Joining Forces: The Spillover Effects of EPA Enforcement Actions and the Role of Socially Responsible Investors*

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Abstract

We show that firms reduce emissions at their local plants following EPA enforcement actions against nearby plants of peer firms operating in the same product market. The emission reductions are larger for plants located close to socially responsible mutual funds (SRMFs) that hold the parent firm's shares and for plants belonging to firms with high operational flexibility. The close proximity to SRMFs is also associated with the adoption of abatement measures. While plants increase emissions again in the long run, these reversals are prevented for plants located close to SRMFs. We provide evidence that the threat of exit by SRMFs has real consequences for how the local plants respond to the enforcement action. The results suggest that local SRMF monitoring complements EPA enforcement.

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1. Introduction

Governments devote large amounts of resources in regulating the environmental impact of firms' production activities, and firms, in turn, spend significant amounts in complying with these regulations. In the U.S., the Environmental Protection Agency (EPA) is the primary body responsible for setting up the regulatory framework for environmental monitoring under various statutes such as the Clean Air Act.[1] Increasingly, however, the EPA is not the only actor in the area of environmental monitoring. Socially responsible investors (henceforth, SRIs)—who have sustainability goals when making investment decisions—are arguably an influential stakeholder because they can use voice and threat of exit to influence a firm (Dimson, Karakas, and Li, 2015; Dyck, Lins, Roth, and Wagner, 2019; Hong, Karolyi, and Scheinkman, 2020; Krueger, Sautner, and Starks, 2020).[2]

The presence of socially responsible funds in a region raises an important question on which empirical evidence is still limited: Do these investors complement the EPA in monitoring environmental compliance of their investee firms? Economic theory does not provide unambiguous guidance for this question.[3] On one hand, heightened enforcement activities in a region by the EPA could cause SRIs to spend less resources on pursuing environmental actions. On the other hand, EPA enforcement could alert SRIs about

[1] The Clean Air Act (CAA), along with the Clean Water Act (CWA) and the Resource Conservation and recovery Act (RCRA), get the bulk of the resources for monitoring and enforcement (Shimshack, 2014). While the primary authority of inspections and enforcements under the various acts belongs to the states' departments of environment and local authorities, these "primary authorities" work closely with the regional and federal EPA offices. The latter also conduct their own inspections (especially when the local efforts are deemed inadequate and the potential for harm is especially high), and impose penalties on their own on violators. Penalties include administrative, civil, as well as criminal penalties.

[2] Recently, courts have also joined forces with shareholders and regulators. For example, a Dutch court has recently ruled that Royal Dutch Shell is obliged to cut its carbon emissions by 45% by the year 2030 to align with the goals of the Paris Agreement. Community organizations and other non-governmental organizations (NGOs) are also important stakeholders (Grant and Grooms, 2017; Grant and Langpap, 2019; Heyes and King, 2020). In general, our understanding of the role of non-government enforcement and how it complements the EPA enforcement is limited, perhaps due to the lack of granular data on the involvement of these agents. For this reason, our study of SRIs offers insights into this important issue.

[3] A theoretical literature in regulatory and public economics suggests that whether the monitoring actions of multiple agents are substitutes or complements depends on, among other factors, the relative costs of private versus agency enforcement, the expected penalty, the public information production from each type of monitoring, and the nature of the "enforcement game" (Langpap, 2007; Goeshl and Jürgens, 2012).

regulatory risk to their portfolio firms, especially when these firms are more likely to come under the regulator's scrutiny following the enforcement action. Moreover, SRIs may not have genuine social purposes after all, as has been claimed in recent studies (e.g. Michaely, Ordonez-Calafi, and Rubio, 2021). Ultimately, whether SRIs complement EPA enforcement is an empirical issue that we investigate in this study.[4]

