Access to Debt and Corporate Environmental Performance: Evidence from Anti-Recharacterization Laws

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Abstract

This study examines the impact of improved debt access, brought by the staggered adoption of anti-recharacterization (AR) laws in U.S. states, on corporate environmental performance. We find that firms with enhanced debt financing capabilities reduce their toxic emissions. This effect is more pronounced in firms using Special Purpose Vehicles (SPVs), issuing more long-term debt, facing greater debt market constraints, and backed by long-term and environmentally conscious institutional investors. Better debt access also encourages investments in environmental technologies and compliance with regulations. These findings highlight the crucial role of debt financing in promoting environmental sustainability, offering valuable insights for stakeholders and policymakers.

Keywords: Environment Protection, Financing Friction, Access to Debt, ESG Institutional Investors

JEL classification: G30, Q52, Q53

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1. Introduction

Environmental pollution poses a significant threat to both nature and humanity, and it has a considerable impact on the global economy. According to a research report by the World Economic Forum, air pollution alone costs the United States a staggering $600 billion annually, which is equivalent to 3 percent of the nation's GDP[1]. Since a substantial portion of these hazardous emissions stems from industrial production processes, it is crucial to understand the factors that influence corporate environmental decision-making.

Addressing toxic emissions requires significant financial resources to facilitate the adoption of various measures, including the acquisition of pollution abatement equipment, adherence to regulatory compliance practices, and the development of eco-friendly technology and innovations. In this study, we focus on the financial aspect by exploring how access to debt financing can affect firms' environmental performance. Using the staggered implementation of anti-recharacterization (AR) laws across various U.S. states as a quasi-natural experiment that strengthens creditors' rights, we find that improved access to debt financing significantly reduces the level of toxic emissions produced by firms.

Under Chapter 11 of the U.S. Bankruptcy Code, secured lending's collateral is placed under an automatic stay, limiting the ability of secured lenders to repossess the collateral promptly. However, the automatic stay provision does not apply to assets held by a company's special purpose vehicles (SPVs) unless a judge reclassifies these assets as loans instead of genuine sales. In an effort to minimize the risk of reclassification and ensure that secured lending through SPVs remains unaffected by automatic stay, seven U.S. states between 1997 and 2005 have enacted anti-

[1] How does air pollution affect the economy? | World Economic Forum (weforum.org)

recharacterization laws. This legal mechanism offers creditors heightened protection, resulting in the increased value of firms' collateral as perceived by debtholders and improving firms' borrowing capacity.

Ex-ante, it is unclear how increased debt capacity, stemming from the adoption of AR laws affects firms' environmental performance. On the one hand, better access to the debt market can reduce borrowing costs for firms, affording them additional financial resources to support environmental protection activities. As articulated by Starks (2023), there are two primary motivations driving firms to allocate greater financial resources to environmental investments. The first is to manage environmental risks, particularly those arising from regulatory violations and subsequent lawsuits, which can impose hefty financial burdens on firms and reputational damages on their leadership. Consequently, firms must continually evaluate their current environmental investments in light of projected future expenditures related to fines and legal costs. When financially constrained, firms may make suboptimal investments in pollution mitigation and be exposed to heightened environmental risks. Therefore, with the adoption of AR laws improving firms' access to the debt market, firms are likely to increase environmental investments.

The second motivation is to cater to investors' preferences. The recent decades have witnessed a focus on climate change and corporate environmental sustainability. Large institutional investors have increasingly incorporated their environmental concerns into the strategic management of firms within their portfolios (Cohen et al. 2023). Given the competing demands on financial resources, managers are likely to increase environmental investments if they have sufficient resources to meet both profitability targets and environmental standards. Hence the adoption of AR laws, by boosting firms' borrowing capacity, is likely to encourage increased environmental investments, thus catering to shareholders' environmental expectations. Furthermore, insights from

Environmental, Social, and Governance (ESG) studies suggest that sustainable environmental investment may align with the long-term interests of shareholders, even when they may not explicitly prioritize environmental concerns.[2]

On the other hand, there are compelling reasons to believe that improved debt capacity might negatively impact firms' environmental performance. For instance, with the adoption of AR laws bolstering firms' access to the debt market, firms leveraging more debts may enlarge the production scale, potentially leading to more toxic emissions. Additionally, increased debt capacity may encourage managers to pursue more aggressive expansion strategies, which could include acquiring businesses with environmentally unsound practices, thereby exacerbating pollution levels. Thus, the impact of the adoption of AR laws on corporate environmental performance is an empirical question, which is the focus of this study.

Establishing a causal link between access to debt and toxic emissions is difficult because firm-level proxies for access to debt are often endogenous to firms' toxic emissions. For example, firms may be more likely to use debt financing when they tend to pollute more, based on the "asset substitution" argument in Jensen and Meckling (1976) and evidenced by Lyu et al. (2022). Moreover, some unobservable factors at the firm- and industry- level could affect firms' decisions on both debt financing and pollution, such as some technology firms may be environmentally conscious and use less debt in their financing simultaneously. This means that whatever the correlation we might observe between access to debt and pollution, it would be difficult to rule out the possibility of reverse causality and omitted variables.

[2] For example, the recent survey by Kavadis and Thomsen (2022) find a positive effect of institutional ownership on sustainability, particularly for long-term institutional investors, in most cases. However, a long-term ownership horizon is an enabling but not sufficient condition for sustainability.

We overcome this obstacle by exploiting the staggered adoption of AR laws by seven U.S. states between 1997 and 2005 as a plausibly exogenous shock to firms' access to the debt market. Specifically, employing a difference-in-differences (DiD) framework, we examine the effect of AR laws on firms' toxic emissions by analyzing the emission data at the plant level, which are obtained from the Toxics Release Inventory (TRI) maintained by the U.S. Environmental Protection Agency (EPA). For our analysis, we use a panel of 70,869 plant–year observations from 10,929 firm–year observations incorporated in 51 U.S. states from 1993 to 2015. The treatment group includes plants whose parent firm incorporated in states where an AR law was enacted during our sample period, and the control group includes plants whose parent firm incorporated in states where no AR law was enacted.

Our study yields the following results. First, we find that the treated firms reduce their toxic chemical emissions after the adoption of AR laws. The impact is economically significant: there is a reduction of 20.8% per plant-year on average for the treated plants in our sample. The dynamic analysis reveals no pre-trend effect before the adoption of AR laws and a persistent decline in toxic emissions that are evident from the third year after the AR law adoption, indicating a reasonable latent effect of improved financial conditions on the reduced level of pollution. Moreover, Table IA1 in the online Internet Appendix shows that the toxic pollution level cannot predict the adoption of an AR law at the state level, suggesting that the adoption of AR laws provides a plausible exogenous setting to study our topic.

Secondly, we examine whether AR laws mitigate toxic emissions by facilitating firms to utilize Special Purpose Vehicles (SPVs) and raise more debt. As previous research indicates, with AR laws increasing firms' access to the debt market, firms incorporated in states with AR laws tend to use more SPVs and then issue more debts, especially long-term debt (Tut 2021, Gao et al. 2022).

Moreover, Favara et al. (2021) suggests that even if firms do not currently use SPVs, the enactment of AR laws still benefits them, given the potential to secure collateral through SPVs in the future. Supporting this conjecture, we find that after the adoption of AR laws, the declines in toxic emissions are observed in the whole sample, but stronger in firms that increased their use of SPVs and long-term debt. Additionally, the AR law effect is more pronounced in firms that previously faced significant debt market constraints[3], suggesting that AR laws are particularly beneficial to firms that were already financially constrained.

Thirdly, we explore three economic channels through which AR laws can mitigate firms' toxic emissions, namely, increased abatement investments, enhanced adherence to regulations, and advancement of environmentally friendly technology. Following the enactment of AR laws, we find that treated firms increase their abatement investments significantly in the reduction, elimination, or control of pollution or environmental hazards; spend more on regulatory compliance and improve their adherence to the EPA regulations; and increase their investments in green technology, evidenced by the increase of "green" patents. In addition, while we find no significant changes in firms' production growths, there is a significant improvement in firms' emission efficiency, as the ratio of total emissions to the production volume declines. The latter further corroborates our findings of increased environmental investments.

Lastly, we shed light on the underlying motivations for enhanced environmental investments following the enactment of AR laws, considering both environmental risk management and shareholders' environmental preferences factors (Starks 2023). To support the notion that increased access to debt empowers firms to manage environmental risks more effectively, we show that the effect of AR laws is more pronounced for firms with higher prior litigation risk and regulatory

[3] The debt market constraint measure is adopted from Hoberg and Maksimovic (2014).

penalty, which suggests that improved access to debt financing helps firms mitigate environmental and legal risks. Moreover, large institutional investors have progressively integrated environmental considerations into the strategic decision-making process of their portfolio firms. Given that AR laws enhance firms' financial accessibility and enable them to be better aligned with shareholders' environmental preferences, our study indicates that the AR law effect is particularly evident in firms with a strong presence of environmentally sustainable ownership, higher presence of the "Big Three" ownership (i.e., Blackrock, Vanguard, and State Street)[4], and a high proportion of "dedicated" institutional ownership.

This study contributes to the literature on the connection between firms' financial conditions and their environmental performance. Goetz (2019) finds that lower financing costs reduce toxic emissions. Lyu et al. (2022) document that firms increase their toxic releases and pollution intensity after issuing debt. Thomas et al. (2022) find that firms release more toxins by cutting back on pollution abatement costs to boost earnings to meet earnings benchmarks. Xu and Kim (2022) document that financial constraints increase firms' toxic emissions. Shive and Forster (2020) find that better corporate governance may decrease greenhouse gas emissions. We complement these existing studies by showing that improvement access to debt markets has a positive role in firms' environmental performances.

This study also extends our understanding of the importance of enhanced creditors' rights and improved access to debt financing brought by the passing of AR laws on various corporate financial decisions. Previous studies have documented a significant role of AR law adoption on corporate precautionary behavior (Favara et al. 2022), trade credit (Billett et al. 2022), risk management (Fairhurst and Nam 2021), acquisition activities (Rainville et al. 2022), efficient

[4] The "Big Three" institutions are known for their commitment to tackling ESG issues, see Azar et al. (2021) and Gormley et al. (2023).

production technology adoption and improved productivity (Ersahin 2020), and gender pay gap (Gao et al. 2022). We fill the gap by focusing on the effect of AR laws on firms' environmental investments.

