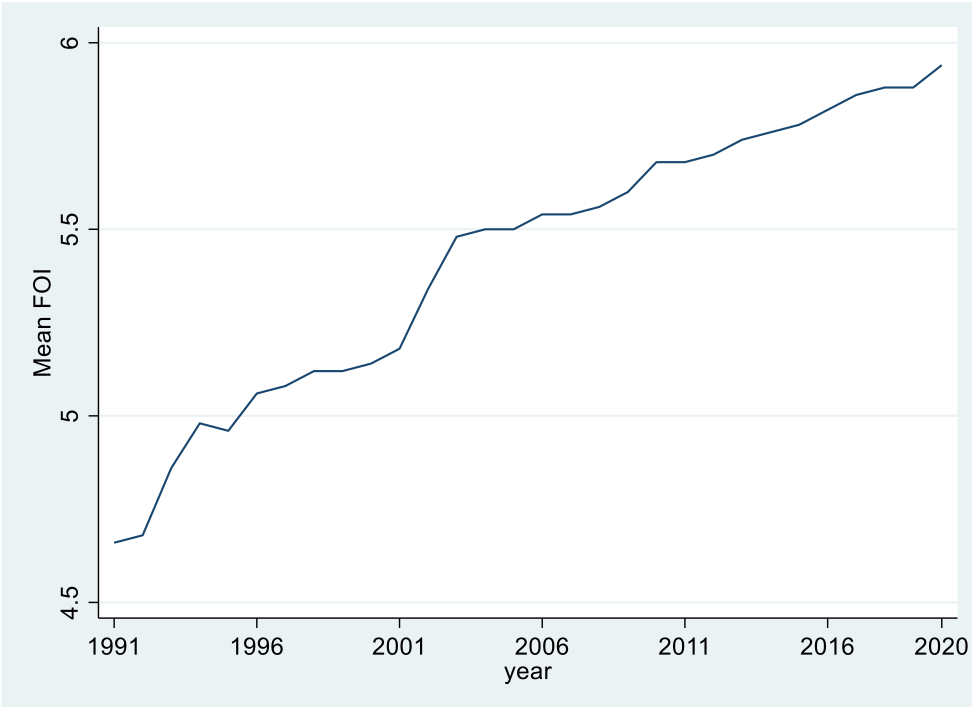


Figure 4 Average Annual FOIA Requests Scaled by Number of State Facility

The figure provides a visual representation of the average number of FOIA requests per facility in each state during our sample period.