The issue of whether SRIs "walk their talk" has been at the center of recent debate, and our study attempts to shed light on this debate. Both practitioners and regulators have raised concern that a "green" posture enables fund managers to attract funds and benefit from higher fees associated with ESG (Environmental, Social and Governance)-oriented funds, but investments by these funds do not deliver anything tangible to the investors either in terms of higher returns or better ESG performance by the portfolio firms.[5] Some recent research also suggests that the environmental footprints of their investments do not reflect their publicly disclosed purposes (Gibson Brandon, Glossner, Krueger, Matos, and Steffen, 2021; Heath, Macciocchi, Michaely, and Ringgenberg, 2021; Liang, Sun, and Teo, 2021). On the other hand, Dyck, Lins, Roth, and Wagner (2019) find that higher levels of institutional ownership are associated with higher firm-level E&S-scores worldwide, especially when the institutional investors are signatories to the UN Principles on Responsible Investing.[6]

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[4] Grant and Grooms (2017) examine the role of nonprofits and compliance with the Clean Water Act, and their effect on government monitoring and enforcement. They find that nonprofits engage directly with the facilities, and severe violations and government inspections both decrease as the number of local groups increases. Grant and Langpap (2019) find that increased presence of watershed groups results in higher proportions of swimmable and fishable water bodies, and that increased donations to and expenditures by the groups also improve water quality.

[5] This practice has been termed "greenwashing", which is now an official entry in the Meriam-Webster dictionary, which defines it as, "expressions of environmentalist concerns especially as a cover for products, policies, or activities".

[6] Dimson, Karacaş and Li (2021) study engagements by coalitions of PRI signatories under the PRI Collaboration Platform with target firms, and find that the coalition targets firms with more equity holding by the coalition, and higher ESG scores than their peers (possibly reflecting reputational concerns of target firms). Success rates are higher when a local signatory leads the coalition. Pension funds with pro-environmental goals can also pressure portfolio firms to improve environmental performance (Naaraayanan, Sachdeva, and Sharma, 2021). Financial institutions can sponsor and support ESG-oriented shareholder proposals (Cao, Liang, and Zhan, 2019; Kim, Wan, Wang, and Yang, 2019). Akey and Appel (2019) find that a possibly unintended outcome of hedge fund activism is a decrease in toxic chemical

Not much is known about what triggers SRI engagement, if any. Dyck, Lins, Roth, and Wagner (2019) show that firms with more institutional ownership improve environmental performance following the BP Deepwater Horizon oil spill. Thus, it is plausible that complementary effects via SRI engagement occur if, for example, the EPA enforcement sends a signal about the prevailing compliance level in a region that leads SRIs to elevate their monitoring efforts. Heath, Macciocchi, Michaely, and Ringgenberg (2021) distinguish between "selection" and "treatment". Selection refers to investing in companies because of their better ESG footprints, and treatment involves actively engaging with the companies to improve their environmental and social performance. While selection in the absence of engagement could be associated with greenwashing, as the authors note, the threat of entry or exit by SRI funds could change firm behavior. More importantly, it could also make SRI engagement more credible. This is because the SRI fund is likely to care for its reputation or ESG rating/profile if that helps attract investor fund inflow, and this will motivate it to engage with a portfolio firm if it behaves badly. In addition, engagement with these firms can be more effective since other ESG-conscious shareholders may join the call and make their voices heard (e.g., through shareholder-initiated ESG proposals and the shareholder voting process). Other SRIs will join because this will further enhance their reputations as being socially responsible (Dimson, Karacaş, and Li, 2021).[7]

We contribute to this debate by using a unique setting in which the EPA first takes an enforcement action against a violating plant. We then investigate whether and how, after such EPA enforcement actions, local socially responsible mutual funds (SRMFs) play a role in ensuring the environmental compliance of local plants that produce similar products and use similar technology as the violating plant but are not targeted by the EPA. We show evidence consistent with the interpretation that monitoring or

emissions by plants of the targeted firms. However, the decrease is not driven by abatement measures, rather, more operational efficiency.

[7] Dimson, Karacaş, and Li (2021) note that the argument has parallels with the idea of "wolf-pack activism" by hedge funds (Brav, Dasgupta, and Matthews, 2021).

engagement by SRMFs becomes more effective after such EPA enforcement actions, and emissions at monitored plants are reduced both in the short term and in the longer term.