The findings of our study have important policy implications. Environmental protection is no longer just a regulatory obligation for corporations; it is a strategic imperative that has an impact on firms' value and risk. Embracing sustainability and environmentally responsible practices can lead to improved reputation, reduced risks, access to new markets and investors, and enhanced green innovation and competitiveness. It also caters to investors, especially long-term oriented institutional investors, with ESG preferences. As sustainability continues to be a driving force in global business, corporations that prioritize environmental protection are better positioned to thrive in the long run. Our study contributes to a deeper understanding of corporate environmental performances by spotlighting the role of improved access to debt markets in curbing toxic emissions. The results obtained in this paper warrant the attention of regulators, shareholders, and corporate managers alike.

2. Institutional Background and Data Sources

2.1. Anti-Recharacterization Law

According to the U.S. Bankruptcy Code, the collateral underlying secured lending is subject to the *automatic stay* provision, which imposes a halt on most collection activities and legal actions by creditors against the debtor and their assets. It puts a temporary freeze on creditors' attempts to pursue or enforce their claims while the bankruptcy case is pending. The purpose of the automatic stay is to provide the debtor with a breathing space to reorganize their finances and develop a feasible plan to repay their debts. However, the presence of automatic stay protection in bankruptcy weakens creditors' rights, as it increases the uncertainty of when the creditors will get paid and the collateral values may deteriorate during the lengthy process.

It should be noted that the automatic stay may not necessarily apply to assets owned by a firm's special purpose vehicles (SPVs)[5]. Many borrowers evade the automatic stay by selling their collateral to a bankruptcy-remote SPV, which remains solvent (and thus free to transfer the collateral to the lender) if the borrower files for bankruptcy. This allows firms to obtain a lower cost of financing through the SPV instead of borrowing directly from the lender.

As with many legal matters, the treatment of SPV assets during bankruptcy can be complex. The extent to which SPVs may shield creditors from bankruptcy costs depends on whether judges recharacterize an asset transferred to the SPV as a loan. If this recharacterization takes place, a lender becomes a secured creditor of the firm, instead of the SPV. Therefore, even secured lending through SPVs may be subject to the automatic stay provision. While the automatic stay and the recharacterization of assets transferred to SPVs aim to favor business continuation, this provision hinders firms' access to debt by decreasing the value of pledged collateral to secured lenders. To reduce the likelihood that secured lending through SPVs is recharacterized, and thus collateral is subject to the automatic stay, seven U.S. states introduced anti-recharacterization (AR) laws between 1997 and 2005. AR laws strengthen the rights of creditors by limiting the circumstances under which recharacterization can occur, thus having a significant impact on firms' finances. These laws preserve the bankruptcy-remote nature of SPVs, improving firms' access to secured lending by giving firms the option to increase the value of pledged collateral to secured lenders through an SPV.

[5] A Special Purpose Vehicle (SPV) refers to a legal and financial entity that is established with a specific and limited purpose. SPVs are often utilized to isolate certain financial assets or liabilities from a parent company's balance sheet. They are structured in a way that they are distinct from the parent company and possess their own legal identity.

However, as noted in the previous literature (Li et al. 2016), the federal court in its 2003 ruling for *Reaves Brokerage Company, Inc v. Sunbelt Fruit & Vegetable Company, Inc.* (336 F.3d 410, 413 (5th Cir. 2003)) overruled the anti-recharacterization law statute in Texas and re-characterized the transfer of assets from the debtor to its SPV as a loan. While this ruling does not nullify the existing and future anti-recharacterization laws at the state level, it does introduce uncertainty to the effectiveness of those state AR laws. We will conduct robustness checks with the exclusion of the states adopting the law in or after 2003, namely, South Dakota which passed the law in 2003, Virginia in 2004, and New York in 2005.

2.2. Toxic Emissions Reporting

In the aftermath of the Union Carbide toxic emission incident in 1984, the U.S. Congress passed the Emergency Planning and Community Right-to-Know Act (EPCRA) which was signed into law by President Ronald Reagan on October 17, 1986. Under this act (Section 313, 42 U.S.C. §11023), the Environmental Protection Agency (EPA) is required to establish the Toxics Release Inventory (TRI), an inventory of routine toxic chemical emissions from certain facilities. The program provides the public with valuable information about the types and quantities of toxic chemicals being released into the environment by industrial facilities since 1987. It aims to encourage companies to reduce their toxic emissions, improve waste management practices, and facilitate public participation in environmental decision-making.

Under the TRI program, companies in specific industry sectors must annually report their releases and waste management activities for 774 listed toxic chemicals in 33 chemical categories. These chemicals include substances that are known or suspected to cause adverse effects on human health or the environment. The TRI data includes information about the name and location of plants and their parent companies, and the quantity of chemicals released at the plant level. Examples of reported chemicals include lead, mercury, benzene, and various pollutants.

Going beyond reporting toxic emissions, the Federal Pollution Prevention Act of 1990 further established pollution prevention as the public policy of the United States. The Act declares that pollution should be prevented or reduced at the source wherever feasible, while pollution that cannot be prevented should be recycled in an environmentally safe manner.[6] Thus, data on Pollution Prevention (P2) measures and investments are further collected by the EPA.

2.3. Data Sources and Summary Statistics

For this study, we rely on three main sources of information: the states that adopted AR laws, the toxic emission data on the plant level, and financial and accounting data at the firm level. The information on the AR law adoption is obtained from Favara et. al (2021) and listed in Table A in the Appendix. Because some firms may change their incorporation state over time, we code the AR law adoption based on a firm's historical state of incorporation for correct inference.[7]

The plant-level toxic emissions data are obtained from the EPA's Toxics Release Inventory (TRI) Program[8], which reports the quantity (in units of pounds) of chemicals emitted into air, ground, and waterways, respectively. The data related to pollution prevention measures are collected from the TRI's Pollution Prevention (P2) database. Figure IA.1 in the online Internet Appendix presents the geographic distribution of plants under the TRI reporting program in the U.S. (Panel A) and toxic emissions of plants (Panel B) by state in 2021.

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[6] For more details of the EPA TRI program, please see https://www.epa.gov/toxics-release-inventory-tri-program/pollution-prevention-p2-and-tri.

[7] The data for historical incorporation states are obtained from the website of Professor Bill McDonald. About 5% of the firms in our sample changed their incorporation state during the sample period. Since these changes are likely endogenous, in an unreported exercise, we repeat the analysis excluding them and our main results continue to hold.

[8] https://www.epa.gov/toxics-release-inventory-tri-program/tri-data-and-tools.

The remaining data are obtained from various sources, including accounting data from Compustat; institutional ownership data from Thomson Reuters 13F Holdings; analyst forecast data from I/B/E/S; shareholder activism data from Audit Analytics; SPV usage data from WRDS SEC Analytics Suite[9], and patent data from KPSS GitHub.

After merging the TRI data with the Compustat database, we exclude observations with either missing information for firms' historical incorporation states or other crucial variables of interest. We further exclude financial and utility firms. All continuous variables are winsorized at the 1st and 99th percentiles to reduce outliers' influence. Our final sample contains 70,869 plant-year observations and 10,929 firm-year observations between 1993 and 2015.[10] The treatment group includes 637 firms and 4,732 plants. The control group has 326 firms and 2250 plants. Among the 963 firms in our sample, 73.3% (706/963) firms are headquartered outside their incorporation states. Among the 6,982 plants, 94% (6558/6982) are located outside their parent firm's incorporation state. The summary statistics for plant-level and firm-level variables are reported in Table 1. Notably, the sample mean of annual total toxic emissions at the plant-level is 49,767 pounds, which is comparable with other studies such as Jiang and Kong (2023).

[Please Insert Table 1 Here.]

Our study involves several additional cross-sectional tests and robustness checks. The data required will be explained in the context of those tests.

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[9] We follow Feng et al. (2009) and Gao et al. (2022) to identify whether firms have SPV-like subsidiaries. Using SEC Filings Queries powered by Wharton Research Data Services (WRDS) SEC Analytics Suite, we proxy for a firm's usage of SPVs by searching for the keywords of "limited partnerships", "limited liability partnerships", "limited liability companies", and "trusts" among the firm's subsidiaries and affiliates that are disclosed in Exhibit 21 of the SEC Form 10-K. An indicator *SPV(0/1)* is constructed to be equal to one if a firm discloses at least one SPV-like entity in Exhibit 21 in a year, and zero otherwise.

[10] The sample starts in 1993, which is the earliest year we have reliable historical data on firms' state of incorporation, sourced from Professor Bill McDonald's website. The last state adopting the AR law is New York in 2007. The sample period extends until 2015, enabling us to capture the long-term and enduring impacts of AR laws and properly assess their impact on financing constraints and environmental investments.

3. Empirical Methodology and Regression Results

3.1. Empirical Methodology and the Baseline Regression Results

We exploit the staggered state adoption of AR laws as a source of exogenous variation in the protection of creditors' rights and then use the Difference-in-Differences (DiD) method to conduct our analysis. We first run the following baseline regression:

$$Ln(1 + Total\ Emissions)_{i,j,l,k,s,t} = \alpha + \beta_t * AR\ Law_{k,t} + \delta F_{j,t} + \theta_i + \mu_{l,t} + \pi_{s,t} + \epsilon_{i,j,l,k,s,t} \quad (1)$$

where the subscripts i, j, l, k, s, and t refer to a plant, the parent firm of a plant, the 4-digit NAICS industry of a plant, the incorporation state of the parent firm, the location state of a plant, and the year, respectively. $AR\ Law_{k,t}$ is an indicator variable that equals one for the t-th year relative to the AR law adoption for plants of firms incorporated in state k. $F_{j,t}$ is a vector of firm-level control variables; θ_i is the plant fixed effect; $\mu_{l,t}$ is the plant industry-by-year fixed effect; $\pi_{s,t}$ is the plant state of location-by-year fixed effects; and $\epsilon_{i,j,l,k,s,t}$ is the error term. We cluster heteroskedasticity-robust standard errors at the incorporation state level. Thus, the AR law effect is identified by comparing changes in emission rates around the adoption of AR law for treated plants with those for control plants that are in the same industries and located in the same states.

We conduct the analysis at the plant level. The main reason we do not aggregate the plant-level pollutant emissions data into the parent firm level is that the aggregated measure can be biased as the surveyed plants in the EPA program might represent an incomplete list of the plants operated for some firms. Moreover, companies often operate in many different locations and industries, thus, using the plant-level data allows us to assess the impact of AR laws more accurately by taking into account some unobservable variables based on the plant's location and industry classification. After all, pollution varies among geographical locations and industry characteristics.