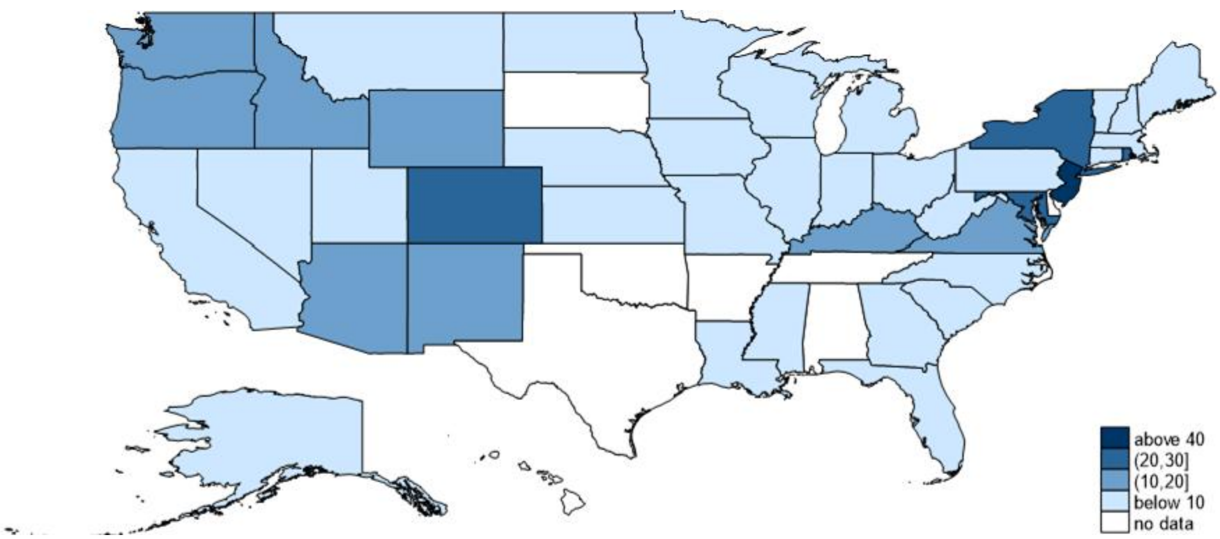


Table 1 Descriptive Statistics

The sample consists of 38,385 firm-year observations from 1991 to 2020. Panel A reports the descriptive statistics of the main variables. All variable definitions are provided in Appendix B. The continuous variables are winsorized at the 1st and 99th percentiles.

	Obs	Mean	S.D.	P25	Median	P75
Toxicity	38,385	352105.90	1238590.70	204.31	10081.50	86545.06
Toxicity/Emp	38,385	864.73	4009.80	0.28	13.49	135.74
FOIA	38,385	5.53	1.73	5.00	6.00	7.00
ΔFOIA	38,385	0.16	0.79	0.00	0.00	0.00
Total assets	38,385	25976.55	58459.67	1222.78	4748.88	21824.60
Firm size	38,385	8.50	1.98	7.11	8.47	9.99
Firm Tobin's Q	38,385	1.70	0.75	1.19	1.48	1.95
Firm ROA	38,385	0.05	0.05	0.03	0.05	0.08
Firm leverage	38,385	0.29	0.14	0.18	0.27	0.38
Firm_state emp	38,385	1926.50	3731.39	194.00	621.00	1804.00
State GDP (in million$)	38,385	392777.57	400640.15	141089.95	259612.06	480912.13

Table 2 Difference-in-differences Analysis

The table reports the firm-state-level regressions results that examine the effect of FOIA law changes on local emissions. *Ln(Toxicity)* is the natural logarithm of one plus the amount of toxic release by a firm in a state. *Ln(Toxicity/Emp)* is the natural logarithm of one plus the amount of toxic release by a firm in a state divided by the number of employees working in the state. *ΔFOIA* is computed by treating a change in a state's FOIA score as an "event" and collecting information for the 6 years surrounding the change (3 years before and 3 years after the change). It takes the value of 0 in the 3 pre-event years and takes the numerical value of the score change in the 3 post-event years. All other variable definitions are provided in Appendix B. All continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors clustered by state are in parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Ln(Toxicity)	(2) Ln(Toxicity/Emp)	(1) Ln(Toxicity)	(2) Ln(Toxicity/Emp)
ΔFOIA	-0.045*	-0.035**	-0.037*	-0.032***
	(0.023)	(0.013)	(0.021)	(0.012)
Firm size			0.205***	0.114***
			(0.065)	(0.040)
Firm Tobin's q			-0.177***	-0.084**
			(0.059)	(0.032)
Firm ROA			-0.176	-0.265
			(0.461)	(0.306)
Firm leverage			-0.371	-0.347**
			(0.274)	(0.134)
Ln(State emp)			0.149***	-0.579***
			(0.048)	(0.040)
Ln(State GDP)			1.245*	0.802**
			(0.621)	(0.360)
Year fixed effects	Yes	Yes	Yes	Yes
Firm*State fixed effects	Yes	Yes	Yes	Yes
Observations	38,385	38,385	38,385	38,385
Adjusted R2	0.788	0.810	0.790	0.824