We introduce a notion of *compliance slack* whereby a firm's operating practice does not comply with environmental regulations, possibly unbeknown to the EPA, and is at risk of EPA scrutiny, which potentially exposes it to an enforcement action. Compliance slack can arise because, given limited resources, the EPA is unable to detect and pursue all noncompliant firms (Yaeger, 1991; Heyes and Rickman, 1999). Zou (2021) shows that non-continuous enforcement in a region by the EPA can lead to higher pollution levels on non-monitoring days. Similarly, the full extent of compliance slack could also be unknown to local SRMFs (until they are alerted by an EPA enforcement action in the region) because fund managers do not monitor investees' plants on a regular basis.

To guide our empirical analysis, we present in Appendix A a simple model that motivates most of our hypotheses and empirical tests for the spillover effects of EPA enforcement on non-target plants and the role of local SRMFs. In the presence of compliance slack, our first prediction is that a firm would reduce its toxic emissions at a local plant after observing an EPA enforcement action taken against a peer firm's plant that is located in close proximity.[8] Peer firms are those operating in the same product market according to Hoberg and Phillips's (2016) Text-based Network Industry Classifications (TNIC3), which is calibrated to be as fine as 3-digit SIC. The EPA provides detailed industry-specific guidelines based on the nature of the production process (Xu and Kim, 2021).[9] We empirically verify that the quantities of emissions of harmful chemicals from plants of TNIC3-peer firms are more correlated with each other than emissions from plants of the broader TNIC2 network, which is calibrated to be as coarse as 2-digit SIC.

An EPA enforcement action in a region could raise concerns among peer plants that they could be the targets of investigations. This risk possibly ensues from the EPA's

[8] Empirically, we use 100-mile radius to define vicinity. This choice balances the need for a large enough sample of treated plants that are close enough to a violating plant for a meaningful spillover effect. We show that the spillover effect becomes weaker as the distance from the violating plant is larger.
[9] See also https://www.epa.gov/regulatoryinformation-sector.

"neutral selection" inspection policy, which is in part based on geographic proximity to other facilities scheduled to be inspected (Shimshack, 2014). Once the EPA uncovers a violation, the violating plant will be subjected to more intensive inspections (Blundell, Gowrisankaran, and Langer, 2020), which potentially increases the risk that nearby plants will also be visited and inspected by the regulatory authorities. These heightened regulatory activities in the area, coupled with the high similarity of toxic releases among peer plants, suggest that, after observing an EPA enforcement action against a peer plant, treated plants (i.e. same-TNIC3 plants that are located in close proximity to the violating peer plant) would have stronger incentives to take actions to reduce emissions to avoid being the next enforcement target.[10]

Consistent with the presence of compliance slack, we find that treated plants significantly reduce their toxic emissions in the three years following an enforcement action against a nearby peer plant. We obtain this finding using a stacked difference-in-differences regression analysis with TNIC2 firms acting as the control group and controlling for plant, year, and county fixed effects. The effect is economically meaningful – equivalent to drop in toxic releases from the 60th percentile level to the median level of the sample distribution.

We carefully check for parallel trends to establish the validity of our difference-in-differences methodology. In addition, our results remain robust when we proxy for plant-level emissions using air quality index that is objectively measured using monitoring stations located within 1-mile radius from a plant.[11] We also find that the spillover effects are more pronounced when EPA enforcement penalties imposed on the local violating

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[10] Throughout this paper, we refer to the plant facing enforcement action as the target plant or violating peer plant, and the firm that owns the target plant as the target firm. We refer to same-TNIC3 plants that are located in close proximity to a violating peer plant as treated plants or non-target treated plants.

[11] A county can be placed under nonattainment status if its air quality is below an environmental benchmark specified by the EPA. Such a status will subject the county to stricter regulatory monitoring than attainment counties (Dai, Duan, and Ng, 2021). It is therefore plausible that plants respond to their counties' nonattainment status rather than a nearby peer enforcement action. In untabulated analysis, we obtain historical data on county-level nonattainment status in a given year from the EPA, which evaluates a county's air quality based on six criteria pollutants, namely, carbon monoxide, particulate matter, sulfur dioxide, ozone, lead, and nitrogen. We find that our effects remain strong regardless of a county's nonattainment status, suggesting that nonattainment status does not confound our results.

peer plant are higher and when the enforcement action involves a violation of a major environmental law. This result suggests that treated plant response is stronger when local regulatory risk is higher. Last, consistent with the existence of compliance slack, we find that treated plants' responses are stronger when the EPA did not take any enforcement actions in the area over the past five years.