Table 2 reports the estimates from two variants of Equation (1): in the odd-numbered columns, the coefficients are estimated without any control variables, while in the even-numbered columns, we add parent-firm level control variables, such as parent firm size (measured by the natural logarithm of total assets) and other financial characteristics that are likely correlated with firm operations (thus the amount of toxic emissions), for example, the leverage ratio, plant, property, equipment (PPE) over total assets, capital expenditure over total assets, ROA, and Tobin's Q. Furthermore, as firms' pollution are subjected to both internal and external corporate control measures, we add the variables representing analyst coverage, institutional ownership, and shareholder activism[11]. *Institutional Ownership* is the percentage of outstanding shares owned by institutional investors in a year, based on Thomson/Refinitiv Form-13F filings. *Analyst Coverage* is the natural logarithm of one plus the number of analyst earnings forecasts in a year, sourced from the I/B/E/S database. *Shareholder Activism* is an indicator variable that equals one if a firm experiences at least one shareholder activism event in a year, as identified by Schedule 13D filing required by the SEC.

[Please Insert Table 2 Here]

We find that the adoption of AR laws significantly reduces the total toxic emissions. Column 2 of Table 2 reveals that the reduction in the total toxic emissions represents a 20.8% drop in the total toxic emissions per plant-year for the treated plants. Category-wise, AR laws' impact on both air emissions and water emissions is statistically significant, while the impact on ground emissions, although negative, is not statistically significant.

3.2. Dynamic Effects of AR Laws

[11] Jing et al. (2022) find a link between analyst coverage and corporate environment performance. Dyck et al. (2019) find an association between institutional ownership and corporate ESG performance. Chu and Zhao (2019) find the link between shareholder activism and firms' toxic emissions.

Identification in the DiD approach builds upon the parallel trend assumption. In our setting, this requires that emission rates in treated and control plants follow a parallel time trend in the absence of AR laws. To check the validity of this assumption, we estimate the timing of the AR law effect by replacing the single *ARLaw* indicator in Equation (1) with ten indicator variables to track years relative to the year the AR law is adopted.

$$Ln(1 + Total\ Emissions)_{i,j,l,k,s,t} = \alpha + \beta_t * \sum_{t \in (-5-,-2) \cup (0,+5+)} AR\ Law_{k,t} + \delta F_{j,t} + \theta_i + \mu_{l,t} + \pi_{s,t} + \epsilon_{i,j,l,k,s,t}$$

where $ARLaw_k$ is an indicator that equals one for the *k*th year relative to the year AR law is adopted and zero otherwise.[12] For example, $ARLaw_{-2}$ equals one for the year that is two years before the adoption of the AR law; $ARLaw_{+5+}$ equals one for the years that are five years and beyond after the adoption of the AR law. We then estimate the new regression equation using the full sample. Consistent with the parallel trends, the estimated coefficients on the years before the adoption of AR laws are statistically insignificant, as shown in Table 3. The difference in emissions rates between treatment and control plants becomes positive after the adoption of AR laws and statistically significant for year 3 and beyond. The delayed treatment effect suggests that it takes time for the effect of AR laws to fully impact toxic emissions rates.

[Please Insert Table 3 Here]

We also check for the presence of reverse causality in the AR law setting and estimate a Weibull hazard model at the parent firm incorporation state-year level. Table IA.1 of the online Internet Appendix shows that average emissions rates at the incorporation state level do not predict the timing of AR law adoption by the state, after controlling for some state-level economic and political factors.

[12] $ARLaw_{-1}$ is excluded so that all estimates are relative to the base year. The graphical illustration of the trend is shown in Figure IA1 in the online Internet Appendix.

3.3. *SPV Usage, Debt Issuance, and Debt Market Constraint*

So far, we have argued that conceptually, firms' access to debt markets improves after the passage of AR laws because it becomes easier to pledge assets as collateral through Special Purpose Vehicles (SPVs). Favara et. al (2021) show that firms incorporated in states with AR laws should be more likely to use SPVs. They also argue that firms that do not use SPVs should still benefit from the passage of the laws, as AR laws increase the likelihood that firms may pledge collateral through SPVs in the future. In our sample, we confirm their findings: the adoption of AR laws promotes the use of SPVs in firms, as shown in Table IA.2 in the online Internet Appendix. On average, SPV usage increases by 3% at the firm level after the adoption of AR laws. This represents an increase of 15.6% in the SPV usage compared with the sample mean of 19.2% at the 5% level of significance.

Although all firms should be affected by the enactment of AR laws, we expect that the impact of AR laws on firms' toxic emissions is different based on the change in their SPV usage. Let ΔSPV denote the change in the average SPV usage from five years before to five years after the adoption of the law. A dummy variable, *High ΔSPV*, is equal to one if such a change in SPV usage is above the sample median and zero otherwise. Table 4 shows the impact of AR laws on firms' emissions is more pronounced for those firms that have increased their SPV usage.

Another consequence of AR laws' enactment is that firms may be more likely to use debt, particularly, long-term debt. Generally speaking, firms with long-term debt tend to use assets as collateral more frequently than firms with short-term debt in their financing (Tut 2021). *Long-term Debt Issuance* is the change in the average long-term debt issuance from five years before to five years after the adoption of the law. We find that the impact of AR laws on firms' toxic emissions is more pronounced for firms that increased in debt financing. The effect is stronger for those firms with an increase in long-term debt issuance[13].

A direct result of the enactment of AR laws is to improve access to the debt market. Following Hoberg and Maksimovic (2014), we use the variable *Debt Market Constraint* as the debt-focused financial constraint measure by counting the instances in which a firm is at risk of delaying investments due to debt constraints. We find evidence that the AR law effect is stronger for these treated firms subject to more stringent debt market constraints in the two years prior to the enactment of the law.

In sum, the results in Table 4 are consistent with the conjecture that AR laws improve access to the debt market and ultimately lead to firms' improved environmental performances.

[Please Insert Table 4 Here.]

4. AR Laws and Environmental Investments

In this section, we investigate the channels of influence and offer evidence that AR laws affect the treated firms' abatement investments, improving their compliance with the EPA regulations, and increasing investments in green technology, thus providing the missing links to how AR laws affect corporate environmental performances.

4.1. AR laws, Production, and Emission Efficiency

As stated in the introduction section, there is a concern that if the adoption of AR laws facilitates firms' debt financing, it could potentially lead to a larger scale of production, which may be associated with an increased level of toxic emissions, *ceteris paribus*. To examine the validity of this claim, we construct a variable, *Production Ratio*, which is the ratio of the current production

[13] In unreported results, we also find that the effects of AR laws on toxic emssions are not significantly different between firms with high short-term debt issuance and low short-term debt issuance, indicating that short-term debt financing does not play an important role in reducing pollution. This result is not surprising, since short term debt such as commercial papers are usually unsecured and thus not affected by the adoptions of AR laws.

volume over the previous volume at a plant in a year. As seen in Table 5, we find that there are no statistically significant changes to firms' production growth after AR laws are adopted.

To check the AR laws' impact on the plant-level emission efficiency, we construct a variable, *Ln(1+Emissions/Production),* the natural logarithm of one plus the total emissions over the total production volume at a plant in a year from EPA TRI data. We find that this ratio for the treated plants drops significantly after the enactment of AR laws, which suggests that the treated plants become more environmentally efficient, as the pollution level as measured against the production volume, declines. The subsequent three subsections attempt to explain why this could happen.

[Please Insert Table 5 Here.]

4.2. AR laws and Abatement Investment

Under the Pollution Prevention Act of 1990 (PPA), the Toxics Release Inventory (TRI) Program collects information to track industry progress in reducing waste generation and moving towards safer waste management alternatives. The EPA TRI P2 database includes information regarding *abatement* investments, which refers to the reduction, elimination, or control of pollution or environmental hazards to protect human health and the environment. As a general measure, *Abatement(0/1)* is an indicator variable that equals one if a plant has at least one abatement investment to mitigate toxic emissions in a year. A more operations focused measure, *Process/Operating Abatement(0/1),* is an indicator variable that equals one if a plant has at least one process modification-related or operating practice-related abatement investment to mitigate toxicity in a year. Table 6 shows that the passage of AR laws motivates the treated firms to increase their abatement investments to reduce toxic emissions. In Column 2 of Table 6, the coefficient of *Abatement(0/1)* is 0.032, representing an increase of 17.1% over the sample mean of 0.129.

[Please Insert Table 6 Here.]

4.3. Compliance with Laws and Regulatory Standards

Compliance with environmental laws and regulations is not a matter of choice - it is a requirement. The EPA has a range of options available to promote and support compliance, deter and penalize offenders, and remediate damage caused to the environment. The violation of these laws and regulations leads to fines and often subsequent legal actions.

We define two variables related to compliance with the EPA requirements. An indicator variable, *Compliance (0/1),* equals one if a plant invests financially in compliance actions with regulatory standards. Another variable, *Compliance Expenses,* is the amount of environmental regulatory compliance expenses at a plant in a year. This data item is collected from the EPA's Federal Enforcement and Compliance (FE&C) database from the Integrated Compliance Information System (ICIS). We find that the treated firms spend more on regulatory compliance after the passage of AR laws, as shown in Table 7.

[Please Insert Table 7 Here.]

4.4. Green Patenting

"Green patenting" refers to the process of filing and obtaining patents for inventions or technologies that have a positive impact on the environment or contribute to sustainability efforts. These patents are granted for innovations that address environmental challenges, promote clean technologies, or contribute to the reduction of greenhouse gas emissions. If the adoption of AR laws can promote corporate environmental investments, it should also manifest itself in increased green patenting activities at the firm level.

We collect patent filing data from Kogan et al. (2017) (KPSS) database[14] for the period 1993-2015. To identify whether a patent can be considered a "green" one, we follow the procedure

[14] KPSS database is available from Professor Noah Stoffman's website.

described in Gao and Li (2021): from the Organization for Economic Co-operation and Development (OECD)'s Green Growth Indicators Framework, we can identify whether the patents can be termed as "green" based on the Cooperative Patent Classification (CPC) system.

Furthermore, as stated in Manso (2011), patents in general can be classified into two categories: exploitative vs. explorative. Conceptually, *exploitative patents* are referred to as those with incremental improvements or optimizations of existing technologies. In contrast, *explorative patents* cover groundbreaking and innovative ideas that have the potential to shape new industries.

