Spillover Effects of Environmental Enforcement Actions through Private Lending

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Current Version: January 21, 2024

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Abstract

This study examines how exposures to Environmental Protection Agency (EPA) enforcement actions against a borrower increase lenders' incentives to monitor other borrowers' polluting activities, resulting in pollution reduction by their other borrowers. Findings reveal that, following the enforcement actions, firms borrowing from exposed lenders significantly reduce their toxic releases relative to firms borrowing from unaffected lenders. Additional findings reveal that the spillover effects are more pronounced when lenders' environmental monitoring incentives are greater and when they exert greater influence over borrowers. We also find that lenders are more likely to terminate lending relationships with borrowers that do not sufficiently reduce polluting activities, which suggests that termination is a credible threat to nonresponsive borrowers. Taken together, our study's findings suggest that the EPA can achieve its environmental goals–reaching a broader set of firms while limiting the scope of environmental enforcement actions–by leveraging the private lending markets.

Keywords: EPA Enforcement, Private Lending, Spillover Effect.

JEL codes: G21; G32; M41.

I Introduction

The Environmental Protection Agency (EPA) can bring enforcement actions against firms that violate environmental laws, which can be costly for the targeted firms. Such costs include direct financial penalties and cleanup costs, as well as indirect reputational costs with various corporate stakeholders including customers, suppliers, and capital providers (Banerjee, Chang, Fu, Li and Wong, 2014; Chen and Ho, 2019; Dai, Liang and Ng, 2021). Enforcement actions can also be costly to stakeholders of firms targeted by the EPA. Lenders, as key corporate stakeholders, can be responsible for potential cleanup and remediation costs if the targeted borrowers become bankrupt, as well as the impairment loss from loans to the bankrupt borrowers. Lenders also face potential political and reputational costs, including increased scrutiny from public policymakers and state & local regulatory agencies and higher costs of retaining depositors (Heitz, Wang and Wang, 2021; Chen, Hung and Wang, 2022). Accordingly, lenders exposed to targeted firms (hereafter, "exposed lenders") may be incentivized to exert greater monitoring and disciplinary efforts over non-targeted borrowers' polluting activities to reduce their further exposures to environmental regulation risks. This raises the question of whether, to ensure compliance with environmental laws, firms borrowing from exposed lenders significantly reduce their pollution relative to firms borrowing from other lenders.

Recent anecdotal evidence suggests that public pressure brought onto financial institutions has led them to factor into their lending decisions the risks posed to them by borrowers that face public scrutiny from engaging in unsound or unpopular environmental practices. For instance, Citizens Bank experienced numerous branch level protests and withdrawal of deposits in response to its 2016 agreement to fund the Dakota Access Pipeline, an underground oil pipeline from North Dakota to Illinois. Following major public pressure, Citizens withdrew from the pipeline loan in March 2018. Despite the anecdotal evidence suggesting that private lenders are concerned about risks arising from borrowers' poor environmental performance, research on lenders' responses to borrowers' adverse environmental incidents is limited.

The growing public interest in environmental issues, coupled with limited public resources to meet environmental challenges, suggests that leveraging private sector resources may be necessary to achieve society's environmental goals. One potentially efficient leveraging mechanism is the private lending markets. This is because virtually all corporate entities that are subject to EPA oversight also access the private lending markets, and lenders can exert significant influence over borrowers' operating decisions. Thus, if private lenders are incentivized to reduce their exposure to environmental regulation risks, they can facilitate spillover effects of EPA enforcement actions, leading non-targeted borrowers to reduce pollution. Such spillover effects create positive environmental externalities. In essence, the EPA can achieve its environmental goals–reaching a broader set of firms while limiting the scope of environmental enforcement actions–by leveraging the private lending markets.[1]

Hence, our primary prediction is that exposure to EPA enforcement actions increases lenders' incentives to monitor borrowers' polluting activities and exert significant influence on borrowers' environmental decisions. As a result, firms borrowing from exposed lenders will reduce significantly their pollution relative to firms borrowing from other lenders. We test this prediction using a sample of 33,924 firm-year observations from 1987 to 2020. We select environmental enforcement actions from the Integrated Compliance Information System database maintained by the EPA. We identify an exposed lender as the lead arranger who has an outstanding loan agreement with a borrower targeted by an enforcement action. To measure firms' polluting activities, we use the toxic release data from the Toxics Release Inventory database. We specify a stacked difference-in-differences model to test the spillover effects of EPA enforcement actions through the lending network.

Our findings reveal that, in the five years following the enforcement actions, firms borrowing from exposed lenders significantly reduce their toxic releases relative to firms borrowing

[1]Analogously, in the financial sector, national banking regulators, such as the Federal Reserve Bank in the U.S., rely on market discipline to achieve the desired goal of minimizing systemic risks to the financial system (See Core Principles for Effective Banking Supervision of the Basel Framework at https://www.bis.org/publ/bcbs230.htm)

from unaffected lenders. The estimated effect is economically significant, representing approximately a 25% reduction in toxic releases relative to the sample mean. The evidence of spillover effects through lending networks is consistent with a sobering effect of EPA enforcement actions on lenders' environmental monitoring efforts over their borrowers that are not directly targeted by the EPA.

The spillover effects are likely to vary with lenders' environmental monitoring incentives and their influence over borrowers. Monitoring incentives are likely to increase more when the EPA enforcement actions affect a larger proportion of a lender's loan portfolio and when the environmental liabilities are more severe to their EPA-targeted borrowers. Consistent with this, we predict and find evidence that the spillover effects are more pronounced when loans to firms targeted by EPA enforcement actions represent a larger proportion of a lender's loan portfolio or when the environmental liabilities as a fraction of loans to targeted firms are larger. We also predict and find evidence of greater spillover effects when lenders have greater influence over borrowers. In particular, spillover effects are significantly larger when the exposed lender is a relationship lender with the borrower or when a lender manages a larger proportion of a borrower's total debt. Finding that the spillover effects are stronger for more influential lenders suggests that lenders *ex ante* can credibly threaten to take costly actions against nonresponsive borrowers by terminating the lending relationship with the borrower. Thus, we further predict and find that, following EPA enforcement actions, lenders are *ex post* more likely to terminate lending relationships with borrowers that do not sufficiently reduce polluting activities.

To provide evidence on the source of borrowers' pollution reduction, we next test whether borrowers of exposed lenders increase their abatement activities following EPA enforcement actions. There are two broad types of abatement activities, process-related and practice-related, where the former is likely to be more costly because process-related abatement requires non-trivial reconfiguration of the production technologies and coordination with supply chain partners. Despite the cost differences, we find evidence that borrowers from exposed lenders significantly increase both types of abatement activities. We also find evidence that such borrowers experience short-term reductions in profitability, which suggests that borrowers take costly actions in response to the greater monitoring pressure from exposed lenders.

Although our primary and supplementary tests provide evidence that private lending is a channel through which EPA enforcement actions against targeted firms result in spillover effects on other firms, it is possible that other channels also contribute to spillover effects. In particular, such spillover effects can manifest if borrowers share a common location or industry with a target firm or common institutional ownership and common analysts' coverage. Findings from tests in which we control for the presence of these commonalities reveal significant spillover effects on firms borrowing from exposed lenders, which suggests that the private lending network channel is distinct from these alternative channels.

We contribute to the literature in several ways. First, our study extends the emerging literature on the complementarity between private stakeholders' efforts and public enforcement in addressing environmental problems. Existing studies exploit the variations in local EPA enforcement intensity to study the role of corporate stakeholders in facilitating spillover effects of public environmental enforcement to nearby industry peers (e.g., Choy, Jiang, Liao and Wang, 2023; Dasgupta, Huynh and Xia, 2023). However, evidence on the interaction between public enforcement and private environmental monitoring thus far is confined to local effects. Our findings suggest that private lending networks serve as a transmission mechanism that spreads the effects of EPA enforcement actions to a broader set of firms, including those in different geographic locations and industries that are not subject to heightened EPA scrutiny.[2] This mechanism implies that, by targeting a small number of firms that violate environmental laws, the regulator can reduce the scope of non-compliance by many other firms through the force of private lending relationships.

[2]In contrast, Bartram, Hou and Kim (2022) and Dasgupta et al. (2023) find that variations in local environmental policies and enforcement intensity can lead to regulatory arbitrage, such that firms shift their polluting activities across locations to minimize their regulatory risk exposures.

Second, our study is related to the stream of studies examining how the effects of economic and regulatory events propagate through the private lending network. Numerous studies examine how lenders pass on shocks to their lending capacity to corporate borrowers that are not directly affected by these shocks, thereby affecting these borrowers' financial constraints and investment activities (e.g., Gilje, Loutskina and Strahan, 2016; Cortés and Strahan, 2017; Chakraborty, Goldstein and MacKinlay, 2018; Ivanov, Macchiavelli and Santos, 2022; Rehbein and Ongena, 2022). Other studies show that a lender's recent exposure to large-scale borrower defaults or fraudulent accounting restatements is associated with more punitive loan contract terms for the lender's other corporate borrowers (Murfin, 2012; Files and Gurun, 2018; Christensen, Macciocchi, Morris and Nikolaev, 2022). We add to the literature by illustrating that lending networks also facilitate spillover effects on borrowers' non-financial activities and outcomes.