Table 3 Paired Facilities across State Borders

The table reports the facility-level regression results that examine the effect of FOIA law changes on local emissions. *Ln(Toxicity_f)* is the natural logarithm of one plus the amount of toxic releases by a facility. *Ln(Toxicity/Emp_f)* is the natural logarithm of one plus the amount of toxic releases by a facility divided by the number of employees working in the facility. All other variable definitions are provided in Appendix B. All continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors clustered by pair are in parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Ln(Toxicity_f)	(2) Ln(Toxicity/Emp_f)	(3) Ln(Toxicity_f)	(4) Ln(Toxicity/Emp_f)
ΔFOIA	-0.086	-0.070**	-0.097*	-0.066**
	(0.053)	(0.032)	(0.052)	(0.032)
Firm size	-0.023	0.026	0.194**	0.110
	(0.025)	(0.023)	(0.094)	(0.082)
Firm Tobin's q	0.050	0.004	-0.047	-0.045
	(0.064)	(0.051)	(0.074)	(0.061)
Firm ROA	-1.524	-0.449	-1.266	-0.542
	(1.392)	(0.668)	(1.143)	(0.443)
Firm leverage	0.191	0.683**	0.776	0.636*
	(0.444)	(0.300)	(0.480)	(0.356)
Ln(State emp)	0.023	-0.139**	-0.039	-0.183**
	(0.037)	(0.055)	(0.062)	(0.077)
Ln(State GDP)	0.075	0.028	2.044	0.487
	(0.099)	(0.083)	(1.356)	(0.991)
Pre-change Ln(Toxicity_f)	0.935***		0.931***	
	(0.016)		(0.023)	
Pre-change Ln(Toxicity/Emp_f)		0.932***		0.864***
		(0.023)		(0.035)
Year fixed effects	Yes	Yes	Yes	Yes
Paired fixed effects	Yes	Yes	No	No
Firm*State fixed effects	No	No	Yes	Yes
Observations	2,524	2,524	2,522	2,522
Adjusted R2	0.897	0.920	0.896	0.918

Table 4 FOIA requests

The table reports the state-level regression results that examine whether FOIA law changes affect local emissions through FOIA requests. *FOIA requests per facility* is the number of FOIA requests submitted to a state's environmental department or agency per state facility. In Panel A, we analyze the impact of the FOIA law changes on FOIA requests per state facility. *Annual change in FOIA* is percentage increase in FOIA score from last year to the current year. In Panel B, we examine the impact of FOIA requests on local emissions. All other variable definitions are provided in Appendix B. All continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors clustered by state are in parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A The change of FOIA scores and FOIA requests per facility

VARIABLES	FOIA requests per facility
Annual change in FOIA	7.505*
	(4.255)
Ln(State GDP)	-22.558*
	(12.876)
State personal income per capita	-0.243
	(3.828)
State unemployment rate	-0.618*
	(0.340)
State education	1.162
	(0.803)
Ln(State facility #)	-39.408**
	(16.274)
Ln(State public firm #)	0.234
	(0.911)
Ln(State population)	960.446*
	(518.265)
Year fixed effects	Yes
State fixed effects	Yes
Observations	353
Adjusted R2	0.874

Panel B The effects of FOIA requests on pollution

	(1)	(2)	(3)	(4)
VARIABLES	Ln(Toxicity)	Ln(Toxicity/Emp)	Ln(Toxicity)	Ln(Toxicity/Emp)
FOIA requests per facility	-0.020*	-0.010***	-0.017*	-0.011***
	(0.010)	(0.002)	(0.010)	(0.003)
Firm size			0.327***	0.187**
			(0.102)	(0.077)
Firm Tobin's q			-0.130*	-0.086**
			(0.069)	(0.034)
Firm ROA			-0.076	-0.022
			(0.262)	(0.241)
Firm leverage			0.045	0.215
			(0.382)	(0.204)
Ln(State emp)			0.037	-0.657***

			(0.038)	(0.045)
Ln(State GDP)			0.786	-0.152
			(0.866)	(0.484)
Year fixed effects	Yes	Yes	Yes	Yes
Firm*State fixed effects	Yes	Yes	Yes	Yes
Observations	12,961	12,961	12,961	12,961
Adjusted R2	0.878	0.898	0.879	0.909