We next examine our main question of whether a treated plant's reduction of toxic releases is stronger when it is located close to an SRMF, who holds shares in the treated plant's firm. We contend that an enforcement action against a nearby peer plant indicates heightened regulatory risk in the area, possibly prompting a local SRMF to make plant visits and engage with local treated plants more intensively. While a direct test of SRMF engagement at the plant level is not possible due to the lack of such granular data, we conduct tests based on the predictions derived from the monitoring role of SRMFs.

A recent literature finds that technology adoption, management practices, and knowledge spillovers have a significant geographic component, and decline with geographic distance (Dougal, Parsons, and Titman, 2015; Agha and Molitor, 2018; Bloom, Brynjolfsson, Foster, Jarmin, Patnaik, Saporta-Eksten, and Van Reenen, 2019; Matray, 2021). Proximity is important for soft information gathering even in the present day, especially for the fund management industry (Bai and Massa, 2021). Based on this literature, we argue that the local presence of an SRMF matters for two reasons. First, an SRMF's prior information about potential violations by peer plants is likely to be of higher quality when it is local, which makes it cost-effective for it to engage with the local plants after the EPA action once the perceived regulatory threat increases. Second, engagement is less costly when the plant is local. Therefore, we expect that following the enforcement action, the SRMF engages with nearby plant managers to ensure that necessary abatement measures are taken to mitigate emissions; however, we expect its influence is more pronounced on close plants than distant plants. Consistent with this prediction, we find that when an SRMF is located in close proximity (within 100 miles) to the investee's plant and to the violating peer plant, the total reduction of toxic releases at the investee's treated plant is quantitatively twice as large as that of treated plants without a close

SRMF. We also find that the effects of SRMF decay monotonically as the distance from a treated plant to its nearest SRMF increases.[12] We obtain similar findings by matching treated plants located close to SRMFs to those located far away from SRMFs based on plants' parent firms' environmental scores, suggesting that better monitoring ability of SRMFs located closer to the treated plants, rather than the self-reaction of firms with good environmental performance, explain our results. [13]

Not all firms can respond to EPA enforcement by reducing local emissions, possibly due to high compliance costs. Those firms that could respond to heightened regulatory risk in a region could take advantage of their operational flexibility. Indeed, we find that treated plants that reduce emissions following a nearby peer's enforcement action are those belonging to parent firms with sufficient operational flexibility or resources, such as those with higher levels of inventory holding, more plants, and a lower value of a measure of inflexibility which is based on the range of variation of a firm's operating cost-to-sales ratio.

For a typical flexible firm, we find that it reduces emissions at the local treated plants by engaging in short-term, opportunistic tactics such as using up its inventory (possibly to meet current customers' demand and reduce production at the same time) or shifting toxic emissions to other distant plants (possibly by reallocating productions to distant plants). Yet we find that the net emissions reduction at the aggregate firm level is still large and statistically significant. Further investigation into the destination to which these flexible firms shift emissions reveals that the distant plants are located in regions where the local EPA office does not scrutinize their industries intensively (as proxied by the number of past enforcement actions taken against these industries in the region).

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[12] These results are not driven by institutional investors that hold both the violating peer firm and the treated firm.

[13] It is possible that treated firms respond more strongly to EPA enforcement in the presence of local SRMFs because the latter's monitoring could crowd out EPA monitoring, which, in turn, causes more compliance slack. This hypothesis, however, implies that SRMFs are actively monitoring treated plants and are unlikely to be surprised by a nearby enforcement action. The tests discussed below on how (i) SRMFs adjust their portfolios when a local plant fails to respond to nearby enforcement action, and (ii) the role of close SRMFs in mitigating emissions in the longer term by local plants, provide additional evidence in support of the complementarity of EPA and SRMF enforcement.