Finally, we add to the growing literature on how a firm's environmental profile affects lending relationships. A large stream of studies shows that lenders' loan initiation decisions and contract terms are associated with borrowers' environmental profiles, which suggests that lenders view environmental issues as a source of material risks (e.g., Amiram, Gavious, Jin and Li, 2021; Huang, Kerstein, Wang and Wu, 2022; Houston and Shan, 2022; Luneva and Sarkisyan, 2023). Several studies examine the specific contract terms that lenders use to motivate borrowers to meet environmental and social performance goals (Aleszczyk, Loumioti and Serafeim, 2022; Caskey and Chang, 2022; Choy et al., 2023). Other studies seek to identify various factors affecting lenders' engagement with environmental issues, such as disclosure requirements, legal liability, and depositors' demand (Bellon, 2020; Chen et al., 2022; Wang, Whited, Wu and Xiao, 2022). Although these studies show that lenders have *ex ante* incentives to internalize borrowers' environmental performance, there is limited evidence on how lenders react to borrowers' negative environmental events *ex post*.

II Related Literature and Predictions

Lenders' Environmental Monitoring Incentives

As key corporate stakeholders, lenders have incentives to monitor borrowers' firm performance, including their compliance with environmental laws and regulations (e.g., Houston and Shan, 2022; Wang et al., 2022). Lenders' monitoring over borrowers' polluting activities is likely to increase in the future following the passage in 2023 of the Climate Corporate Data Accountability Act in the state of California. The Act not only requires businesses with revenues over $1 billion that do business in California to calculate and disclose carbon emissions but also requires lenders to disclose carbon pollution associated with their borrowers.[3]

Although loan contracts typically require borrowers to ensure full compliance with environmental laws, lenders may not stringently monitor their borrowers' polluting activities in the absence of immediate regulatory risks. This is because monitoring borrowers' polluting activities can be costly for lenders when obtaining pollution-related data requires nontrivial investments in data infrastructure, and verifying borrower-disclosed pollution information may require site inspections and technical knowledge of borrowers' production processes (Brunetti, Dennis, Gates, Hancock, Ignell, Kiser, Kotta, Kovner, Rosen and Tabor, 2021; Beltran and Uysal, 2023). In addition, the lack of consistent reporting standards for corporate emissions can lead to difficulties for lenders in tracking, comparing, and synthesizing their borrowers' emissions data, which hinders lenders' ability to effectively monitor borrowers' environmental compliance (California Bankers Association, American Bankers Association and California Credit Union League, 2023).

EPA enforcement actions against borrowers in a lender's portfolio pose several direct and indirect financial risks to the lender. The most immediate direct risk is the possibility that the targeted borrower poses increased credit risk arising from environmental liabilities and potential loss of customers who are sensitive to environmental impacts (Banerjee et al., 2014; Chen and Ho, 2019; Dai et al., 2021). The lender also could be liable for a borrower's

[3] See https://leginfo.legislature.ca.gov/faces/billNavClient.xhtml?bill_id=202320240SB253.

environmental liabilities if the lender actively participates in the management and operations of the borrower.[4] In addition, as the Citizens Bank / Dakota Pipeline example illustrates, the lender can also face significant indirect costs arising from increased scrutiny from public policymakers and state & local regulatory agencies and higher costs of retaining depositors (e.g., Heitz et al., 2021; Chen et al., 2022). Therefore, to the extent that EPA enforcement actions increase lenders' perceived costs associated with borrowers' noncompliance, lenders are likely to become more incentivized to carry out additional costly monitoring efforts over their borrowers' compliance with environmental laws.

Lenders' Influence on Borrowers' Environmental Performance

Prior studies suggest that lenders are powerful stakeholders that can influence various crucial corporate decisions, such as merger and acquisition, strategic alliance formation, and product market coordination (Ivashina, Nair, Saunders, Massoud and Stover, 2009; Frankel, Kim, Ma and Martin, 2020; Saidi and Streitz, 2021; Frattaroli and Herpfer, 2023). In a similar vein, lenders can use their position of power to impose various contract terms to monitor and influence borrowers' environmental performance (e.g., Amiram et al., 2021; Aleszczyk et al., 2022; Caskey and Chang, 2022; Choy et al., 2023). These loan terms include, for example, environmental disclosure covenants, remediation covenants, site inspection rights, carbon emission commitments, and sustainability-linked performance pricing.

Although lenders may monitor their borrowers' polluting activities through their contractual rights, the effectiveness of their monitoring depends on the extent of lenders' influence over borrowers. In particular, a lender's ability to enforce the environmental terms is greater when the lender has bargaining power over the borrower. This is likely to be the case when the lender is a relationship lender or when the lender is the primary source of debt financing for the borrower (e.g., Bharath, Dahiya, Saunders and Srinivasan, 2011; Frankel et al., 2020; Bellon, 2020). In these circumstances, the implied threat for the lender to terminate the

[4]The Comprehensive Environmental Response, Compensation, and Liability Act, as amended by US Congress in 1986, provides details regarding conditions under which lenders are liable for borrowers' environmental liabilities.

lending relationship can be a powerful means to discipline the borrower's polluting activities (Houston and Shan, 2022).

Following EPA enforcement actions, when exposed lenders have bargaining power over borrowers through their lending relationships, they can exert greater influence on the environmental policies and decisions of non-targeted borrowers.

Predictions

Our main prediction is that an EPA enforcement action targeted at one firm can lead to spillover reductions in pollution by other firms through a common lender. The basis of our prediction is as follows. To the extent that the EPA enforcement actions increase lenders' incentives to monitor borrowers' polluting activities and they have sufficient influence over borrowers' operating decisions, following EPA enforcement actions, borrowers of exposed lenders significantly reduce their pollution relative to borrowers of other lenders.

Furthermore, we expect the spillover effects to be increasing functions of lenders' environmental monitoring incentives and lenders' influence over borrowers. First, regarding monitoring incentives, we hypothesize that EPA enforcement actions that affect a larger proportion of a lender's loan portfolio may alert the lender to a greater extent to the potential environmental regulatory risk arising from its portfolio in the future, thus stimulating the lender's incentive to engage with other borrowers to ensure their environmental compliance and minimize the future regulatory risk exposure. We also expect that exposures to EPA enforcement actions are more concerning to lenders when the resulting environmental liabilities are more severe to their EPA-targeted borrowers. Large liabilities can cause short-term financial difficulties for targeted borrowers, which may induce immediate lenders' attention. Furthermore, increasing exposures to a large liability amount may alert lenders to the risk of higher-than-expected financial impacts of violations of environmental laws, motivating lenders to intensify monitoring of other borrowers' environmental compliance. Therefore, we predict that the spillover effects are more pronounced when loans to firms targeted by EPA enforcement actions represent a larger proportion of a lender's loan portfolio or when the environmental liabilities as a fraction of loans to targeted firms are larger.

Second, regarding lenders' influence over borrowers, we expect that lenders with greater impacts within their lending relationships can induce greater reductions of toxic releases by treated borrowers. In particular, prior research suggests that relationship lenders not only have lower information asymmetries but also bear lower monitoring costs with respect to their borrowers and thus can exert greater influences over borrowers (e.g., Bharath et al., 2011). Also, when a lender manages a larger proportion of a borrower's total debt, the borrower is more likely to rely on the lender to maintain its capital structure, allowing the lender to exert greater impacts on its environmental practices. Therefore, we predict that the spillover effects are more pronounced when the exposed lender is a relationship lender with the borrower or when a lender manages a larger proportion of a borrower's total debt.

III Research Design

We specify a stacked difference-in-differences (DiD) model to examine whether an EPA enforcement action targeted at one firm can lead to spillover reductions in polluting activities by other firms through a common lender.[5] Specifically, for each year with EPA enforcement actions initiated against public firms, we construct a cohort of treated and control firms using firm-year observations in the ten years surrounding the enforcement actions, i.e., the [-5, +5] window in which year zero refers to the treatment year. To ensure that the enforcement actions are material, corporate events that likely attract lenders' attention, we eliminate cases that do not result in any penalty, compliance cost, or cost recovery. Because we focus on the spillover effects of EPA enforcement actions, we remove firms that the EPA targeted

[5]Our research design differs from the traditional staggered DiD approach, which generalizes the standard single-event DiD regressions to multiple treatment events with different timing using the two-way fixed effects design. As explained in Baker, Larcker and Wang (2022), this approach can result in biased estimates of the average treatment effects because it effectively uses previously treated units as part of the control units for later treatment events. The stacked DiD approach, along with several other alternative estimators, can provide more reliable estimates of the average treatment effects. Recent studies using the stacked DiD approach include Gormley and Matsa (2011), Cengiz, Dube, Lindner and Zipperer (2019), and Dasgupta et al. (2023). Findings from additional tests reported below reveal that the inferences we draw using these alternative estimators, as well as using the traditional staggered DiD approach, are the same as those based on our primary findings.

in previous years and those that will be targeted within five years following the current cohort's event year zero.

In each cohort, we identify treated firms as non-targeted firms that share a common lead arranger with a firm targeted by an EPA enforcement action in the cohort year. Control firms are other non-targeted firms that have debt contracts managed by other lead arrangers whose borrowers are not targeted in any EPA enforcement action in the cohort year. To ensure that control observations are not contaminated throughout the event window, we require that control firms have not been treated in a past cohort and will not become treated within five years of the current cohort (Baker et al., 2022; Dasgupta et al., 2023). Firms need not have non-missing observations throughout the entire event window to be included in a cohort, but they must have at least one valid observation in the pre-event window [-5, -1] and one in the post-event window [0, +5].