Table 5 Pollution Abatement Capital Expenditure

The table reports the firm-state-level regression results that examine whether the impact of FOIA law changes on local emissions varies with local pollution abatement costs. *High (Low) cost* is a dummy variable that equals 1 if the pollution abatement cost (state-level pollution abatement capital expenditure divided by state GDP) of the state in 1990 is above (below) median of all states, and 0 otherwise. All other variable definitions are provided in Appendix B. All continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors clustered by state are in parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Ln(Toxicity)	(2) Ln(Toxicity/Emp)	(3) Ln(Toxicity)	(4) Ln(Toxicity/Emp)
ΔFOIA × High cost	-0.139***	-0.075**	-0.118***	-0.070**
	(0.043)	(0.032)	(0.042)	(0.026)
ΔFOIA × Low cost	-0.010	-0.021	-0.008	-0.019
	(0.027)	(0.013)	(0.025)	(0.012)
Firm size			0.205***	0.114***
			(0.065)	(0.040)
Firm Tobin's q			-0.178***	-0.084**
			(0.059)	(0.032)
Firm ROA			-0.168	-0.262
			(0.460)	(0.305)
Firm leverage			-0.370	-0.347**
			(0.274)	(0.134)
Ln(State emp)			0.148***	-0.579***
			(0.048)	(0.040)
Ln(State GDP)			1.208*	0.784**
			(0.616)	(0.358)
Year fixed effects	Yes	Yes	Yes	Yes
Firm*State fixed effects	Yes	Yes	Yes	Yes
Observations	38,385	38,385	38,385	38,385
Adjusted R2	0.788	0.810	0.790	0.824

Table 6 Political Corruption

The table reports the firm-state-level regression results that examine whether the impact of FOIA law changes on local emissions varies with local political corruption. *High (Low) corruption* is a dummy variable that equals 1 if the corruption level (number of public corruption convictions in each state divided by state population) of the state in 1990 is above (below) median of all states, and 0 otherwise. All other variable definitions are provided in Appendix B. All continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors clustered by state are in parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Ln(Toxicity)	(2) Ln(Toxicity/Emp)	(3) Ln(Toxicity)	(4) Ln(Toxicity/Emp)
ΔFOIA × High corruption	-0.067**	-0.047***	-0.059**	-0.042***
	(0.029)	(0.017)	(0.026)	(0.014)
ΔFOIA × Low corruption	0.004	-0.009	0.011	-0.009
	(0.041)	(0.019)	(0.035)	(0.018)
Firm size			0.205***	0.114***
			(0.065)	(0.040)
Firm Tobin's q			-0.177***	-0.083**
			(0.059)	(0.032)
Firm ROA			-0.179	-0.267
			(0.461)	(0.306)
Firm leverage			-0.374	-0.349**
			(0.274)	(0.134)
Ln(State emp)			0.149***	-0.579***
			(0.048)	(0.040)
Ln(State GDP)			1.238*	0.798**
			(0.623)	(0.361)
Year fixed effects	Yes	Yes	Yes	Yes
Firm*State fixed effects	Yes	Yes	Yes	Yes
Observations	38,385	38,385	38,385	38,385
Adjusted R2	0.788	0.810	0.790	0.824

Table 7 Political Alignment

The table reports the firm-state-level regression results that examine whether the impact of FOIA law changes on local emissions varies with local political alignment. *High (Low) PAI* is a dummy variable that equals 1 if the political alignment index of the state in 1990 is above (below) the median of all states, and 0 otherwise. All other variable definitions are provided in Appendix B. All continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors clustered by state are in parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	Ln(Toxicity)	Ln(Toxicity/Emp)	Ln(Toxicity)	Toxicity/Emp
ΔFOIA × High PAI	-0.067**	-0.053**	-0.059**	-0.045***
	(0.030)	(0.020)	(0.026)	(0.016)
ΔFOIA × Low PAI	-0.003	-0.001	0.005	-0.007
	(0.041)	(0.015)	(0.035)	(0.017)
Firm size			0.205***	0.114***
			(0.065)	(0.040)
Firm Tobin's q			-0.177***	-0.083**
			(0.060)	(0.032)
Firm ROA			-0.179	-0.267
			(0.461)	(0.306)
Firm leverage			-0.372	-0.348**
			(0.274)	(0.134)
Ln(State emp)			0.149***	-0.579***
			(0.048)	(0.040)
Ln(State GDP)			1.241*	0.800**
			(0.623)	(0.362)
Year fixed effects	Yes	Yes	Yes	Yes
Firm*State fixed effects	Yes	Yes	Yes	Yes
Observations	38,385	38,385	38,385	38,385
Adjusted R2	0.788	0.810	0.790	0.824