We follow the literature and categorize patents into exploratory or exploitative patents (Almeida et al. 2019; Custódio, Ferreira, and Matos 2019). A patent is considered exploitative if at least 80% of its citations are based on the existing knowledge of the firm, whereas a patent is exploratory if at least 80% of its citations are based on new knowledge. Existing knowledge includes all the patents that the firm has invented and all the patents that are cited by the firm's patents filed over the past five years. The number of exploitative/exploratory new patents aggregated at the firm-year level is indicative of whether a firm's innovations likely extend the existing knowledge or focus on exploring new green technologies.

We find evidence that firms invest more in green technology, leading to a significant increase in both explorative and exploitative green patents, as shown in Table 8.

[Please Insert Table 8 Here.]

5. Potential Explanations

5.1. Managing Environmental Regulatory and Legal Risks

As an effective enforcement and compliance program is necessary to protect the environment, the EPA handed out the assessment of over $1.06 billion in penalties in 2021 and in some cases lengthy years of incarceration for defendants sentenced in criminal enforcement investigations.[15] Corporate environmental lawsuits are detrimental to shareholder wealth as stocks of defendant firms experience significant negative abnormal returns around the lawsuit filing dates (Wei et al. 2021). As Starks (2023) states corporate environment protection measures are effective tools for managing legal and regulatory risks, it would be important to assess whether AR laws have a significant impact in managing environmental legal risk, including both regulatory penalties and lawsuits.

The data on regulatory penalties is collected from the EPA TRI P2 database. More specifically, we construct a variable, *Environmental Penalty,* based on the amount of environmental penalty for a firm in a given year from the EPA's Federal Enforcement and Compliance (FE&C) data from the Integrated Compliance Information System (ICIS).

We study the likelihood of being sued in an environmental lawsuit, initiated by shareholders, government agencies such as the EPA, and environmental NGOs. The likelihood is estimated with all firms in the Compustat and Audit Corporate Legal databases based on a modification of Model 3 of Kim and Skinner (2012). First, we define the dependent variable as being "*Sued*" if a firm has at least one environmental lawsuit in a year. Secondly, we regress "*Sued*" on the FPS (Francis, Philbrick, and Schipper, 1994) industry indicator, and the lagged values of book assets, sales growth, market-adjusted return, return skewness, return standard deviation, and asset turnover. Finally, we obtain the fitted value as the probability of being sued by a firm, which defines the variable of *Environmental Suit Risk*. The High/Low classification is based on the sample median of the two-year average before the adoption of the AR law.

[15] See https://www.epa.gov/enforcement/enforcement-annual-results-fiscal-year-2021

As reported in Table 9, we find that the impact of AR laws is more significant for the treated firms with higher environmental penalties and with environmental lawsuit risk before the adoption of AR laws. Consequently, the penalty imposed by the FDA for environmental violations has been reduced and environmental-related lawsuits have been reduced as well. These results suggest that the passage of AR laws has significantly reduced corporate environmental regulatory and legal risks.

[Please Insert Table 9 Here.]

5.2. Shareholders' Preference on Environmental Sustainability

Even though notable environmental disasters, such as Union Carbide Bhopal chemical emission in 1984, the Exxon Valdez oil spill in 1989, and the Deepwater Horizon rig explosion and associated oil spill in 2010, damaged shareholder value swiftly and significantly, environmental performances mainly affect the long-term, sustainable value of a firm. These disastrous events usually are the manifestation of managers' pursuing short-term profits at the expense of ongoing investments in environmental protection. Long-term oriented shareholders are likely to pay closer attention to firms' emissions than short-term shareholders. While long-term shareholders want managers to balance the benefits and costs of environmental investment to maximize long-term firm value, short-term shareholders may prioritize near-term firm performance, often at the expense of environmentally related investments.

We examine ownership by ESG-oriented shareholders who value environmental protection more highly. With improved access to debt financing and the resultant more financial resources after the passage of AR laws, we expect that this will allow firms some leeway to spend on environmental protection measures and the role of ESG-oriented institutional shareholders can be amplified. To test this hypothesis, we calculate the percentage of shares outstanding owned by environmentally sustainable institutional investors. Following Cao et al. (2022) and Thomas et al. (2022), we identify institutions from Form 13-F of Thomson/Refinitiv based on the environmental footprint of their portfolio firms. First, we calculate the KLD environment net score for each portfolio firm in a year. Second, we measure the environmental orientation of an institutional investor by taking the average of the environment net score of all stocks in its portfolio at the end of each quarter. Third, we sort all institutions into three groups based on the average environment net score of their holding portfolios each quarter and define those in the top tercile as environmentally sustainable institutions. Finally, the variable Sustainable IO is defined as the percentage of shares outstanding owned by environmentally sustainable institutions.

The result in Column (1) of Table 10 shows that the impact of AR laws is only significant when there is a high presence of sustainability-oriented institutional investors, underscoring the importance of institutional investors' preference.

Large long-term oriented shareholders who possess substantial voting power and can threaten to exit may take a more intervening approach in their firms' environmental performance. They will be more cost-effective if they provide monitoring services even if all shareholders share the benefits (Shleifer and Vishny 1986). We thus expect that the impact of AR laws is greater for firms with higher ownership by long-term shareholders. We measure ownership of long-term shareholders by the percentage of outstanding shares owned by *dedicated investors,* defined as institutions that hold concentrated ownership in their portfolio firms with low portfolio turnover (Bushee, 2001). We then separate treated firms into high/low groups using the sample median ownership by these investors in the two years preceding the passage of AR laws and estimate separate AR law effects for the two groups. In support of our prediction, Column (2) of Table 10 shows that the AR law effect is larger and more pronounced for treated firms with high ownership by dedicated institutional investors.

Investors and academics have often referred to BlackRock, Vanguard, and State Street Global Advisors as the Big Three asset managers. The "Big Three" institutions are known for their commitment to tackling ESG issues, see Azar et al. (2021) for their impact on environmental issues around the world. In the context of the adoption of AR laws on toxic emissions, we expect that when firms have more financial resources, they may be able to cater to the "Big Three" preferences more. Thus, a variable *Big-three IO* is constructed based on the percentage of shares outstanding owned by Blackrock, Vanguard, and State Street. High/Low is defined by the sample median of the two-year average before the adoption of the law. We find that the AR law effect is only significant for these treated firms with the presence of the Big Three institutions above the sample median prior to the adoption of AR laws.

[Please Insert Table 10 Here.]

6. Robustness Checks

We conduct three additional robustness checks. First, we provide evidence at the plant-chemical level. Instead of using the aggregate toxic emissions at the plant level, we test the relationship between AR laws and toxic emissions for chemicals controlled by the EPA. Our main results are qualitatively the same at the plant-chemical level. The results are included in Table IA.3 in the online Internet Appendix.

Another concern is about potential biases of applying the traditional two-way fixed effects DiD method to the staggered DiD setting (Borusyak, Jaravel, and Spiess, 2021; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). To check the robustness of our main results to the removal of potential biases in the two-way fixed effects DiD estimates, we use three methods: a two-state least squares model (Freyaldenhoven et al., 2019); an imputation-based DiD method (Borusyak et al. 2021), which uses all pre-treatment observations of establishments in the not-yet-treated group to impute the potential outcome for the treatment group; and the doubly robust inverse probability-weighted DiD method (Callaway and Sant'Anna 2021), which computes an inverse probability weighted estimating function with all establishments in the not-yet-treated group. As reported in Table IA4 in the online Internet Appendix, the results are consistent with our main findings that AR laws have a significant impact on firms' toxic emissions at the plant level.

The third robustness test involves conducting a DiD regression analysis with the exclusion of states that enacted AR laws in and after 2003, specifically South Dakota, Virginia, and Nevada. As noted in Section 2.1, the federal court ruled in favor of recharacterization in the case of *Reaves Brokerage Company v. Sunbelt Fruit & Vegetable Company*. While the federal court's ruling may not negate state-level statutes, it introduces uncertainty regarding the effectiveness of anti-recharacterization laws at the state level. Consequently, we opt to remove the data from South Dakota, Virginia, and Nevada. After re-running the regression, we observe similar results, as detailed in Table IA5 in the online Internet Appendix.

7. Conclusion

This study investigates the intricate relationship between corporate environmental performance and financial constraints, focusing on the consequences of improved debt access facilitated by the staggered adoption of anti-recharacterization (AR) laws across various U.S. states. These laws strengthen creditors' rights and offer a unique context of improved access to the debt market to explore their implications for firms' environmental performance. Our analysis shows a substantial reduction in toxic emissions for treated firms that benefit from enhanced access to debt financing as a result of the adoption of AR laws. This effect is more pronounced in firms characterized by a higher reliance on Special Purpose Vehicles (SPVs), more use of long-term debt financing, greater constraints in the debt market access, and a stronger commitment to environmental sustainability and long-term objectives as characterized by a higher presence of dedicated and ESG-oriented institutional investors.

Further investigation into the channels through which firms reduce toxic emissions reveals that improved debt access stimulates investments in abatement technologies and green initiatives, while simultaneously promoting better adherence to environmental regulations.

Collectively, our findings suggest an important role of enhanced debt financing in fostering corporate environmental investments and regulatory compliance. These insights hold significant implications for policymakers, investors, and other stakeholders seeking to incentivize corporate environmental performance.