These findings suggest that environmental compliance is costly even for a typical flexible firm as it finds ways to opportunistically reduce exposure to heightened regulatory risk in a region. Local SRMF engagement is complementary to and reinforces EPA enforcement. If local SRMFs become more active in monitoring following a nearby EPA enforcement action, we expect that the opportunistic behavior of flexible firms will also be mitigated. Indeed, we find that the transfer of emissions is thwarted when treated plants are close to an SRMF who owns the parent firms' shares. We next conduct a number of tests to examine how local SRMFs influence local plants' emissions.

First, we study the adoption of abatement measures as an indication of plant-level actions to tackle emissions. For treated plants that are located close to an SRMF, we find that, following a nearby enforcement action, these plants are more likely to implement abatement initiatives involving manufacturing process modifications such as modifying equipment, changing input chemicals, or improving chemical reaction conditions.

Second, we examine whether the treated firms (i.e. firms that have treated plants close to SRMFs) implement abatement measures at distant plants that are located outside 100 miles of the violating peer plant. In the three years after a peer enforcement action, we do not observe changes in abatement at these distant plants. However, in the period from 4 to 10 years after the enforcement action, we find that these distant plants are more likely to undertake abatement investment to reduce emissions. Again, this gradual adoption is consistent with the nature of abatement investment, which is costly and takes several years to implement. While local SRMFs influence the treated firm to implement abatement measures at local treated plants in the short run because these plants face an immediate regulatory risk, they also demand a comprehensive plan to reduce emissions at distant plants in the longer run.

Third, we show that in the absence of a close SRMF, the opportunistic behavior of treated firms does not sustain in the longer term. Over the period from years t+4 to t+10 after an enforcement action against a local peer plant in year t, emissions at treated plants increase back to 100% of the short-run reduction amount (after removing confounding enforcement actions over the same period). By contrast, treated plants that are located close to an SRMF continue to reduce emissions in the longer term.

We also examine whether the long-run effects of local SRMFs on the firm-level emissions aggregated across all plants. Consistent with the plant-level results, we find that treated firms increase their aggregate emissions again in the long run, but these long-run reversals are prevented for treated firms with treated plants located close to an SRMF.[14] Taken together, these results are consistent with the notion that local SRMFs elevate their monitoring intensity after observing a nearby enforcement action, and the abatement measures that are taken by firms held by these SRMFs are effective.

Next, we provide evidence that the threat of exit by SRMFs has real consequences for how the local plants respond to the enforcement action.[15] We find that all SRMFs reduce the portfolio weights of firms whose treated plants do not reduce emissions immediately after a local enforcement action (hereafter referred to as non-responding treated plants), and this effect is larger if the SRMF is located in close proximity (i.e. within 100 miles of the target and treated plants). In contrast, SRMFs increase the portfolio weights in firms whose treated plants reduce emissions after observing an enforcement action against a local peer plant, and again, the effect is larger if the SRMF is located in close proximity.

The mere threat of exit arising from local SRMFs' selling of non-responding treated firms' shares could cause the responding treated firms to keep their emissions low in the long run. We find that when responding treated plants are located close to a non-responder, long-term emission reversals at these plants are mitigated. These long-run reversals of emissions are completely prevented when the local non-responder has an SRMF located in close proximity.

Related Literature and Contribution

Our study contributes to a strand of climate finance literature that examines the effects of regulations on firm environmental behavior. Prior research has examined how

[14] These firm-level results are inconsistent with the window-dressing hypothesis, which implies that the effects of SRMFs on long-run emissions at the aggregate firm level are insignificant.