Following prior studies (e.g., Akey and Appel, 2021), we measure firms' polluting activities using their on-site releases of toxic chemicals as recorded by the EPA. We estimate the average treatment effect of lenders' exposure to EPA enforcement actions on borrowers' toxic releases using the following stacked DiD model:

$$Toxic\ Releases_{c,i,j,t} = \beta \times Treat_{c,i} \times Post_{c,t} + \mathbf{\Gamma}'\mathbf{Z}_{c,i,j,t} + \theta_{c,i} + \eta_{c,j,t} + \epsilon_{c,i,j,t}. \tag{1}$$

$Toxic\ Releases_{c,i,j,t}$ is the natural logarithm value of total on-site toxic releases by firm i of industry j in year t, included in cohort c. $Treat_{c,i}$ is an indicator variable that equals one if firm i is treated in cohort c, and zero otherwise. $Post_{c,t}$ is an indicator variable that equals one if year t falls in the post-event window [0, +5] in cohort c, and zero otherwise. $\theta_{c,i}$ and $\eta_{c,j,t}$ denote cohort-specific firm and industry-year fixed effects. Because a firm is either a treated or a control firm throughout the entire event window in a cohort, the main effects of $Treat_{c,i}$ and $Post_{c,t}$ are subsumed by the cohort-specific firm and industry-year fixed effects. Following Dasgupta et al. (2023), the vector $\mathbf{Z}_{c,i,j,t}$ represents a set of control variables, including the natural logarithm value of a firm's total sales ($Sales$), logarithm value of market capitalization of equity ($Size$), total debt divided by book value of common equity ($Leverage$), operating profit divided by total assets (ROA), and the book value of common equity divided by market capitalization of equity (BM). All variables are as defined in Appendix A.

To the extent that an EPA enforcement action against a borrower triggers the lender's engagement with its other borrowers to improve their environmental practices, we expect treated firms to reduce their toxic releases in response to the lender's elevated monitoring efforts. Therefore, we predict a significantly negative estimate β coefficient in Equation (1), which is consistent with a significant spillover effect of EPA enforcement on pollution reduction through a common lender.

One of the key assumptions underlying the validity of DiD analyses is that the trends of the dependent variables for the treated and control firms are similar in the pre-treatment period. Specifically, the parallel trend assumption requires that the relative reduction in toxic releases by treated firms must not precede the initiation of the EPA enforcement action against a peer firm with a common lender. To validate this assumption, we specify the following dynamic event study model:

$$\begin{aligned} Toxic\ Releases_{c,i,j,t} = {} & \beta \times Treat_{c,i} \times Post_{c,t} + \delta_1 \times Treat_{c,i} \times Year_{-1,c,t} \\ & + \delta_2 \times Treat_{c,i} \times Year_{-2,c,t} + \delta_3 \times Treat_{c,i} \times Year_{-3,c,t} \\ & + \delta_4 \times Treat_{c,i} \times Year_{-4,c,t} + \mathbf{\Gamma}'\mathbf{Z}_{c,i,j,t} \\ & + \theta_{c,i} + \eta_{c,j,t} + \epsilon_{c,i,j,t}. \end{aligned} \tag{2}$$

The indicator variables, $Year_{-\tau,c,t}$ ($\tau = 1, 2, 3, 4$), are set to one if year t is τ year(s) before the treatment year c, and zero otherwise.[6] This specification effectively uses the average difference in toxic releases between the treated and control firms in year –5 as the benchmark

[6] For ease of exposition, we do not disaggregate the indicator $Post_{c,t}$ in tabular results. However, in Figure 1, we plot the full dynamics of the treatment effects through the [-5, +5] event window.

difference, and the coefficients δ_1, δ_2, δ_3, and δ_4 reflect the changes in the difference in each of the four pre-treatment years relative to year –5. If the parallel trend assumption is valid, we expect the δ_1, δ_2, δ_3, and δ_4 to be statistically indistinguishable from zero, and the difference-in-differences coefficient estimate β to be negative. We estimate Equations (1) and (2) in an entropy-balanced sample, where the control observations are re-weighted to ensure the co-variate balance between the treated and control firms within each cohort.[7]

IV Data and Sample

Data Sources

Toxic Release Data

Our main sample consists of U.S. public firms with plants monitored by the EPA Toxics Release Inventory (TRI) program over the 1987-2020 period. The TRI program maintains a database that reports the annual plant-level releases of nearly 600 chemicals from 1987 onwards, covering all U.S. plants that have over ten employees, operate in roughly 400 industries at the six-digit North American Industry Classification System (NAICS) level, and use one of nearly 600 chemicals. In our analyses, we only consider chemicals that are identified as toxic by the EPA's Integrated Risk Information System, which describes the potential human health effects (e.g., nervous, respiratory, developmental) from exposure to over 400 chemicals. We then aggregate the quantity of releases of toxic chemicals from the plants to the parent firm level and obtain a firm-year measure of total toxic releases. Specifically, we define Toxic Release as the natural logarithm of one plus the firm's total amount of on-site releases of all toxic chemicals in pounds (Akey and Appel, 2021; Xu and Kim, 2022; Thomas, Yao, Zhang and Zhu, 2022).

[7]Untabulated findings reveal that our inferences remain unchanged by estimating versions of these two equations alternatively in 1) the analyses based on the cohort-by-cohort propensity-score matching method, 2) the analyses using a sample with only control firms that are never treated throughout the sample period, and 3) the analyses in a sample imposing firms to remain treated after the first-ever treatment controlling for firm and year fixed effects. We also find our inferences remain unchanged when estimating versions of these equations using alternative estimators, including the DiD estimators suggested by Callaway and Sant'Anna (2021) and Sun and Abraham (2021).

We match the parent firms of the plants in the TRI database to public firms in the Compustat-CRSP Merged (CCM) database. For a subset of plants where the DUNS numbers are available in the TRI database, we match the plants to parent firms in CCM using the DUNS-GVKEY linking table provided by (Akey and Appel, 2021)[8]. In all other cases, we match the plants to their parent firms in CCM by company names. This procedure is facilitated by a textual comparison program and verified manually. Specifically, we first remove common characters and suffixes from company names recorded in both databases.[9] Next, we calculate the Levenshtein similarity scores for all pairs of company names in CCM and those in TRI. We keep all pairs with similarity scores above 85 and then drop those pairs where the CCM names and TRI names point to different firms.[10]

Private Lending Data

We construct a corporate lending networks dataset using the Thomson Reuters DealScan database, which allows us to identify treated firms by tracing target firms through common lenders. In determining common lenders, we consider only lenders in single-lender loans or lead arrangers in syndicated loans. Because the main monitoring responsibilities in the loan syndicate are typically delegated to the lead arranger, we ignore any link with an EPA enforcement target firm through a participant lender in a syndicated loan. To ensure that the common lender can exert significant influence on the treated firm's environmental practices, we require that the treated firm have an active loan contract with the lender at the time when the enforcement action against the target firm is initiated. For each identified loan contract linked to a common lender with the violating firm targeted by the EPA, we obtain the loan amount, maturity, and previous lending relationship between the lender and the treated firm.

[8] The DUNS number is a unique identifier for a plant supplied by Dun and Bradstreet (D&B) database. We thank the authors for sharing a DUNS-GVKEY linking table via https://doi.org/10.1111/jofi.12978.

[9] The full list of removed characters includes: "Inc," "Corp," "Co," "Ltd," "-," "Group," "LLC," ".," "/," "LP," "(," ")," "PLC," "Partners," "The," "Incorporated," and "&."

[10] We manually check 200 firms' names and find out that all correctly matched names have similarity scores above 85, and therefore use the value of 85 as the cutoff for screening pairs of firms from CCM and TRI.

EPA Enforcement Action Data

We obtain data on EPA enforcement actions from the Integrated Compliance Information System (ICIS) database, which provides the historical details of enforcement actions taken by the EPA, including key dates of enforcement actions, the types of enforcement cases (civil, judicial, and administrative), the environmental statutes violated (e.g., the Clean Air Act), the violating firms and plants, the parties and persons charged, case monetary liabilities (including fines, compliance costs, and cost recovery amounts), as well as enforcement case conclusions (e.g., administrative orders).

We match the targeted plant in the enforcement actions to those in the TRI database using the EPA's Facility Registry Service data, which ultimately allows us to identify EPA enforcement actions against public companies through the TRI-CCM matching procedure described above. We restrict our attention to enforcement actions with a final decision. To ensure that the enforcement actions are material corporate events, we keep enforcement cases that result in total monetary costs, including the penalty, compliance cost, or cost recovery, of at least $100,000 based on inflation-adjusted amounts in December 2020.

The above procedures allow us to construct a sample of 33,924 firm-year observations between 1987 and 2020 by stacking all the cohorts with treated firms linked to lenders exposed to EPA-targeted firms and control firms associated with lenders not exposed to EPA enforcement actions. We select EPA enforcement cases initiated between 1992 and 2016 because our DiD analyses employ the [-5, +5] event window in which year zero refers to the treatment year. A firm is identified as an "EPA-targeted" firm if an EPA enforcement action against this firm reaches the first conclusion date in the treatment year. We exclude firms from each cohort that are ever targeted by the EPA throughout the entire event window [-5, +5] for both treatment and control groups.[11]

[11] Inclusion of targeted firms in the control group would make it difficult to identify spillover effects because targeted firms are required to take remedial actions promptly (Blundell, 2020). Conversely, for the same reason, including other targeted firms in the treatment group could lead to overstatement of spillover effects.