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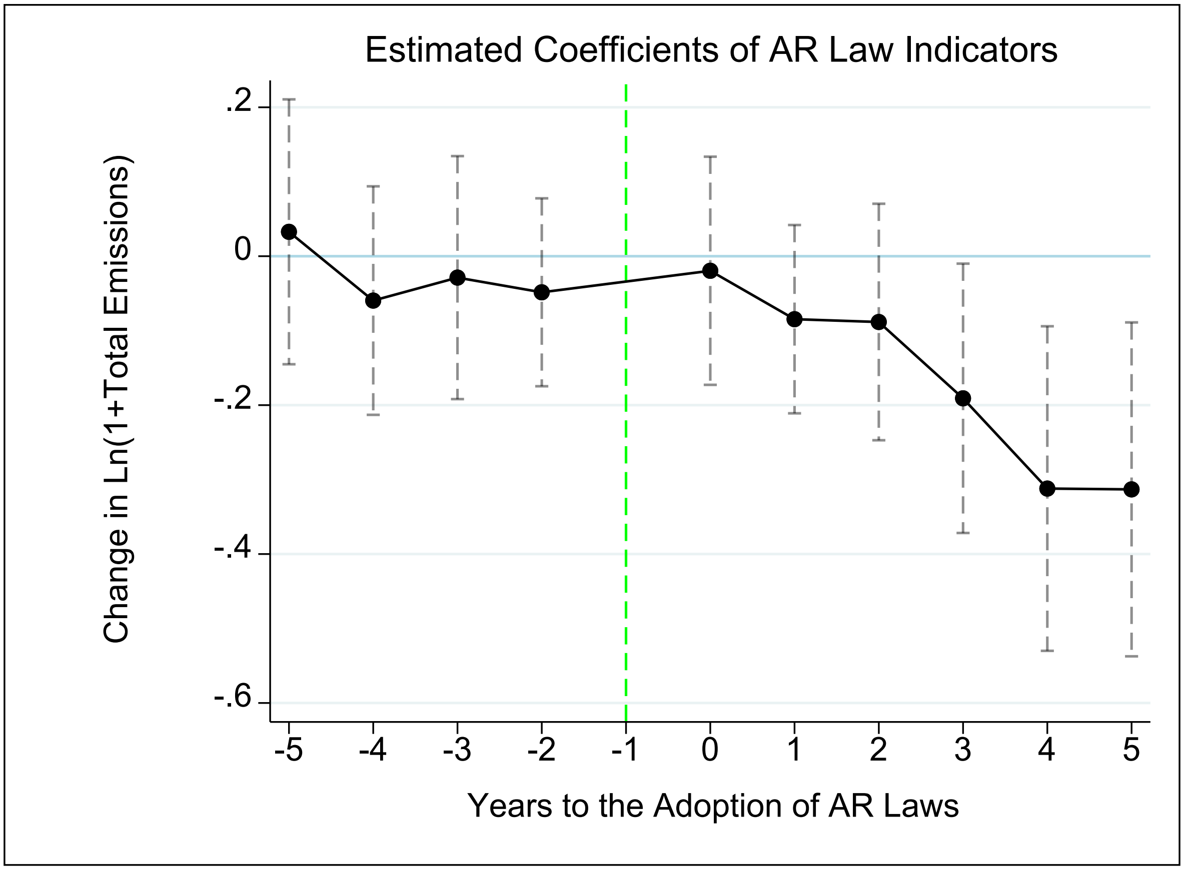
Figure 1. Dynamic Effects of Anti-Recharacterization Laws



This figure plots the dynamic effects of AR laws on plant-level toxic emissions around the adoption of the laws. The coefficient estimates on *AR Law*$_{k,t,}$ and their 95% confidence intervals from the following model are plotted in the figure.

$$Ln(1 + Total\ Emissions)_{i,j,l,k,s,t} = \alpha + \beta_t * \sum_{t \in (-5-,-2) \cup (0,+5+)} AR\ Law_{k,t} + \delta F_{j,t} + \theta_i + \mu_{l,t} + \pi_{s,t} + \epsilon_{i,j,l,k,s,t}$$

where subscripts *i, j, l, k, s,* and *t* refer to a plant, the parent firm of a plant, the 4-digit NAICS industry of a plant, the incorporation state of the parent firm, the location state of a plant, and the year, respectively. *AR Law*$_{k,t}$ is an indicator variable that equals one for the t-th year relative to the AR law adoption for plants of firms incorporated in state k. *AR Law*$_{-1}$ is excluded so that all estimates are relative to the base year. *Ln(1+Total Emissions)*$_{i,j,l,k,s,t}$ is the natural logarithm of one plus the pounds of total air, water, and ground emissions at a plant in a year; $F_{j,t}$ is a vector of firm-level control variables; θ_i is plant fixed effects; $\mu_{l,t}$ is plant industry by year fixed effects; $\pi_{s,t}$ is plant state of location by year fixed effects; and $\epsilon_{i,j,l,k,s,t}$ is the error term. Standard errors are clustered at the incorporation state level.

Table 1. Summary Statistics

Plant-level Variables				
	N	Mean	Median	S.D.
Ln(1+Total Emissions)	70,869	10.815	6.686	12.099
Ln(1+Air Emissions)	70,869	10.733	6.553	12.029
Ln(1+Water Emissions)	70,869	6.285	0.000	8.305
Ln(1+Ground Emissions)	70,869	8.131	0.000	10.176
Production Ratio	63,718	1.306	1.000	4.363
Ln(1+Emissions/Production)	63,718	9.962	6.051	11.502
Abatement(0/1)	70,869	0.187	0.000	0.390
Process/Operating Abatement(0/1)	70,869	0.129	0.000	0.335
Compliance(0/1)	70,869	0.022	0.000	0.147
Ln(1+Compliance Expenses)	70,869	10.616	0.000	14.825
Firm-level Variables				
	N	Mean	Median	S.D.
Firm Size	10,929	7.139	7.052	1.788
Cash	10,929	0.094	0.057	0.101
Leverage	10,929	0.256	0.240	0.171
ROA	10,929	0.153	0.146	0.089
Tobin's Q	10,929	1.700	1.453	0.840
Dividend	10,929	0.015	0.009	0.021
Capital Expenditures	10,929	0.055	0.043	0.045
Tangibility	10,929	0.293	0.264	0.161
R&D	10,929	0.024	0.012	0.033
Institutional Ownership	10,929	0.540	0.608	0.318
Analyst Coverage	10,929	1.409	1.576	0.903
Shareholder Activism	10,929	0.054	0.000	0.227
SPV(0/1)	10,929	0.192	0.000	0.394
Ln(1+Green Patents)	6,080	1.991	0.000	3.321
Ln(1+Explorative Green Patents)	6,080	0.863	0.000	1.714
Ln(1+Exploitative Green Patents)	6,080	1.217	0.000	2.502

Notes. This table reports the summary statistics of the variables in our study for the period 1993–2015. All continuous variables are winsorized at 1% and 99%. All variables are defined in Table B in the Appendix.

Table 2. AR Law and Corporate Emissions

Dependent Variable	*Ln(1+Total Emissions)*		*Ln(1+Air Emissions)*		*Ln(1+Water Emissions)*		*Ln(1+Ground Emissions)*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AR Law	-0.233***	-0.233***	-0.233***	-0.238***	-0.061**	-0.055**	-0.017	-0.010
	(0.081)	(0.082)	(0.080)	(0.082)	(0.024)	(0.024)	(0.036)	(0.034)
Size		0.016		0.016		-0.028		-0.001
		(0.061)		(0.054)		(0.018)		(0.026)
Cash		0.018		0.044		0.137		0.113
		(0.176)		(0.194)		(0.089)		(0.094)
Leverage		0.296**		0.291**		0.104***		0.106**
		(0.112)		(0.116)		(0.034)		(0.047)
ROA		0.165		0.105		-0.137*		-0.176
		(0.172)		(0.170)		(0.068)		(0.138)
Tobin's Q		0.037		0.045*		-0.011		0.016
		(0.022)		(0.023)		(0.008)		(0.011)
Dividend		0.545		0.613		0.766***		0.214
		(0.546)		(0.619)		(0.223)		(0.406)
Capital Expenditures		-0.461		-0.613**		0.474***		0.788***
		(0.295)		(0.271)		(0.174)		(0.188)
Tangibility		-0.342*		-0.298		-0.502***		-0.203**
		(0.191)		(0.192)		(0.103)		(0.084)
R&D		1.426		1.485		1.448***		1.008
		(0.941)		(0.975)		(0.321)		(0.735)
Institutional Ownership		0.067		0.071		0.069		-0.002
		(0.070)		(0.073)		(0.051)		(0.033)
Analyst Coverage		0.035		0.053		-0.023		-0.026**
		(0.049)		(0.046)		(0.014)		(0.011)
Shareholder Activism		0.065		0.054		0.019		0.032
		(0.044)		(0.040)		(0.034)		(0.020)
Plant FE	Y	Y	Y	Y	Y	Y	Y	Y

Industry × Year FE	Y	Y	Y	Y	Y	Y	Y	Y
State × Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.848	0.848	0.849	0.849	0.845	0.845	0.794	0.794
Observations	70,869	70,869	70,869	70,869	70,869	70,869	70,869	70,869

Notes. This table presents results from estimating the effects of the staggered adoption of Anti-Recharacterization Laws on corporate toxic emissions at the plant level. The sample consists of plants of firms from the intersection of EPA TRI data and Compustat data for the period 1993-2015. *AR Law* is an indicator variable that equals one if a firm is incorporated in a state that adopted an Anti-recharacterization Law in a year and zero otherwise. *Ln(1+Total Emissions)* is the natural logarithm of one plus the pounds of total air, water, and ground emissions at a plant in a year from EPA TRI data. Control variables are the same as those in Column (2) of Table 2. See variable definitions in Table B in the Appendix. Standard errors are clustered at the incorporation state level and are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table 3. The Dynamic Effects of AR Law

Dependent Variable	*Ln(1+Total Emissions)*	
	(1)	(2)
AR Law -5-	0.009	0.021
	(0.088)	(0.090)
AR Law -4	-0.066	-0.059
	(0.074)	(0.074)
AR Law -3	-0.037	-0.032
	(0.078)	(0.078)
AR Law -2	-0.071	-0.059
	(0.062)	(0.064)
AR Law 0	-0.007	-0.008
	(0.076)	(0.078)
AR Law +1	-0.077	-0.080
	(0.064)	(0.064)
AR Law +2	-0.082	-0.076
	(0.080)	(0.082)
AR Law +3	-0.183*	-0.181*
	(0.092)	(0.093)
AR Law +4	-0.305***	-0.300**
	(0.110)	(0.112)
AR Law +5+	-0.310***	-0.303**
	(0.113)	(0.115)
Controls	N	Y
Plant FE	Y	Y
Industry × Year FE	Y	Y
State × Year FE	Y	Y
Adjusted R^2	0.848	0.848
Observations	70,869	70,869

Notes. This table presents results from estimating the dynamic effects of the staggered adoption of Anti-Recharacterization Laws on corporate toxic emissions at the plant level. The sample consists of plants of firms from the intersection of EPA TRI data, Compustat data, and other relevant data for the period 1993-2015. *AR Law*$_k$ is an indicator equal to one for the k-th year relative to the year of AR law adoption and zero otherwise. For example, *AR Law*$_{+5+}$ equals one for the five years and beyond of AR law adoption and zero otherwise. *AR Law*$_{-1}$, which equals one for one year before the year of AR law adoption, is excluded from the regression. *Ln(1+Total Emissions)* is the natural logarithm of one plus the pounds of total air, water, and ground emissions at a plant in a year from EPA TRI data. Control variables are the same as those in Column (2) of Table 2. See variable definitions in Table B in the Appendix. Standard errors are clustered at the incorporation state level and are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table 4. SPV Usage, Debt Issuance, and Toxic Emissions