[15] Edmans (2020) contends that institutional investors' threat of exit is a powerful mechanism that influences firms to undertake socially responsible investment, thereby benefiting the society as a whole.

firm response to environmental regulations is determined by reputation (Karpoff, Lott, and Wehrly, 2005), financial constraints (Cohn and Deryugina, 2018; Goetz, 2018; Bartram, Hou, and Kim, 2021; Xu and Kim, 2021), supply chain (Schiller, 2018; Dai, Liang, and Ng, 2021), and corporate legal and listing status (Shive and Forster, 2020; Akey and Appel, 2021). Other studies examine the effects of environmental regulatory risks in financial markets (de Greiff, Delis, and Ongena, 2018; Hoepner, Oikonomou, Sautner, Starks, and Zhou, 2020; Seltzer, Starks, and Zhu, 2020). Whereas prior research focuses on the direct effects of environmental regulations on firms, our study examines the spillover effects of EPA enforcement actions on local peer firms.[16]

To the best of our knowledge, our paper is also the first to empirically examine the interactions between the monitoring roles of socially responsible financial institutions and regulators. We find strong evidence that local SRMF's monitoring complements EPA enforcement especially in ensuring local plants' long-run environmental compliance. Examining the direct effects of SRMF on a firm could be confounded by an EPA enforcement action taken against the firm itself, which forces the firm to reduce emissions. Our setting overcomes this issue by taking advantage of the action chain by the EPA and local SRMFs. Specifically, in our setting, an EPA enforcement action against a peer plant triggers local SRMF's monitoring of other local plants that are not targeted by the enforcement action, thereby allowing us to empirically attribute the emissions reductions at non-target treated plants to the local SRMF's influence following the enforcement action. We provide a detailed discussion of the role of SRMF and related endogeneity concerns in Section 4.6. Our findings have important policy implications as environmental activism by private monitors is increasing rapidly, and economic theory does not provide definitive answers as to whether private monitoring increases the

[16] In addition to regulatory risk, the climate finance literature also examines the effects of physical climate risk (Barrot and Sauvagnat, 2016; Dessaint and Matray, 2017; Hsu, Lee, Peng, and Yi, 2018; Bernstein, Gustafson, and Lewis, 2019; Hong, Li, and Xu, 2019; Alok, Kumar, and Wermers, 2020; Baldauf, Garlappi, and Yannelis, 2020; Painter, 2020; Giglio, Maggiori, Rao, Stroebel, and Weber, 2021; Goldsmith-Pinkham, Gustafson, Lewis, Schwert, 2021; Massa and Zhang, 2021; Huynh and Xia, 2021) and the effects of transition risk/carbon emissions (Barnett, Brock, and Hansen, 2020; Choi, Gao, and Jiang, 2020; Hsu, Li, and Tsou, 2020; Bolton and Kacperczyk, 2021a, 2021b).

efficacy of public monitoring (Langpap, 2007; Goeshl and Jürgens, 2012).[17] An important policy implication of our findings is that the returns to repeat inspections and enforcement actions by the EPA are lower when socially responsible institutions are also present locally, and this could inform the EPAs monitoring and enforcement strategy.

Our results provide strong evidence in support of SRI engagement in the mitigation of adverse environmental issues, consistent with Dimson, Karakaş, and Li (2015, 2021), Dyck, Lins, Roth, and Wagner (2019), and others. It is notable that SRMFs in our study are based in the U.S. Several recent papers find that U.S.-based SRI's, in contrast to those based in some countries with higher country-level norms on social and environmental issues, are either less likely to influence portfolio firms on E&S issues, or deviate from their stated pro-E&S positions in terms of the ESG footprints of their portfolio firms (e.g. Gibson Brandon, Glossner, Krueger, Matos, and Steffen, 2021). Our results are related to Heath, Macciocchi, Michaely, and Ringgenberg (2021) who study how unexpected increases in SRI fund-flows affect emissions of portfolio firms. They do not find such inflows to have any effects on several E&S categories, including emissions. Finally, the issue of "engagement" versus "portfolio selection" (exit or not enter when a firm's ESG footprint is below the mark) has received much attention, with some arguing that the former is more effective (Broccardo, Hart, and Zingales, 2020). We find that entry and exit are related to how firms respond to a perceived increase in regulatory risk, and this effect is particularly strong for a local SRMF.