EPA Pollution Abatement Data

We use the EPA's Pollution Prevention (P2) database to measure firms' abatement activities. Plants reporting to the TRI database are required to document source reduction techniques used to limit the amount of toxic releases. The P2 database captures a wide range of abatement activities, such as raw material modifications, cleaning and degreasing, and surface preparation and finishing.

Following Akey and Appel (2021), we further classify firms' abatement activities into two categories: "process improvements" and "good operating practices." Process improvements refer to functional changes to the firm's production process, such as pre-conditioning raw materials, replacing key production inputs, and upgrading production equipment. These activities are costly abatement measures that often involve nontrivial investments and complex coordination along the supply chain. Good operating practices involve activities that refer to less costly and the most common types of abatement activities, such as improving maintenance scheduling, record keeping, inventory handling, and quality control. These activities better align the firm's day-to-day operations to their environmental performance goals but do not require renovating the production technologies.

To measure a firm's overall abatement efforts, we create a variable, $Abatement_{All}$, which is the average number of unique abatement activities undertaken by the firm across all of its plants. We also create two more abatement variables, $Abatement_{Process}$ and $Abatement_{Practice}$, to measure abatement efforts through process improvements and operating practices separately. In addition to these abatement metrics, we construct three additional proxies to reflect alternative pollution reduction strategies, i.e., the number of unique chemical types released by a firm ($\#Chemical\ Types$), the number of polluting plants possessed by a firm ($\#Pollution\ Plants$), and the average production index of a firm across its plants ($Production\ Intensity$).

Summary statistics

Table 1 provides some key descriptive statistics of lenders that are exposed to EPA enforcement actions. On average, there are 40 treated lenders that are exposed to at least one EPA enforcement action against one of their borrowers each year, and a typical treated lender experiences three such enforcement cases during the year. The average annual monetary costs relating to borrowers' EPA enforcement cases for a treated lender amount to \$1,092 million.[12] The statistics also reveal that for an average treated lender, the loans associated with EPA-targeted borrowers account for 2.4% of the lender's loan portfolio (*Loan Exposure*), and the total monetary enforcement costs account for 18% of targeted borrowers' loans (*Liability Exposure*). On average, 47% of treated lenders have a prior lending relationship with treated borrowers (*Relationship Lender*), and the amount of loan outstanding of a treated borrower with a treated lender accounts for 62% of the borrower's total long-term debt (*Borrower Dependence*).

[Insert Table 1 here]

Table 2, Panel A, presents the summary statistics of variables employed in the main analyses based on the full sample of 33,924 firm-year observations from 1987 to 2020. The variable of Toxic Release has a mean of 9.50, suggesting that an average firm releases 13,399 ($= e^{9.503} - 1$) pounds of toxic chemicals per year (*Toxic Releases*). On average, a typical firm in our sample uses 1.29 unique types of abatement measures each year ($Abatement_{All}$) and generates \$738 million in sales ($= e^{6.605} - 1$) (*Sales*), with a market capitalization of \$486 million ($= e^{6.189} - 1$) (*Size*), a leverage ratio of 0.91 (*Leverage*), a return on assets of 0.10 (*ROA*), and an equity book-to-market ratio of 0.73 (*BM*).

[Insert Table 2 here]

[12] The costs of EPA enforcement actions are not limited to the direct monetary costs. Blundell (2020) shows that an initial enforcement action with small monetary liability can lead to quickly escalated follow-up cases that may eventually result in more intensive scrutiny and large penalties, particularly if environmental compliance is not restored in time. Therefore, enforcement actions with small fines can have material long-term financial implications for targeted firms.

Table 2, Panel B, compares the mean values of these variables across the treatment and control groups in one year prior to the treatment year. The statistics reveal that there are no statistically significant mean differences between treated and control firms, suggesting that lenders' exposures to EPA enforcement actions are not correlated with the *ex ante* observed characteristics of borrowing firms related to toxic emissions, environmental strategies, and corporate fundamentals.

V Results

Lenders' Exposure to EPA Enforcement Actions and Borrowers' Toxic Releases

Table 3 presents the regression results of the stacked DiD tests and parallel trend analyses examining whether a lender's exposure to EPA enforcement actions against one of its borrowers is associated with reductions in toxic releases of other non-targeted borrowers.

Column 1 presents the findings from the stacked DiD estimation of Equation (1) without including time-varying firm-level control variables. Instead, we rely on the within-cohort firm and industry-year fixed effects as controls for the potential confounding factors. The coefficient on $Treat \times Post$, –0.291, is significantly negative (t-statistic = –5.67), which suggests that treated firms significantly reduce their $Toxic\ Releases$ compared to control firms following the EPA enforcement actions. The estimated treatment effect roughly translates to a 25% reduction in toxic releases relative to the sample mean.[13] The magnitude of this treatment effect is comparable with previous studies in similar settings. For instance, Thomas et al. (2022) finds an increase of toxic releases by approximately 15% for firms likely engaging in earnings management, and Dasgupta et al. (2023) reports a 22% reduction in chemicals releases after a nearby industry peer is targeted by an EPA enforcement action.

[Insert Table 3 here]

[13] Given the sample mean value of $Toxic\ Releases$ (13,399 pounds), the coefficient -0.291 suggests a decrease in toxic releases of 3,383 pounds $= 13,399 - (e^{ln(13,399+1)-0.291} - 1)$. Therefore, the percentage reduction relative to the sample mean is about $25\% = 3,383/13,399$.

Column 2 presents the findings from the estimation of Equation (2) without control variables. Consistent with the parallel trend assumption, the coefficient estimates of the pre-treatment interaction terms, $Treatment \times Year_{-\tau}$ ($\tau = 1, 2, 3, 4$), are all statistically indistinguishable from zero, and the coefficient $Treat \times Post$, –0.260, remains significantly negative (t-statistic = –4.59). These findings suggest that the relative reduction in toxic releases for treated firms does not precede the EPA enforcement action that triggers the spillover effect. To provide the full details of dynamic effects, Figure 1 plots the point estimates and 95% confidence intervals of the average differences in toxic releases between treated and control groups across years through the event window.

[Insert Figure 1 here]

Columns 3 and 4 present findings from estimations of Equations (1) and (2) including time-varying control variables. The $Treat \times Post$ coefficients, –0.322 and –0.295, are significantly negative (t-statistics = –6.27 and –5.22), which again suggests that treated firms significantly reduce their *Toxic Releases* compared to control firms following the EPA enforcement actions. In addition, as in Column 2, the coefficients of the interaction terms $Treatment \times Year_{-\tau}$ ($\tau = 1, 2, 3, 4$) in Column 4 are all statistically indistinguishable from zero. Taken together, the findings in Table 3 are consistent with lenders exposed to EPA enforcement actions exert greater monitoring over non-targeted borrowers to reduce their further exposures to environmental regulation risks.

Lenders' Monitoring Incentives

As Section II describes, lenders' monitoring incentives are likely to be greater when loans to firms targeted by EPA enforcement actions represent a larger proportion of a lender's loan portfolio or when the environmental liabilities as a fraction of loans to targeted firms are larger. As a result, we predict that the spillover effects are more pronounced under these two circumstances.

To test this prediction, we alternately split the treatment group into two mutually exclusive sub-groups based on the two partitioning variables. The first metric, *Loan Exposure*, is the loan amount of EPA-targeted borrowers with a treated lender scaled by the total amount of the lender's loan portfolio. The second measure, *Liability Exposure*, is the total monetary costs associated with enforcement actions against EPA-targeted borrowers scaled by the loan amount to these borrowers with the lender. We then define an indicator variable $Treat^{Low}$ ($Treat^{High}$) that equals one if the value of *Loan Exposure* or *Liability Exposure* for a treated firm in a given cohort is lower (higher) than the median value of all treated observations, and zero otherwise. We then re-estimate Equation (1) after replacing the interaction term $Treat \times Post$ with two interactions, $Treat^{Low} \times Post$ and $Treat^{High} \times Post$ based on both partitioning variables.

Columns 1 and 2 of Table 4 present the results. In Column 1, where the partitioning variable is based on *Loan Exposure*, the magnitude of coefficient on $Treat^{High} \times Post$, -0.414, is 68% larger than that on $Treat^{Low} \times Post$, -0.246, and the difference is statistically significant based on the F-test of coefficient equality (p-value = 0.057). Similarly, the findings in Column 2, where the partitioning variable is *Liability Exposure*, reveal that the coefficient magnitude of $Treat^{High} \times Post$ is twice larger than that of $Treat^{Low} \times Post$ (coefficients on $Treat^{Low} \times Post$ and $Treat^{High} \times Post$ = -0.131 and -0.397) and the difference is also statistically significant (p-value = 0.007).

[Insert Table 4 here]

These findings indicate that the environmental spillover effects through lending networks are more pronounced for lenders with stronger monitoring incentives when their exposures to EPA enforcement actions are more pervasive in their loan portfolios and when the resulting environmental regulatory costs of targeted borrowers are greater, thereby providing further support for the inference that lenders' engagement contributes to the incremental pollution reduction of treated firms.

Lenders' Influences over Borrowers

As Section II describes, we predict that the spillover effects are more pronounced when the exposed lender is a relationship lender with the borrower or when the lender manages a larger proportion of the borrower's total debt.