Dependent Variable	*Ln(1+Total Emissions)*		
	(1)	(2)	(3)
AR Law × High ΔSPV	-0.297***		
	(0.083)		
AR Law × Low ΔSPV	-0.165*		
	(0.096)		
AR Law × High ΔLong-term Debt Issuance		-0.273***	
		(0.090)	
AR Law × Low ΔLong-term Debt Issuance		-0.216**	
		(0.083)	
AR Law × High Debt Market Constraint			-0.259***
			(0.091)
AR Law × Low Debt Market Constraint			-0.218**
			(0.085)
F-stat (High - Low)	5.310	3.470	5.180
Prob > F	0.027	0.070	0.029
Controls	Y	Y	Y
Plant FE	Y	Y	Y
Industry × Year FE	Y	Y	Y
State × Year FE	Y	Y	Y
Adjusted R^2	0.847	0.847	0.845
Observations	67,709	67,641	65,592

Notes. This table presents results from estimating the effects of the staggered adoption of Anti-recharacterization Laws on corporate toxic emissions with ex ante debt constraint, SPV usage, and debt issuance. The sample consists of plants of firms from the intersection of EPA TRI data, Compustat data, and other relevant data for the period 1993-2015. *AR Law* is an indicator variable that equals one if a firm is incorporated in a state that adopted an Anti-Recharacterization Law in a year and zero otherwise. *Ln(1+Total Emissions)* is the natural logarithm of one plus the pounds of total air, water, and ground emissions at a plant in a year from EPA TRI data. Δ*SPV* is the change in the average SPV usage from five years before to five years after the adoption of the law. Δ*Long-term Debt Issuance* is the change in the average long-term debt issuance from five years before to five years after the adoption of the law. *Debt Market Constraint* is the debt-focused financial constraint measure by counting the instances in which a firm is at risk of delaying investments due to debt constraints. High/Low is defined by the sample median of the change of a variable before and after the law adoption for Column (1) and (2) and is defined by the sample median of the two-year average before the adoption of the law for Column (3). Control variables are the same as those in Column (2) of Table 2. See variable definitions in Table B in the Appendix. Standard errors are clustered at the incorporation state level and are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table 5. AR Law, Production, and Emission Efficiency

Dependent Variable	*Production Ratio*		*Ln(1+Emissions/Production)*	
	(1)	(2)	(3)	(4)
AR Law	-0.072	-0.106	-0.143**	-0.144**
	(0.112)	(0.106)	(0.067)	(0.067)
Controls	N	Y	N	Y
Plant FE	Y	Y	Y	Y
Industry × Year FE	Y	Y	Y	Y
State × Year FE	Y	Y	Y	Y
Adjusted R^2	0.098	0.098	0.837	0.837
Observations	63,718	63,718	63,718	63,718

Notes. This table presents results from estimating the effects of the staggered adoption of Anti-Recharacterization Laws on corporate environmental patenting at the firm level. The sample consists of firms from the intersection of EPA TRI data, Compustat data, and other relevant data for the period 1993-2015. *AR Law* is an indicator variable that equals one if a firm is incorporated in a state that adopted an Anti-recharacterization Law in a year and zero otherwise. *Production Ratio* is the ratio of the current production volume over the previous volume at a plant in a year. *Ln(1+Emissions/Production)* is the natural logarithm of one plus the total emissions over the total production volume at a plant in a year from EPA TRI data. Control variables are the same as those in Column (2) of Table 2. See variable definitions in Table B in the Appendix. Standard errors are clustered at the incorporation state level and are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table 6. AR Law and Abatement Investment

Dependent Variable	*Abatement(0/1)*		*Process/Operating Abatement(0/1)*	
	(1)	(2)	(3)	(4)
AR Law	0.034**	0.033**	0.024**	0.024**
	(0.014)	(0.013)	(0.011)	(0.011)
Controls	N	Y	N	Y
Plant FE	Y	Y	Y	Y
Industry × Year FE	Y	Y	Y	Y
State × Year FE	Y	Y	Y	Y
Adjusted R^2	0.430	0.430	0.404	0.404
Observations	70,869	70,869	70,869	70,869

Notes. This table presents results from estimating the effects of the staggered adoption of Anti-Recharacterization Laws on corporate environmental patenting at the firm level. The sample consists of firms from the intersection of EPA TRI data, EPA TRI P2 data, Compustat data, and other relevant data for the period 1993-2015. *AR Law* is an indicator variable that equals one if a firm is incorporated in a state that adopted an Anti-recharacterization Law in a year and zero otherwise. *Abatement(0/1)* is an indicator variable that equals one if a plant has at least one abatement investment to mitigate toxicity in a year. *Process/Operating Abatement(0/1)* is an indicator variable that equals one if a plant has at least one process modification-related or operating practice-related abatement investment to mitigate toxicity in a year. Control variables are the same as those in Column (2) of Table 2. See variable definitions in Table B in the Appendix. Standard errors are clustered at the incorporation state level and are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table 7. AR Law and Regulatory Compliance Spending

Dependent Variable	*Compliance(0/1)*		*Ln(1+Compliance Expenses)*	
	(1)	(2)	(3)	(4)
AR Law	0.009**	0.009**	0.084***	0.080***
	(0.003)	(0.004)	(0.023)	(0.026)
Controls	N	Y	N	Y
Plant FE	Y	Y	Y	Y
Industry × Year FE	Y	Y	Y	Y
State × Year FE	Y	Y	Y	Y
Adjusted R^2	0.087	0.088	0.093	0.094
Observations	70,869	70,869	70,869	70,869

Notes. This table presents results from estimating the effects of the staggered adoption of Anti-Recharacterization Laws on environmental regulatory compliance at the plant level. The sample consists of plants of firms from the intersection of EPA TRI data, ICIS Enforcement and Compliance data, and Compustat data for the period 1993-2015. *AR Law* is an indicator variable that equals one if a firm is incorporated in a state that adopted an Anti-Recharacterization Law in a year and zero otherwise. *Compliance(0/1)* is an indicator variable that equals one if a plant spends on regulatory compliance actions. *Ln(1+Compliance Expenses)* is the natural logarithm of one plus the amount of environmental regulatory compliance expenses for a plant in a year. Control variables are the same as those in Column (2) of Table 2. See variable definitions in Table B in the Appendix. Standard errors are clustered at the incorporation state level and are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table 8. AR Law and Green Patenting

Dependent Variable	*Ln(1+Green Patents)*		*Ln(1+Explorative Green Patents)*		*Ln(1+Exploitative Green Patents)*	
	(1)	(2)	(3)	(4)	(5)	(6)
AR Law	0.111**	0.097**	0.069***	0.063***	0.093***	0.090***
	(0.047)	(0.044)	(0.023)	(0.022)	(0.030)	(0.030)
Controls	N	Y	N	Y	N	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.814	0.819	0.719	0.725	0.741	0.744
Observations	6,080	6,080	6,080	6,080	6,080	6,080

Notes. This table presents results from estimating the effects of the staggered adoption of Anti-Recharacterization Laws on corporate environmental patenting at the firm level. The sample consists of firms from the intersection of EPA TRI data, KPSS patent data, and Compustat data for the period 1993-2015. *AR Law* is an indicator variable that equals one if a firm is incorporated in a state that adopted an Anti-Recharacterization Law in a year and zero otherwise. *Ln(1+Green Patents)* is the natural logarithm of one plus the number of environmental technology-related patents for a firm in a year. Control variables are the same as those in Column (2) of Table 2. See variable definitions in Table B in the Appendix. Standard errors are clustered at the incorporation state level and are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table 9. AR Laws and Managing Environmental Legal Risk

Dependent Variable	*Ln(1+Total Emissions)*	
	(1)	(2)
AR Law × High Environmental Penalty	-0.357***	
	(0.087)	
AR Law × Low Environmental Penalty	-0.163*	
	(0.089)	
AR Law × High Environmental Suit Risk		-0.312***
		(0.087)
AR Law × Low Environmental Suit Risk		0.042
		(0.094)
F-stat (High - Low)	39.920	126.910
Prob > F	0.000	0.000
Controls	Y	Y
Plant FE	Y	Y
Industry × Year FE	Y	Y
State × Year FE	Y	Y
Adjusted R^2	0.845	0.845
Observations	65,592	65,150

Notes. This table presents results from estimating the effects of the staggered adoption of Anti-Recharacterization Laws on corporate toxic emissions with environmental legal risk. The sample consists of plants of firms from the intersection of EPA TRI data, Compustat data, and other relevant data for the period 1993-2015. *AR Law* is an indicator variable that equals one if a firm is incorporated in a state that adopted an Anti-Recharacterization Law in a year and zero otherwise. *Ln(1+Total Emissions)* is the natural logarithm of one plus the pounds of total air, water, and ground emissions at a plant in a year from EPA TRI data. *Environmental Penalty* is the amount of environmental penalty for a firm in a year from EPA ICIS FE&C data. *Environmental Suit Risk* is the likelihood of being sued in an environmental lawsuit. High/Low is defined by the sample median of the two-year average before the adoption of the law. Control variables are the same as those in Column (2) of Table 2. See variable definitions in Table B in the Appendix. Standard errors are clustered at the incorporation state level and are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table 10. AR Laws, Shareholders' Sustainability Preference, and Toxic Emissions

Dependent Variable	*Ln(1+Total Emissions)*		
	(1)	(2)	(3)
AR Law × High Sustainable IO	-0.274***		
	(0.086)		
AR Law × Low Sustainable IO	-0.105		
	(0.089)		
AR Law × High Dedicated IO		-0.206**	
		(0.083)	
AR Law × Low Dedicated IO		-0.129	
		(0.086)	
AR Law × High Big-three IO			-0.256***
			(0.084)
AR Law × Low Big-three IO			-0.021
			(0.102)
F-stat (High - Low)	11.650	3.730	36.980
Prob > F	0.002	0.061	0.000
Controls	Y	Y	Y
Plant FE	Y	Y	Y
Industry × Year FE	Y	Y	Y
State × Year FE	Y	Y	Y
Adjusted R^2	0.848	0.848	0.848
Observations	61,562	59,708	59,482

Notes. This table presents results from estimating the effects of the staggered adoption of Anti-Recharacterization Laws on corporate toxic emissions with sustainable shareholder ownership. The sample consists of plants of firms from the intersection of EPA TRI data, Compustat data, and other relevant data for the period 1993-2015. *AR Law* is an indicator variable that equals one if a firm is incorporated in a state that adopted an Anti-Recharacterization Law in a year and zero otherwise. *Ln(1+Total Emissions)* is the natural logarithm of one plus the pounds of total air, water, and ground emissions at a plant in a year from EPA TRI data. *Sustainable IO* is the percentage of shares outstanding owned by environmentally sustainable institutional investors. *Dedicated IO* is the percentage of shares outstanding owned by dedicated institutional investors. *Big-three IO* is the percentage of shares outstanding owned by Blackrock, Vanguard, and State Street. High/Low is defined by the sample median of the two-year average before the adoption of the law. Control variables are the same as those in Column (2) of Table 2. See variable definitions in Table B in the Appendix. Standard errors are clustered at the incorporation state level and are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Appendix

Table A. The Chronology of Anti-Recharacterization Law Adoption

Adoption Year	Incorporation State
1997	LA
1997	TX
2001	AL
2002	DE
2003	SD
2004	VA
2005	NV

Note. This table presents the chronology of the adoption of the Anti-Recharacterization laws by states from 1989 to 2011. Source: Favara et al. (2021).