2. Data and Variable Construction

Our sample includes plants of U.S. public non-financial firms over the 1990-2015 period. We obtain data on plants and their parent firms from several data sources: plant-level toxic releases from EPA Toxics Release Inventory (TRI) program,[18] enforcement

[17] For example, in models of "regulatory dealing" inspired by Harrington (1988), the regulator optimally tolerates some non-compliance. Private enforcement in this setting can undermine regulator monitoring (Heyes and Rickman, 1999).
[18] More information on EPA TRI program is available via the link.

cases from EPA compliance and enforcement data, plant-level location information from the National Establishment Time-Series (NETS) database, Hoberg and Phillips Text-based Network Industry Classifications (TNIC) from Hoberg-Phillips Data Library, air quality indexes measured at air monitoring sites from EPA Air Quality data, and firm-level accounting and market data sourced from Compustat Fundamentals Annual file and Center for Research in Securities and Prices (CRSP). The definitions of all the key variables are detailed in Appendix Table B1.

2.1. *Plant-level Toxic Releases Measure*

We obtain a plant's toxic emission information from EPA Toxics Release Inventory (TRI) program. The EPA requires all plants that meet their reporting criteria (e.g. have at least 10 employees, operate in certain industry sectors, use certain type of chemicals) to report emissions data.[19] In the reporting form, plants are required to provide the number of pounds per chemical that are released into the ground, air, and water. The TRI database also provides information on the plant's identifier, each chemical's identification information, quantities of each chemical released on-site at the plant each year, and quantities of each chemical transferred off-site to other locations each year.

To identify whether a chemical in TRI is harmful to humans, we obtain information on the toxicity of chemicals from the EPA's Integrated Risk Information System (IRIS), which assesses, characterizes, and standardizes the health hazards of over 400 chemicals in the environment.[20] Using the common chemical identifier—Chemical Abstract Services (CAS) numbers—we match IRIS chemicals with TRI to identify chemicals that cause potential harms to human health. Our plant-level toxic emissions measure, *Toxic*, is then a plant's total amount of on-site releases of all identified harmful chemicals. To ensure that toxic releases are comparable across plants, we standardize toxic releases using the industry mean and standard deviation in each year. We confirm that our results do not qualitatively change when we do not standardize toxic releases.

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[19] The TRI reporting criteria is listed on EPA website.
[20] Details information on IRIS is available via the link.

While it is mandatory for plants to disclose their toxic releases, TRI data could be subject to self-reported bias. Recent research, however, suggests that such bias is idiosyncratic and likely to be negligible on average (Brehm and Hamilton, 1996, EPA, 1998, De Marchi and Hamilton, 2006, Akey and Appel, 2021). Moreover, truthful reports of high emissions are not automatically penalized (Greenstone, 2003). Indeed, the EPA's policy on "Incentives for Self-Policing: Discovery, Disclosure, Correction and Prevention of Violations" is designed to encourage plants to voluntarily disclose violations, allowing violators to avoid up to 100% of severity-based penalties and criminal prosecution if they are cooperative and their disclosure meets the conditions under the policy.[21] In contrast, plants that misreport their emissions can face civil penalties or criminal charges (Greenstone, 2003, Xu and Kim, 2021).

While high emissions are not automatically penalized, it does not necessarily imply that plants do not have to reduce emissions. Blundell, Gowrisankaran, and Langer (2020) document that, once the EPA uncovers a violation, it will place the plant under a "violator" status, which subjects the plant to additional inspections, potentially uncovering more violations and fines. Plants will only return to compliance status once those violations have been resolved. Thus, the cost to the plant of being a violator comes not only from the investment cost required to resolve outstanding violations, but also from an increased level of regulatory oversight. Given these potential costs, plants have an incentive to reduce toxic releases if they wish to avoid being labelled a violator.

Plants may also reduce toxic releases due to pressure from local stakeholders. As we will show in later sections, SRMFs that are located in the area and are in a position to be aware of a local plant's violation can exert pressure on the nearby plants of firms they have ownership positions in to reduce toxic releases. Moreover, because plants in the same product market tend to release similar harmful chemicals (as shown in Appendix Table B2), an enforcement action against a plant could lead the EPA to scrutinize close peer plants in the area, making it riskier for these plants to maintain the existing level of

[21] Information on EPA's audit policy is available via the link.

harmful chemical releases. Taken together, it is plausible that enforcement actions against nearby peer plants can cause firms to respond by reducing emissions.