To test this prediction, we partition the sample based on two metrics of lenders' influences, *Relationship Lender*, an indicator equal one if a treated lender has arranged a previous loan with a treated borrower, and *Borrower Dependence*, the amount of loan outstanding of a treated borrower with a treated lender scaled by the borrower's total long-term debt. Prior research suggests that relationship lenders not only have lower information asymmetries but also bear lower monitoring costs with respect to their borrowers and thus can exert greater influences over borrowers (e.g., Bharath et al., 2011). Also, when a lender manages a larger proportion of a borrower's total debt, the borrower is more likely to rely on the lender to maintain its capital structure, allowing the lender to exert greater impacts on its environmental practices.

As in the cross-sectional analyses of lenders' monitoring incentives, we define indicators $Treat^{Low}$ and $Treat^{High}$, based on the two partitioning variables, *Relationship Lender* (i.e., zero or one for the indicator variable) and *Borrower Dependence* (i.e., lower or higher than the sample median). Then, we re-estimate Equation (1) by replacing $Treat \times Post$ with the two interactions $Treat^{Low} \times Post$ and $Treat^{High} \times Post$. The findings from these estimations, reported in Columns 3 and 4 of Table 4, reveal that the coefficient magnitudes of $Treat^{High} \times Post$ (coefficients = -0.495 and -0.438) are considerably larger than those of $Treat^{Low} \times Post$ (coefficients = -0.200 and -0.242), and these differences are statistically significant (p-values = 0.001 and 0.029), respectively.

These cross-sectional analysis results provide support for the conjecture that when facing exposure to EPA enforcement actions, lenders with greater influences over borrowers are able to induce greater reductions in toxic emissions by treated borrowers, shedding light on the mechanism of the environmental spillover effect arising from corporate lending nexus.

Future Lending Relationship

The findings in Table 4 that the spillover effects are stronger for influential lenders suggest that lenders *ex ante* can credibly threaten to take costly actions against nonresponsive borrowers. One particularly effective costly action is for the lender to terminate the lending relationship with the borrower. Prior studies show that the termination of a lending relationship is costly to the borrower because it creates heightened debt rollover risks, holds back investment opportunities, and subjects borrowers to larger spreads of refinanced debts (e.g., Bharath et al., 2011; Chava and Purnanandam, 2011). Thus, we expect that, following EPA enforcement actions, lenders are *ex post* more likely to terminate lending relationships with borrowers that do not sufficiently reduce lenders' exposures to environmental regulation risks by improving their environmental performance.

To test this prediction, we estimate the following logistic regression using a sample of loans between borrower i and lender l that are active while the lender is exposed to an EPA enforcement action in year τ.

$$Terminate_{i,l,\tau} = \Delta Toxic\ Releases_{i,\tau} + \mathbf{\Gamma}'\mathbf{Z}_{i,\tau} + \theta_\tau + \epsilon_{i,\tau} \tag{3}$$

The dependent variable, $Terminate$, is an indicator variable that equals one if the same lead arranger does not refinance a loan within a year after the maturity date of the current loan and zero otherwise. $\Delta Toxic\ Releases$ is the year-on-year percentage change in toxic releases in year τ. Equation (3) includes the same control variables, $\mathbf{Z}_{i,\tau}$, as those in Equation (1).

Table 5, Column 1, which reports the findings from the estimation of equation (3), reveals that the coefficient on $\Delta Toxic\ Releases$, 0.022, is significantly positive (t-statistic =2.02). This finding is consistent with our conjecture that lenders are more likely to terminate the current lending relationship with treated borrowers who do not adequately reduce their toxic releases.

[Insert Table 5 here]

Table 5, Column 2, presents findings of estimation of Equation (3) in which we expand the sample of loans to include loans in the control group. In particular, to construct the control sample of loans, we select loans that are active in year τ and arranged by lenders that are not exposed to an EPA enforcement action in that year. We augment Equation (3) by interacting the indicator $Treat$, which identifies loans arranged by lenders with exposure to EPA enforcement, with $\Delta Toxic\ Releases$. The findings reported in Column 2 reveal that the coefficient on the interaction term, $Treat \times \Delta Toxic\ Releases$, is significantly positive (coefficient = 0.020, t-statistic = 3.03), but the coefficient on $\Delta Toxic\ Releases$ is not (coefficient = 0.002, t-statistic = 0.32). These findings suggest that lenders' termination decisions are sensitive to the changes in borrowers' toxic releases only when their lending portfolios are exposed to EPA enforcement actions, which is consistent with EPA enforcement actions elevating lenders' perceptions of environmental regulatory risks.

Taken together, the findings in Table 5 provide additional evidence that, following EPA enforcement actions, lenders can exert influence over borrowers' polluting activities by credibly threatening to terminate the lending relationship if the borrower does not take sufficient actions to reduce pollution.

VI Additional Tests

Borrowers' Abatement Activities

The findings in Tables 3 and 4, whichprovide evidence of the spillover effects of EPA enforcement actions, suggest that treated firms make changes to their operating activities to achieve pollution reduction. In this subsection, we examine whether the pollution reduction as a result of the spillover effect of EPA enforcement is associated with treated firms' investments in abatement activities. According to the EPA's 2005 Pollution Abatement Costs and Expenditures Survey, investments in abatement activities represent, on average, 4.6% of firms' capital expenditures, and the associated expenses are mostly sunk costs (EPA, 2005). Therefore, firms' investments in abatement activities are a signal to their lenders of a credible commitment to reduce pollution.

To test whether a spillover effect of EPA enforcement on pollution reduction is associated with firms' abatement activities, we estimate versions of Equations (1) and (2), replacing $Toxic\ Releases$ with $Abatement_{All}$, which is the average number of unique abatement activities undertaken by a firm across all its facilities in a year. The findings presented in Table 6, Columns 1 and 2, reveal that the coefficients on $Treat \times Post$, 0.035 and 0.037, are significantly positive (t-statistics = 6.88 and 6.61). In addition, the Column 2 findings reveal no evidence of a significant pre-trend. These findings suggest that treated firms increase their total abatement activities.

Process-related abatement activities likely are more costly than practice-related abatement activities, as the former often requires non-trivial reconfiguration of the production technologies and coordination with supply chain partners (Akey and Appel, 2021). Such cost differences could result in firms favoring operation-related abatement activities. To test whether this is the case, we re-estimate Equations (1) and (2) after alternately replacing $Toxic\ Releases$ with $Abatement_{Process}$ and $Abatement_{Practice}$. The findings presented in Table 6, Columns 3 to 6, reveal that all $Treat \times Post$ are significantly positive and are of similar magnitude, suggesting that treated firms significantly increase both types of abatement activities.

An important outcome of firms' abatement efforts is the reduction in the number of chemicals released. In particular, firms' abatement efforts may allow them to purge unnecessary releases of certain types of toxic chemicals. Such reductions may result from either process- or operation-related abatement activities. For example, firms may reconfigure their production lines to eliminate the use of certain toxic chemicals, or they can increase their scrutiny over the chemicals used by suppliers. Therefore, we re-estimate Equations (1) and (2) after replacing $Toxic\ Releases$ with $\#Chemical\ Types$, which is the natural logarithm value of the number of unique chemical types released by a firm. The findings reported in Columns 7 and 8 reveal that treated firms release significantly fewer types of toxic chemicals than control firms after the treatment year (e.g., the coefficient of $Treat \times Post$ in Column 2 = -0.081, t-statistic = -9.72).[14]

Taken together, the findings in Table 6 suggest that pollution reductions by treated firms are linked to treated borrowers' abatement efforts, and such efforts involve both short-term changes to the firms' operating practices and long-term changes that optimize their production technologies.

[Insert Table 6 here]

Costs to Borrowers

Finding that treated firms exert incremental abatement efforts relative to control firms suggests that the abatement efforts are costly, and borrowers would not undertake such efforts in the absence of lenders' influence. To the extent that firms must sacrifice short-term profitability to address the greater monitoring of exposed lenders, we expect treated firms to report lower profit margins (Thomas et al., 2022; Xu and Kim, 2022). Specifically, if the abatement efforts require investments in equipment or additional material costs that can be directly traced to the production output, the cost of goods sold may rise, leading to lower gross margins. In addition, changes in operating practices and other expenditures affiliated with pollution abatement equipment may result in higher operating expenses, causing lower net profit margins.

To test whether the effects of lender-linked EPA enforcement actions on the firms' profitability are negative, we estimate versions of Equation (1) in which the dependent variables are $Gross\ Margin$, the sales less cost of goods sold scaled by total sales, and $Profit\ Margin$, the income before extraordinary items scaled by total sales. The findings reported in Table 7, Columns 1 and 2, indicate that treated firms, on average, experience a 20-basis-point

[14] In addition to direct abatement activities, firms could also reduce pollution by indirect means, such as disposing a polluting plant or reducing production intensity. To test whether this is the case, we re-estimate versions of Equations (1) and (2) in which we replace *Toxic Releases* with measures of the number of polluting plants possessed by a firm and the average production index of a firm across its plants. Untabulated findings reveal that treated firms make no significant changes in the number of plants or production intensity following the lenders' exposure to EPA enforcement actions.

decline in gross margins and a 30-basis-point decline in net profit margins, both of which are statistically significant (coefficients on $Treat \times Post$ = -0.002 and -0.003; t-statistics = -2.08 and -2.32). Finding that treated firms experience short-term reductions in profitability is additional evidence in support of the private lending network as a mechanism through which the EPA enforcement actions lead to incremental pollution reduction among non-targeted firms.