Table B. Variable definitions

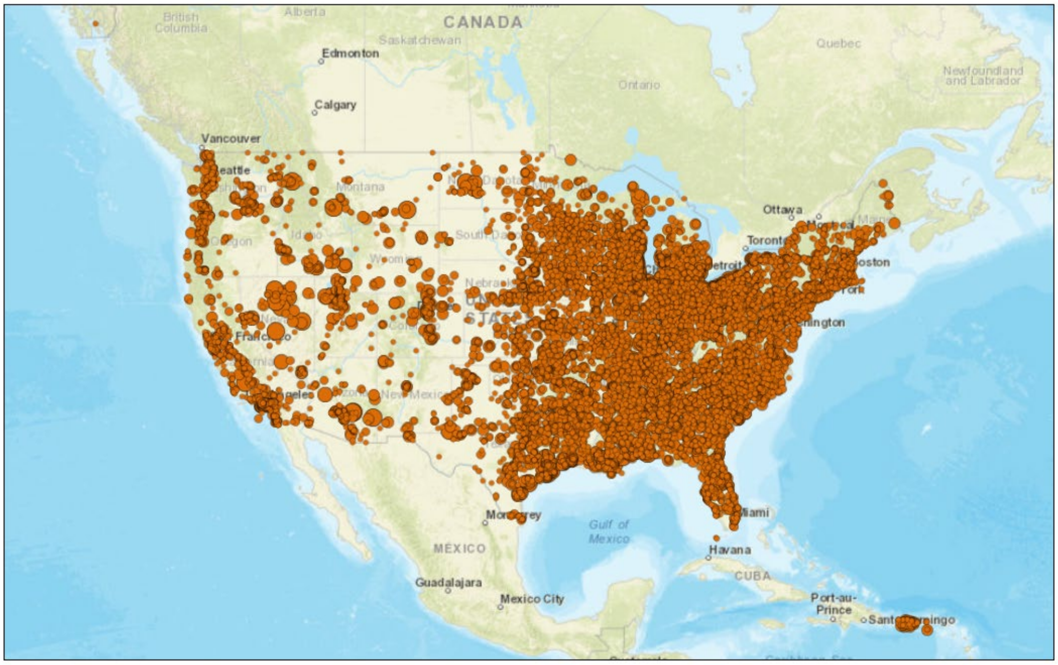
Anti-Recharacterization Laws		**Data Source**
AR Law	An indicator variable that equals one if a firm is incorporated in a state that adopted an Anti-Recharacterization Law in a year and zero otherwise.	Favara et al. (2021)
Plant Characteristics		**Data Source**
Ln(1+Total Emissions)	The natural logarithm of one plus the pounds of total air, water, and ground emissions at a plant in a year.	EPA TRI
Ln(1+Air Emissions)	The natural logarithm of one plus the pounds of total air emissions at a plant in a year.	EPA TRI
Ln(1+Water Emissions)	The natural logarithm of one plus the pounds of total water emissions at a plant in a year.	EPA TRI
Ln(1+Ground Emissions)	The natural logarithm of one plus the pounds of total ground emissions at a plant in a year.	EPA TRI
Production Ratio	The ratio of the current production volume over the previous production volume at a plant in a year.	EPA TRI
Ln(1+Emissions/Production)	The natural logarithm of one plus the total emissions over the total production volume at a plant in a year from EPA TRI data.	EPA TRI
Abatement(0/1)	An indicator variable that equals one if a plant has at least one abatement investment to mitigate toxicity in a year.	EPA TRI P2
Process/Operating Abatement(0/1)	An indicator variable that equals one if a plant has at least one process modification-related or operating practice-related abatement investment to mitigate toxicity in a year.	EPA TRI P2
Compliance(0/1)	An indicator variable that equals one if a plant invests financially in compliance actions with regulatory environmental standards.	EPA ICIS-FE&C
Ln(1+Compliance Expenses)	The natural logarithm of one plus the amount of environmental regulatory compliance expenses at a plant in a year.	EPA ICIS-FE&C
Firm characteristics		**Data Source**
Firm Size	The natural logarithm of the book value of total assets.	Compustat
Cash	The ratio of cash and short-term investment over total assets.	Compustat
Leverage	The ratio of long-term and short-term debt over total assets.	Compustat
ROA	The ratio of operating income over the lagged total assets.	Compustat
Tobin's Q	The ratio of the market value of assets (book value of total assets minus book value of equity minus deferred taxes plus market value of equity) over book value of total assets.	Compustat
Dividend	The ratio of total dividends over the lagged total assets.	Compustat
Capital Expenditures	The ratio of capital expenditures over the lagged total assets.	Compustat

Tangibility	The ratio of net property, plant, and equipment over total assets.	Compustat
R&D	The ratio of research and development spending over the lagged total assets.	Compustat
Institutional Ownership	The percentage of outstanding shares owned by institutional investors in a year	TR 13F
Analyst Coverage	The natural logarithm of one plus the number of analyst earnings forecasts in a year.	IBES
Shareholder Activism	An indicator variable that equals one if a firm experiences at least one shareholder activism in a year. Shareholder activism event is identified by 13D filing.	Audit Analytics
SPV(0/1)	An indicator variable that equals one if a firm reports SPV usage in 10-K filings in a year.	WRDS SEC Analytics Suite
Δ*SPV*	The change of the average SPV usage from five years before to five years after the adoption of the law.	WRDS SEC Analytics Suite
Δ*Long-term Debt Issuance*	The change of the average long-term debt issuance from five years before to five years after the adoption of the law.	Compustat
Debt Market Constraint	The debt-focused financial constraint measured by counting the instances that a firm is at risk of delaying investments due to debt constraints.	Hoberg and Maksimovic (2014)
Environmental Penalty	The amount of environmental penalty for a firm in a year from EPA ICIS FE&C data.	EPA ICIS-FE&C
Environment Suit Risk	The likelihood of being sued in an environmental lawsuit. The likelihood is estimated with all firms in Compustat and Audit Corporate Legal database based on Model 3 of Kim and Skinner (2012). First, we define the dependent variable as "Sued" if a firm is sued in an environmental lawsuit in a year. Second, we regress "Sued" on FPS (Francis, Philbrick, and Schipper) industry indicator, lagged book assets, lagged sales growth, lagged market-adjusted return, lagged return skewness, lagged return standard deviation, and lagged asset turnover. Third, we obtain the fitted value as the probability of being sued for a firm.	Compustat and Audit Analytics Corporate Legal
Dedicated IO	The percentage of shares outstanding owned by dedicated institutional investors (Bushee, 2001)	TR 13F and Bushee's Classification
Sustainable IO	The percentage of shares outstanding owned by environmentally sustainable institutional investors. Similar to Cao et al. (2022) and Thomas et al. (2023), we identify it from 13F institutions based on the environmental footprint of their portfolio firms. First, we calculate the KLD environment net score for each firm in a year. We measure the environmental orientation of an institutional investor by taking the average of the environment net score of all stocks in its portfolio at the end of each quarter. Third, we sort all institutions into three groups based on the average environment net score of their holding portfolios each	TR 13F and MSCI KLD

	quarter and define those in the top tercile as environmentally sustainable institutions. Fourth, Sustainable IO is the percentage of shares outstanding owned by environmentally sustainable institutions.	
Big-three IO	The percentage of shares outstanding owned by Blackrock, Vanguard, and State Street. We include MNGRNO identifiers 90457 for Vanguard and 81540 for State Street. We aggregate the holdings of its six MGRNO identifiers: 9385, 11386, 39539, 56790, 91430, and 12588 for BlackRock.	TR 13F
Ln(1+Green Patents)	The natural logarithm of one plus the number of all environment-contributing patents for a firm in a year.	KPSS
Ln(1+Explorative Green Patents)	The natural logarithm of one plus the number of explorative environment-contributing patents for a firm in a year.	KPSS
Ln(1+Exploitative Green Patents)	The natural logarithm of one plus the number of exploitative environment-contributing patents for a firm in a year.	KPSS

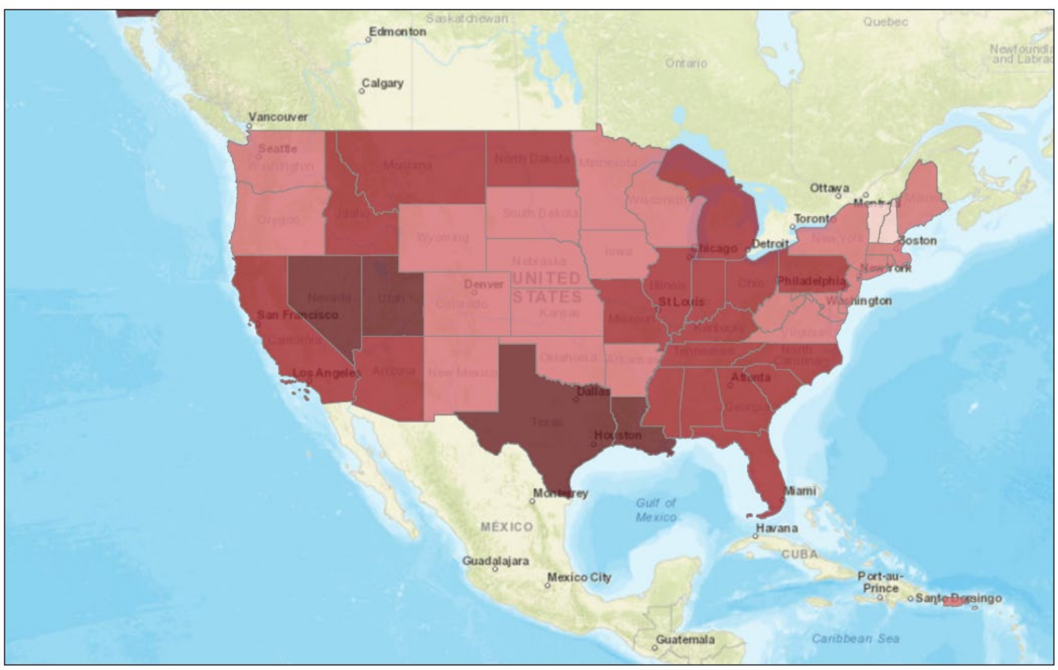
Internet Appendix

Figure IA1. Geographic Distribution of TRI-Reporting Plants in 2021



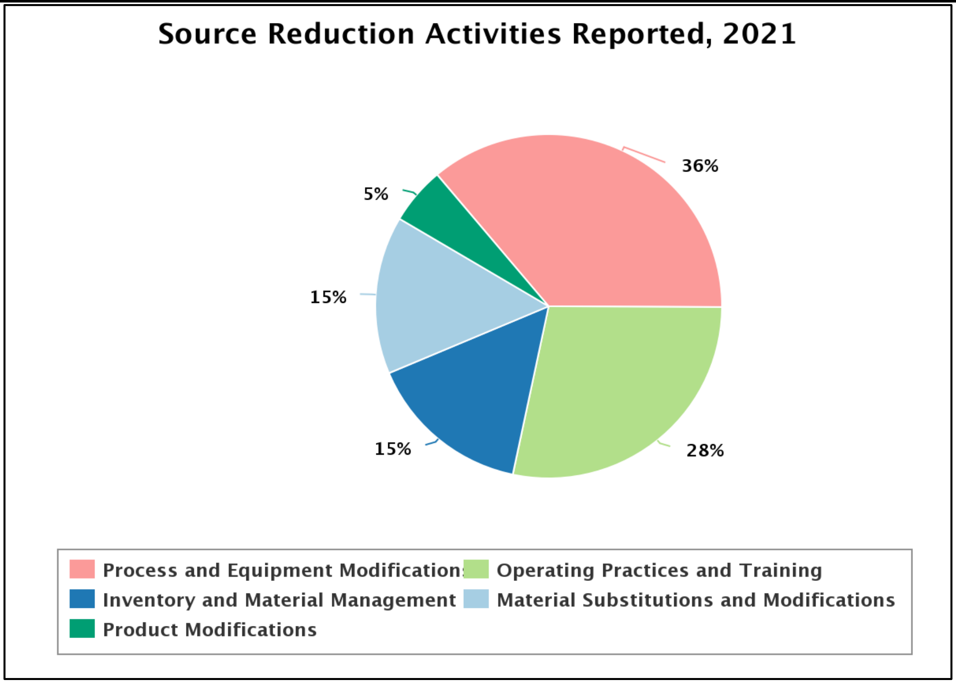
Note. This figure tabulates the geographic distribution of 21,000+ reporting plants in 2021.

Figure IA2. Total Emissions by State in 2021



Note. This figure shows the total emissions of reporting plants by state in 2021. The scale has four bins: pink (<500,000 lb.), light red (500,000 - 35 million lb.), red (35 million - 150 million lb.), and dark red (> 150 million lb.).

Figure IA3. Pollution Prevention Activity by Source in 2021



Note. This figure tabulates the distribution of pollution prevention practices by pollution sources in 2021.

Table IA1. Validity Tests: The Timing of Adopting Anti-Recharacterization Laws

Dependent Variable	*Ln(Number of Years to Adopting AR Law)*	
	(1)	(2)
State Emission	0.415	0.384
	(0.446)	(0.250)
State Real GDP		-0.008
		(0.008)
State GDP Growth		0.142**
		(0.057)
State Unemployment Rate		-0.508
		(0.481)
State HPI Change		-0.018
		(0.096)
State Stock Return		-3.988
		(2.855)
Ln(Number of Firms)		0.806
		(0.748)
State Democratic Governor		-0.014
		(0.651)
State Median Income		-0.000
		(0.000)
Observations	849	849

Notes. This table presents the results from Weibull hazard models where the "failure" event is enacting AR law by a state in a year. The dependent variable is the natural logarithm of the number of years to the adoption of AR law. The sample is at the state of incorporation level, and a state is dropped from the sample once it adopted the AR law, which occurred in 7 states before or during the 1996-2015 period. Our main explanatory variable "*State Emissions"* is the natural logarithm of one plus the pounds of total air, water, and ground emissions at the incorporation state level, computed from EPA TRI data. *State Real GDP* is the annual inflation-adjusted GDP in a state. *State GDP Growth* is the annual GDP growth rate in a state. *State Unemployment Rate* is the annual unemployment rate in a state. *State HPI Change* is the annual housing price index change in a state. *State Stock Return* is the annualized value-weighted monthly stock returns of all firms incorporated in a state. *Ln(Number of Firms)* is the logarithm of the annual number of Compustat firms in a state. *State Democratic Governor* is an indicator variable if a state has a Democratic governor in a year. *State Median Income* is the annual household median income in a state. Standard errors are clustered at the incorporation state level and are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table IA2. AR Law and SPV Usage

Dependent Variable	*SPV(0/1)*	
	(1)	(2)
AR Law	0.030**	0.030**
	(0.014)	(0.014)
Controls	N	Y
Firm FE	Y	Y
Year FE	Y	Y
Adjusted R^2	0.383	0.385
Observations	10,929	10,929

Notes. This table presents results from estimating the effects of the staggered adoption of Anti-Recharacterization Laws on SPV usage at the firm level. The sample consists of firms from the intersection of EPA TRI data, WRDS SEC Analytics data, and Compustat data for the period 1993-2015. *AR Law* is an indicator variable that equals one if a firm is incorporated in a state that adopted an Anti-recharacterization Law in a year and zero otherwise. *SPV(0/1)* is an indicator variable that equals one if a firm reports SPV usage in 10-K filings in a year from WRDS SEC Analytics Suite. Control variables are the same as those in Column (2) of Table 2. See variable definitions in Table B in the Appendix. Standard errors are clustered at the incorporation state level and are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table IA3. Main Result at the Plant-Chemical Level

Dependent Variable	*Ln(1+Total Emissions)*		*Ln(1+Air Emissions)*		*Ln(1+Water Emissions)*		*Ln(1+Ground Emissions)*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AR Law	-0.111***	-0.100***	-0.104**	-0.097**	-0.066***	-0.056***	0.001	0.011
	(0.032)	(0.031)	(0.040)	(0.041)	(0.018)	(0.016)	(0.023)	(0.021)
Controls	N	Y	N	Y	N	Y	N	Y
Plant FE	Y	Y	Y	Y	Y	Y	Y	Y
Chemical × Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Year FE	Y	Y	Y	Y	Y	Y	Y	Y
State × Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.693	0.693	0.707	0.707	0.499	0.500	0.542	0.542
Observations	213,031	213,031	213,031	213,031	213,031	213,031	213,031	213,031

Notes. This table presents results from estimating the effects of the staggered adoption of Anti-Recharacterization Laws on corporate toxic emissions at the plant-chemical level. The sample consists of plants of firms from the intersection of EPA TRI data and Compustat data for the period 1993-2015. *AR Law* is an indicator variable that equals one if a firm is incorporated in a state that adopted an Anti-recharacterization Law in a year and zero otherwise. *Ln(1+Total Emissions)* is the natural logarithm of one plus the pounds of total air, water, and ground emissions for a chemical at a plant in a year. Control variables are the same as those in Column (2) of Table 2. See variable definitions in Table B in the Appendix. Standard errors are clustered at the incorporation state level and are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table IA4. AR Law Effect under Robust Staggered DID Estimates

Panel A: Two-stage Least Squares (Freyaldenhoven et al., 2019)	
Dependent Variable	*Ln(1+Total Emissions)*
	(1)
AR Law	-0.203***
	(0.038)
Controls + FEs	Y
Panel B: Interaction Weighted Estimation (Sun and Abraham, 2020)	
Dependent Variable	*Ln(1+Total Emissions)*
	(1)
AR Law	-0.219***
	(0.086)
Controls + FEs	Y
Panel C: Doubly-Robust Estimation (Callaway and Sant'Anna, 2021)	
Dependent Variable	*Ln(1+Total Emissions)*
	(1)
AR Law	-0.278***
	(0.087)
Controls + FEs	Y

Notes. This table presents results from estimating the effects of the staggered adoption of Anti-Recharacterization Laws on corporate toxic emissions using three recently developed staggered DID estimation models. The sample consists of plants of firms from the intersection of EPA TRI data and Compustat data for the period 1993-2015. *AR Law* is an indicator variable that equals one if a firm is incorporated in a state that adopted an Anti-recharacterization Law in a year and zero otherwise. *Ln(1+Total Emissions)* is the natural logarithm of one plus the pounds of total air, water, and ground emissions at a plant in a year. Panel A estimates a two-state least squares model (Freyaldenhoven et al., 2019). Panel B estimates an interaction weighted two-way fixed effects model (Sun and Abraham, 2020). Panel C estimates a doubly robust model (Callaway and Sant'Anna 2021). Fixed effects and control variables are the same as those in Column (2) of Table 2. See variable definitions in Table B in the Appendix. Standard errors are clustered at the incorporation state level and are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table IA5. Exclude AR Law Adopting States in and after 2003

	Exclude SD(2003), VA(2004), and NV(2005)
Dependent Variable	*Ln(1+Total Emissions)*
	(1)
AR Law	-0.241***
	(0.083)
Controls	Y
Plant FE	Y
Industry × Year FE	Y
State × Year FE	Y
Adjusted R^2	0.848
Observations	69,532

Notes. This table presents results from estimating the effects of the staggered adoption of Anti-Recharacterization Laws on corporate toxic emissions excluding three AR states. The sample consists of plants of firms from the intersection of EPA TRI data and Compustat data for the period 1993-2015. *AR Law* is an indicator variable that equals one if a firm is incorporated in a state that adopted an Anti-Recharacterization Law in a year and zero otherwise. *Ln(1+Total Emissions)* is the natural logarithm of one plus the pounds of total air, water, and ground emissions at a plant in a year. Control variables are the same as those in Column (2) of Table 2. See variable definitions in Table B in the Appendix. Standard errors are clustered at the incorporation state level and are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.