[Insert Table 7 here]

Taken together, the findings in Table 7 suggest that exposed lenders can influence borrowers to take costly abatement actions that they otherwise would not take in the absence of lenders' influence.

Alternative Spillover Channels

The evidence presented thus far provides support for private lending as the channel through which EPA enforcement actions against targeted firms result in spillover effects on other firms. In this subsection, we consider whether the private lending network is distinct from alternative plausible channels as sources of the observed spillover effects.

Common Industry and Geographic Location

Previous studies show that environmental enforcement activities vary substantially by industry and state (e.g., Blundell, 2020; Dai, Duan and Ng, 2020; Heitz et al., 2021; Dasgupta et al., 2023). When some plants in an industry or in a state become recent targets of EPA enforcement actions, peer firms with plants in the same industry or state may learn about the potential elevated local enforcement intensity towards them, which in turn prompts them to reduce pollution to avoid becoming the next target. This suggests that industry and location membership can serve as an alternative spillover channel for the effect of EPA enforcement actions on corporate environmental practices. Furthermore, Choy et al. (2023) find that lenders increase their environmental monitoring efforts on borrowers located in states with elevated EPA enforcement intensities. To the extent that lenders may specialize in certain industries and states, it is likely that the relation between lenders' exposure to EPA enforcement actions and borrowers' pollution reduction is confounded by this alternative spillover channel.

We address this possibility in two ways. First, in each cohort, we measure *Toxic Releases* after excluding the toxic releases of firms' polluting plants belonging to the same industry (as indicated by the 3-digit SIC code) or located in the same state as an EPA-targeted plant. The new measurement of *Toxic Releases* ensures that, although treated firms are linked to targeted firms through common lenders, they do not share the common effect of that increased environmental enforcement intensity at the industry or state level. Columns 1 and 2 of Table 8 present the findings from re-estimating Equations (1) and (2) using the new toxic emission measure. The coefficients of $Treat \times Post$ continue to be negative and statistically significant (coefficients = -0.316 and -0.288, t-statistics = –5.84 and -4.84), and none of the coefficients of the interaction terms $Treatment \times Year_{-\tau}$ ($\tau = 1, 2, 3, 4$) in Column 2 is statistically significant.

[Insert Table 8 here]

As a second approach to address potential industry and state spillover effects, we re-estimate Equations (1) and (2) after removing firms that have any plant that operates in the same industry or state as an EPA-targeted plant in each cohort. This is a more restrictive sample selection criterion because it removes all firms that have linkages with any targeted firm with respect to industry and state membership. In this substantially reduced sample, untabulated results reveal similar treatment effect estimates.

Common Institutional Investors

Further, prior studies also suggest that institutional investors can serve as a transmission channel shaping corporate environmental practices (e.g., Kim, Wan, Wang and Yang, 2019; Dasgupta et al., 2023). If the preferences of lenders in screening borrowers are correlated with the investment criteria of certain institutional investors, the spillover channel between borrowing firms through lenders' loan portfolios may be confounded by the environmental impact that investors impose on invested firms in their equity portfolios.

To address this potential confounding effect, we re-estimate Equations (1) and (2) after excluding treated and control firms that share common block shareholders with EPA-targeted firms in each cohort.[15] The estimation results are reported in Columns 3 and 4. The coefficients of $Treat \times Post$ in Columns 3 and 4 are significantly negative (coefficients = -0.272 and -0.260, t-statistics = -5.03 and -4.34), and the coefficients of the interaction terms, $Treatment \times Year_{-\tau}$ ($\tau = 1, 2, 3, 4$), in Column 4 indicate no significant divergence in the pre-treatment period between the treated and control firms.

Common Financial Analysts

Prior studies show that analysts incorporate firms' environmental performance into their coverage and recommendation decisions and that their monitoring efforts can influence corporate environmental policies (Qian, Lu and Yu, 2019; Jing, Keasey, Lim and Xu, 2023). Therefore, it is possible that analysts' exposures to EPA enforcement actions against firms they follow may increase analysts' environmental monitoring effects over other firms in their coverage portfolios. To the extent that analysts' coverage may correlate with certain lenders' loan portfolios, it is unclear whether the reduction in toxic releases of treated firms can be attributed to the environmental spillover effect through lending networks.

To assess whether there is a treatment effect that is distinct from the potential effects of common analysts' coverage, we re-estimate Equations (1) and (2) for the sub-sample of firms with no common analyst coverage with EPA-targeted firms in each cohort. The findings reported in Columns 5 and 6 continue to indicate a strong negative relation between lenders' exposures to EPA enforcement actions and their treated borrowers' pollution reduc-

[15] We restrict our attention to blockholders to ensure the common shareholding institutional investors have substantial interest in the portfolio firms to influence their environmental practices.

tion (coefficients on $Treat \times Post$ = -0.372 and -0.408, t-statistics = -3.14 and -3.38). These findings suggest that there is a lender treatment effect that is distinct from the influence of common analyst coverage. In addition, as in Columns 2 and 4, the findings in Column 6 reveal that the incremental pollution reduction does not precede the treatment.

Taken together, the results from the analyses in this section reinforce the inferences of our primary analyses by showing that the spillover effects of EPA enforcement actions through lending networks are distinct from the effects of potential alternative spillover channels.

VII Conclusion

This study examines how exposures to EPA enforcement actions increase lenders' incentives to monitor borrowers' polluting activities, thereby resulting in firms borrowing from exposed lenders significantly reducing their pollution relative to firms borrowing from other lenders. We test for this spillover effects prediction using a sample of 33,924 firm-year observations from 1987 to 2020. Our findings reveal that, following the enforcement actions, firms borrowing from exposed lenders significantly reduce their toxic releases relative to firms borrowing from unaffected lenders. The estimated effect is economically significant, representing approximately a 25% reduction in toxic releases relative to the sample mean.

We also predict and find evidence that the spillover effects are more pronounced when loans to firms targeted by EPA enforcement actions represent a larger proportion of a lender's loan portfolio, when the environmental liabilities as a fraction of loans to targeted firms are larger, when the exposed lender is a relationship lender with the borrower, and when a lender manages a larger proportion of a borrower's total debt. These findings are consistent with the spillover effects varying with lenders' environmental monitoring incentives and their influence over borrowers. In addition, we find evidence that lenders are more likely to terminate lending relationships with borrowers that do not sufficiently reduce polluting activities, which suggests that termination is a credible threat to nonresponsive borrowers.

Taken together, our study's findings suggest that the EPA can achieve its environmental goals–reaching a broader set of firms while limiting the scope of environmental enforcement actions–by leveraging the private lending markets. More broadly, our study's findings illustrate that in a world of limited public resources, regulators' leveraging of private sector resources may be an efficient way to meet society's challenges and needs.

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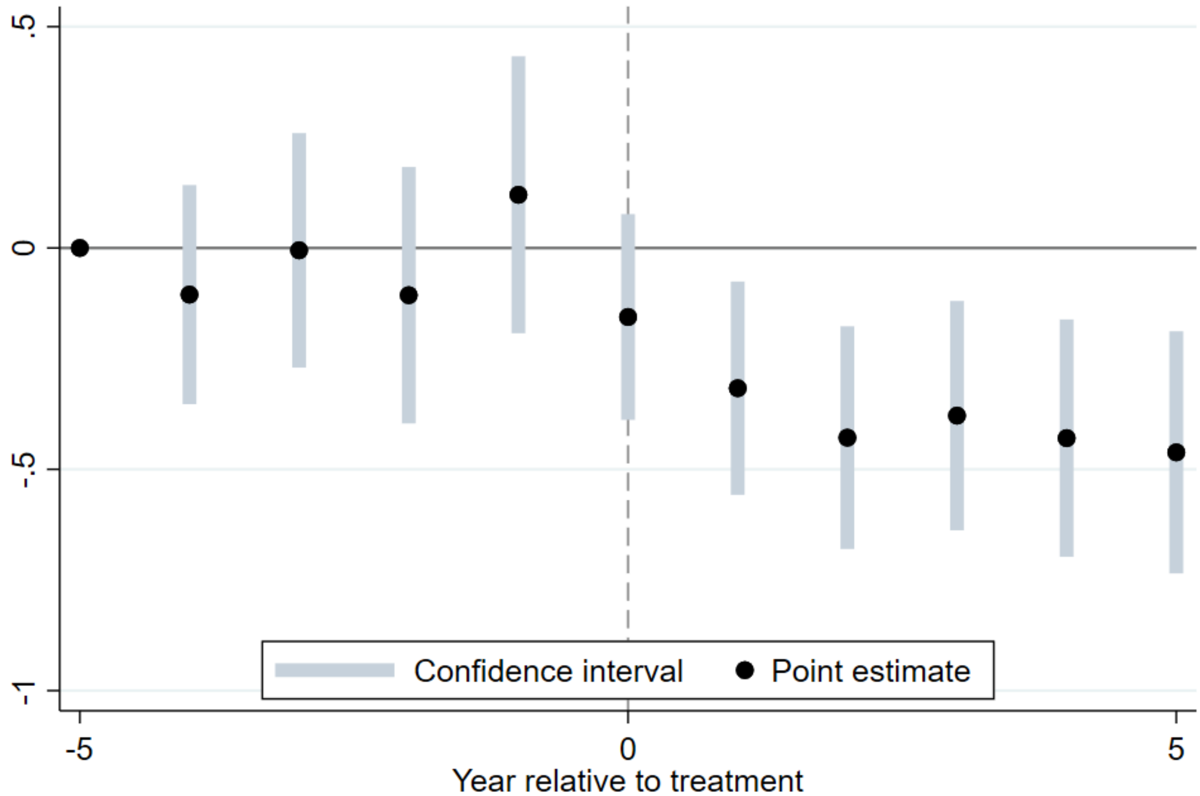
Figure 1
Differences in Toxic Releases between the Treatment and Control Groups



This figure plots the point estimates and the 95% confidence intervals of average differences in the toxic releases between firms in the treatment and control groups around the treatment year relating to EPA enforcement actions, based on an entropy-balanced sample comprising 33,924 firm-year observations from 1987 to 2020.

Appendix A
Variable Definitions

Variable	Definition
Toxic Releases	The natural logarithm of one plus a firm's total amount of on-site releases of toxic chemicals in pounds in a year.
Treat	An indicator that equals one if a firm in a given cohort is identified as a treated firm, and zero otherwise.
Post	An indicator that equals one if a year in a given cohort is in the post-treatment period, and zero otherwise.
$Year_{-\tau}$	An indicator that equals one if a year in a given cohort is τ years prior to the treatment year, and zero otherwise.
Sales	The natural logarithm of one plus a firm's total sales in millions in a year.
Size	The natural logarithm of one plus a firm's market capitalization of equity in millions in a year.
Leverage	The total debt of a firm divided by its book value of common equity in a year.
ROA	The operating profit of a firm divided by its total assets in a year.
BM	The book value of common equity of a firm divided by its market capitalization of equity in a year.
$Abatement_{All}$	The average number of unique abatement activities undertaken by a firm across all its facilities in a year.
$Abatement_{Process}$	The average number of unique abatement activities classified as process improvement undertaken by a firm across all its facilities in a year.
$Abatement_{Practice}$	The average number of unique abatement activities classified as operating practices undertaken by a firm across all its facilities in a year.
#Chemical Types	The natural logarithm of one plus the number of unique chemical types released by a firm in a year.
#Pollution Plants	The natural logarithm of one plus the number of polluting plants possessed by a firm in a year.
Production Intensity	The average production index of a firm across its facilities in a year.

Appendix A
Variable Definitions (Continued)

Variable	Definition
Loan Exposure	The total loan amount of EPA-targeted borrowers with a treated lender, divided by the total amount of the lender's loan portfolio in the EPA enforcement year.
Liability Exposure	The total monetary costs associated with the EPA enforcement actions against EPA-targeted borrowers of a treated lender, divided by the total loan amount to these borrowers with the lender in the EPA enforcement year.
Relationship Lender	An indicator that equals one if a treated lender has arranged at least a loan contract for a treated borrower in five years before the commencement of the current loan.
Borrower Dependence	The amount of loan outstanding of a treated borrower with a treated lender, divided by the borrower's total long-term debt in a year.
$Treat^{Low}$	An indicator that equals one if a firm in a given cohort is identified as a treated firm and the partitioning variable is lower than the sample median, and zero otherwise.
$Treat^{High}$	An indicator that equals one if a firm in a given cohort is identified as a treated firm and the partitioning variable is higher than the sample median, and zero otherwise.
Δ*Toxic Releases*	The year-on-year percentage change in toxic releases in the post-treatment period.
Termination	An indicator variable that equals one if a loan is not refinanced by the same lead arranger within a year after the maturity date, and zero otherwise.
Gross Margin	The gross profit of a firm, i.e., sales less cost of goods sold, divided by its total sales in a year.
Profit Margin	The income before extraordinary items of a firm divided by its total sales in a year.
Advertising	The advertising expense of a firm divided by its total sales in a year.
R&D	The R&D expense of a firm divided by its total sales in a year.
Capex	The capital expenditure of a firm divided by its total assets in a year.
Tobin Q	The market capitalization of equity plus total debt of a firm divided by its book value of common equity plus the total debt in a year.

Table 1
Descriptive Statistics of Lenders' Exposures to EPA Enforcement Actions

Year	# Lenders	# Cases per lender	Liability ($m) per lender	*Loan Exposure*	*Liability Exposure*	*Relationship Lender*	*Borrower Dependence*
1992	23	2	6.85	5.54%	1.33%	24.00%	53.16%
1993	30	3	61.91	3.84%	1.97%	55.51%	76.21%
1994	30	6	13.43	3.00%	0.55%	58.45%	74.32%
1995	18	3	26.49	2.40%	2.01%	72.61%	69.12%
1996	32	3	13.23	2.32%	0.76%	61.25%	84.13%
1997	41	3	56.15	1.43%	1.77%	57.58%	71.52%
1998	42	4	149.76	3.02%	9.12%	48.96%	70.17%
1999	45	6	127.36	2.49%	1.03%	56.54%	73.00%
2000	57	8	1,055.73	2.77%	15.30%	61.41%	71.28%
2001	49	3	149.37	2.49%	12.29%	48.91%	54.69%
2002	35	4	636.11	3.03%	14.05%	42.07%	60.08%
2003	52	4	3,065.39	2.94%	120.14%	48.90%	57.49%
2004	58	3	22.59	1.77%	4.00%	33.61%	43.89%
2005	58	4	1,744.54	1.67%	60.10%	34.09%	46.06%
2006	46	2	134.16	1.66%	16.74%	31.55%	36.95%
2007	44	3	1,059.52	1.20%	37.45%	50.15%	71.13%
2008	48	2	38.34	1.36%	2.47%	50.54%	46.37%
2009	36	2	184.71	2.10%	21.11%	66.27%	76.85%
2010	58	2	275.70	2.62%	6.66%	22.67%	46.27%
2011	43	3	74.74	2.42%	2.06%	44.03%	54.40%
2012	32	3	23.59	1.43%	1.20%	38.69%	80.63%
2013	30	2	206.59	1.12%	10.59%	25.42%	53.04%
2014	24	2	31,630.20	0.85%	90.94%	33.33%	67.12%
2015	36	3	383.71	3.30%	25.39%	36.81%	55.46%
2016	26	6	202.93	3.20%	7.19%	47.83%	70.39%
Mean	40	3	1,092.13	2.40%	17.87%	46.91%	62.05%

This table presents the descriptive statistics of lenders' exposures to EPA enforcement actions. All variables are as defined in Appendix A.

Table 2
Summary Statistics

Panel A: Summary Statistics of Main Variables

Variable	Mean	SD	$P25$	Median	$P75$
$Toxic\ Releases$	9.503	4.123	7.874	10.511	12.161
$Abatement_{All}$	1.291	1.287	0.333	0.800	2.000
$Abatement_{Process}$	1.214	1.293	0.267	0.667	2.000
$Abatement_{Operating}$	1.215	1.293	0.267	0.667	2.000
$Sales$	6.605	1.613	5.425	6.495	7.721
$Size$	6.189	1.956	4.825	6.224	7.624
$Leverage$	0.910	1.616	0.212	0.506	0.997
ROA	0.102	0.079	0.056	0.100	0.146
BM	0.730	0.530	0.386	0.614	0.903

Panel B: Comparison between Treatment and Control Groups

Variable	Control	Treatment	Difference	t-stat
$Toxic\ Releases$	9.510	9.495	-0.015	(-0.275)
$Abatement_{All}$	1.303	1.280	-0.023	(-0.084)
$Abatement_{Process}$	1.209	1.219	0.010	(0.085)
$Abatement_{Practice}$	1.214	1.216	0.001	(0.084)
$Sales$	6.596	6.613	0.017	(0.116)
$Size$	6.206	6.173	-0.033	(-0.151)
$Leverage$	0.898	0.920	0.022	(0.122)
ROA	0.104	0.100	-0.005	(-0.006)
BM	0.709	0.750	0.041	(0.037)

This table presents the description of the sample used in the main analyses. The sample comprises 33,924 firm-year observations from 1987 to 2020. Firms in the treatment (control) group are related to lenders exposed (not exposed) to EPA enforcement actions. Panel A reports summary statistics of the variables for the mean (Mean), standard deviation (STD), the 25th ($P25$), median (Median), and 75th percentiles ($P75$) of the distributions of the variables. Panel B presents the comparison between the treatment and control groups with the mean values and the differences in the means of the variables. All variables are as defined in Appendix A.

Table 3
Lenders' Exposure to EPA Enforcement Actions and Borrowers' Toxic Releases

Dep. Var =	*Toxic Releases*			
	(1)	(2)	(3)	(4)
$Treat \times Post$	-0.291***	-0.260***	-0.322***	-0.295***
	(-5.67)	(-4.59)	(-6.27)	(-5.22)
$Treat \times Year_{-1}$		0.097		0.048
		(0.73)		(0.66)
$Treat \times Year_{-2}$		-0.062		-0.084
		(-0.40)		(-1.07)
$Treat \times Year_{-3}$		-0.004		0.098
		(-0.27)		(1.21)
$Treat \times Year_{-4}$		-0.049		-0.051
		(-0.56)		(-0.58)
Sales			0.503***	0.504***
			(8.38)	(8.38)
Size			0.087*	0.087*
			(1.92)	(1.92)
Leverage			-0.053***	-0.054***
			(-4.12)	(-4.14)
ROA			-2.070***	-2.066***
			(-7.87)	(-7.86)
BM			0.071	0.071
			(1.31)	(1.30)
Observations	33,924	33,924	33,924	33,924
Adj.R^2	0.890	0.890	0.891	0.891

This table presents the effects of lenders' exposure to EPA enforcement actions on borrowers' toxic releases. The sample comprises 33,924 firm-year observations from 1987 to 2020. All regression models include Firm × Cohort and Industry × Year × Cohort fixed effects. Sample observations are re-weighted to ensure co-variate balance based on entropy balancing. The t-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity and firm-level clustering. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. All variables are defined in Appendix A.

Table 4
The Role of Lenders' Incentives and Influence

Dep. Var =	*Toxic Releases*			
Part. Var=	*Loan Exposure*	*Liability Exposure*	*Relationship Lender*	*Borrower Dependence*
	(1)	(2)	(3)	(4)
$Treat^{Low} \times Post$	-0.246***	-0.131	-0.200***	-0.242***
	(-3.77)	(-1.50)	(-3.15)	(-3.83)
$Treat^{High} \times Post$	-0.414***	-0.397***	-0.495***	-0.438***
	(-5.87)	(-6.80)	(-6.70)	(-5.95)
Coefficient comparison:				
$High - Low$	-0.168*	-0.266***	-0.295***	-0.196**
p-value	[0.057]	[0.007]	[0.001]	[0.029]
Sales	0.504***	0.501***	0.507***	0.505***
	(8.39)	(8.35)	(8.44)	(8.40)
Size	0.085*	0.084*	0.087*	0.084*
	(1.88)	(1.86)	(1.93)	(1.85)
Leverage	-0.053***	-0.053***	-0.054***	-0.053***
	(-4.11)	(-4.11)	(-4.13)	(-4.11)
ROA	-2.077***	-2.059***	-2.098***	-2.071***
	(-7.89)	(-7.83)	(-7.97)	(-7.87)
BM	0.070	0.068	0.070	0.067
	(1.29)	(1.26)	(1.29)	(1.23)
Observations	33,924	33,924	33,924	33,924
Adj. R^2	0.891	0.891	0.891	0.891

This table presents the effects of lenders' exposure to EPA enforcement actions on borrowers' toxic releases after separating out treated firms with lower and higher values of the respective measures of lenders' incentives and influences. The sample comprises 33,924 firm-year observations from 1987 to 2020. All regression models include Firm × Cohort and Industry × Year × Cohort fixed effects. Sample observations are re-weighted to ensure co-variate balance based on entropy balancing. The t-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity and firm-level clustering. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. All variables are defined in Appendix A.

Table 5
Borrower Pollution Changes and Future Lending Relationships

Dep. Var =	*Termination*	
	Treated Loans Only	Treated & Control Loans
	(1)	(2)
$\Delta Toxic\ Releases$	0.022**	0.002
	(2.02)	(0.32)
$Treat \times \Delta Toxic\ Releases$		0.020***
		(3.03)
$Treat$		0.579***
		(4.61)
Control Variables	Yes	Yes
$Treat$ x Control Variables	No	Yes
Observations	2,873	6,836
Pseudo R^2	0.097	0.235

This table presents the relation between borrowers' changes in toxic releases and the probability of the termination of current lending relationships, conditional on lenders' exposure to EPA enforcement actions. The sample comprises 2,873 (6,836) existing lending relationships from 1992 to 2016 for those in the treatment group (in both treatment and control groups) of our main analyses. All regression models include year fixed effects. Sample observations are reweighted to ensure covariate balance based on entropy balancing. The t-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity and firm-level clustering. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. All variables are defined in Appendix A.

Table 6
Lenders' Exposure to EPA Enforcement Actions and Borrowers' Other Pollution Reduction Strategies

Dep. Var =	$Abatement_{All}$		$Abatement_{Process}$		$Abatement_{Practice}$		$\#Chemicals$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Treat \times Post$	0.035***	0.037***	0.038***	0.041***	0.033***	0.034***	-0.077***	-0.081***
	(6.88)	(6.61)	(7.82)	(7.80)	(6.65)	(6.30)	(-10.09)	(-9.72)
$Sales$	-0.065***	-0.065***	-0.086***	-0.086***	-0.064***	-0.064***	0.102***	0.102***
	(-10.89)	(-10.90)	(-15.17)	(-15.18)	(-11.09)	(-11.09)	(11.47)	(11.48)
$Size$	0.014***	0.014***	0.016***	0.016***	0.007	0.007	0.001	0.001
	(3.13)	(3.13)	(3.68)	(3.68)	(1.56)	(1.56)	(0.17)	(0.16)
$Leverage$	0.005***	0.005***	0.003**	0.003**	0.003***	0.003***	-0.003	-0.003
	(3.89)	(3.91)	(2.12)	(2.16)	(2.79)	(2.82)	(-1.45)	(-1.50)
ROA	0.058**	0.058**	0.097***	0.097***	0.080***	0.079***	-0.049	-0.049
	(2.22)	(2.22)	(3.91)	(3.91)	(3.17)	(3.17)	(-1.27)	(-1.27)
BM	0.024***	0.024***	0.026***	0.027***	0.020***	0.020***	-0.006	-0.006
	(4.49)	(4.50)	(5.17)	(5.18)	(3.77)	(3.78)	(-0.72)	(-0.74)
$Treat \times Year_{-1}$		0.003		0.012		0.001		-0.025
		(0.25)		(0.92)		(0.06)		(-1.21)
$Treat \times Year_{-2}$		0.021		0.027*		0.020		-0.038*
		(1.41)		(1.89)		(1.38)		(-1.67)
$Treat \times Year_{-3}$		0.005		0.015		0.001		0.003
		(0.30)		(0.95)		(0.07)		(0.13)
$Treat \times Year_{-4}$		0.004		0.007		0.001		-0.004
		(0.21)		(0.38)		(0.08)		(-0.13)
Observations	33,924	33,924	33,924	33,924	33,924	33,924	33,924	33,924
Adj. R^2	0.828	0.828	0.838	0.838	0.839	0.839	0.929	0.929

This table presents the effects of lenders' exposure to EPA enforcement actions on borrowers' abatement efforts. The sample comprises 33,924 firm-year observations from 1987 to 2020. All regression models include Firm × Cohort and Industry × Year × Cohort fixed effects. The t-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity and firm-level clustering. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. All variables are defined in Appendix A.

Table 7
Lenders' Exposure to EPA Enforcement Actions and Borrower Profit Margins

Dep. Var =	*Gross Margin*	*Profit Margin*
	(1)	(2)
Treat × *Post*	-0.002**	-0.003**
	(-2.08)	(-2.32)
Advertising	0.074***	0.033***
	(14.82)	(6.04)
R&D	0.002	-0.011***
	(0.82)	(-4.09)
Capex	0.135***	0.267***
	(24.97)	(36.49)
Tobin Q	0.001*	0.000
	(1.79)	(0.22)
Observations	33,924	33,924
Adj. R^2	0.934	0.521

This table presents the effects of lenders' exposure to EPA enforcement actions on borrowers' profit margins. The full sample comprises 33,924 firm-year observations from 1987 to 2020. All regression models include year fixed effects. Sample observations are re-weighted to ensure co-variate balance based on entropy balancing. The t-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity and firm-level clustering. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. All variables are defined in Appendix A.

Table 8
Excluding Alternative Spillover Channels

Dep. Var =	*Toxic Releases*					
Exclude firms with:	Industry & State		Common Blockholding		Common Analyst Coverage	
	(1)	(2)	(3)	(4)	(5)	(6)
$Treat \times Post$	-0.316***	-0.288***	-0.272***	-0.260***	-0.372***	-0.408***
	(-5.84)	(-4.84)	(-5.03)	(-4.34)	(-3.41)	(-3.38)
$Treat \times Year_{-1}$		0.139		0.087		-0.177
		(0.95)		(0.64)		(-0.61)
$Treat \times Year_{-2}$		-0.167		-0.098		-0.061
		(-1.04)		(-0.65)		(-1.34)
$Treat \times Year_{-3}$		0.273		0.166		0.250
		(1.57)		(1.03)		(0.73)
$Treat \times Year_{-4}$		0.160		0.045		0.394
		(1.40)		(0.25)		(1.06)
Sales	0.468***	0.468***	0.446***	0.446***	0.313***	0.314***
	(7.34)	(7.34)	(6.54)	(6.53)	(3.07)	(3.07)
Size	0.118**	0.118**	-0.118**	-0.118**	0.321***	0.322***
	(2.44)	(2.43)	(-2.36)	(-2.36)	(4.29)	(4.31)
Leverage	-0.059***	-0.059***	-0.048***	-0.048***	-0.079***	-0.080***
	(-4.20)	(-4.21)	(-3.76)	(-3.77)	(-3.75)	(-3.80)
ROA	-2.402***	-2.398***	-0.040	-0.038	-3.371***	-3.384***
	(-8.64)	(-8.62)	(-0.14)	(-0.13)	(-8.15)	(-8.18)
BM	0.020	0.019	-0.118**	-0.119**	0.294***	0.291***
	(0.34)	(0.33)	(-2.02)	(-2.03)	(3.68)	(3.64)
Observations	31,284	31,284	29,357	29,357	11,780	11,780
Adj. R^2	0.893	0.893	0.890	0.890	0.904	0.905

This table presents the effects of lenders' exposure to EPA enforcement actions on borrowers' toxic releases, with treated and control observations selected after excluding alternative spillover channels. The samples are reduced from 33,924 firm-year observations from 1987 to 2020 as additional sample selections are applied. All regression models include Firm × Cohort and Industry × Year × Cohort fixed effects. The t-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity and firm-level clustering. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. All variables are defined in Appendix A.