2.2. *EPA Air Quality Index Data*

To formally address the concern that TRI data are self-reported, our sensitivity analysis uses air quality index obtained from the EPA's Air Quality System (AQS) database. The EPA calculates daily air quality indexes based on five major air pollutants: ozone, carbon monoxide, nitrogen dioxide, sulfur dioxide, and fine particulate matter smaller than 2.5 micrometers. The daily aggregate air quality index is then calculated as the average of these five daily individual indexes. The EPA measures air quality using thousands of independent monitoring stations located throughout the U.S. and thus, it is arguably an objective estimate of the pollution level. A disadvantage of this measure, however, is that it could be noisy, since air quality could be affected by the local weather or the activities of close plants.

To measure the air quality index at a plant's location, we compute the average of the daily aggregate air quality index across all monitoring stations located within one-mile radius from the plant. For a given plant, we construct an annual measure of air quality (*AQI*), which is calculated as the average of daily *AQI* over a year. A high *AQI* indicates a higher emissions level.

2.3. *Plant Data*

We obtain information on plants of U.S. public firms from the NETS database between 1990 and 2015, which is supplied by Dun and Bradstreet (D&B) and is maintained by Walls and Associates. An important feature of the NETS database is that it does not suffer from survivorship bias (Addoum, Ng, and Ortiz-Bobea, 2020). Each plant is given a unique identifier (DUNS number), which does not change even when the plant changes its location. Therefore, it allows us to trace a plant's locations throughout its entire life. We obtain the plant's historical location information (FIPS code, state, county, and longitude and latitude coordinates) and its parent company names from

NETS. We then match parent companies in the NETS database with firms in Compustat and the Center for Research in Security Prices (CRSP) by their historical legal names, supplemented with careful manual checking. We merge plant toxic emissions data from TRI with plant historical locations from NETS using a TRI linking table obtained from the EPA, which provides links between DUNS number and TRI plant identifier. For TRI plants that do not have a DUNS number, we manually match them with plants in NETS using the plant identifying information such as location, name, and parent firm name.

The NETS database has become increasingly popular in finance research (Addoum, Ng, and Ortiz-Bobea, 2020; Barrot and Nanda, 2020; Akey and Appel, 2021). Neumark, Wall, and Zhang (2011) find that the correlations between NETS and Current Employment Statistics (CES) and Quarterly Census of Employment and Wages (QCEW) are 0.99 and 0.95 at the county-by-industry level, respectively. Barrot and Nanda (2020) note that business entities are required to register with Dun & Bradstreet (who supplies the source data to NETS) and obtain a DUNS number if they wish to bid for government contracts. The NETS database and the Census database generally have differences regarding information on sales and the number of employees, rather than plant locations. Moreover, these differences are more pronounced for private firms, rather than publicly-listed firms.

2.4. EPA Enforcement Actions Data

We obtain data on all enforcement actions from the EPA's Integrated Compliance Information System (ICIS), which contains civil, judicial, and administrative federal EPA enforcement cases. ICIS provides historical records of all enforcement actions taken by the U.S. EPA under the following environmental statutes: the Clean Air Act (CAA), the Clean Water Act (CWA), the Resource Conservation and Recovery Act (RCRA), the Emergency Planning and Community Right-to-Know Act (EPCRA) Section 313, the Toxic Substances Control Act (TSCA), the Federal Insecticide, Fungicide, and Rodenticide Act (FIFRA), the Comprehensive Environmental Response, Compensation, and Liability Act

(CERCLA or Superfund), the Safe Drinking Water Act (SDWA), and the Marine Protection, Research, and Sanctuaries Act (MPRSA).

We collect all formal EPA enforcement cases with a conclusion (i.e. final decision). For each enforcement case, we obtain information on the case unique identifier, milestone dates (from initiation to conclusion), plants charged in the case, and the amount of penalties (i.e. the state/local penalties, the total compliance costs, and the federal cost recovery amounts). We match these enforcement cases to plants in NETS/TRI using the TRI linking table provided by the EPA. We identify a plant as violator if the EPA takes an enforcement action against it in a given year.

2.5. *Text-based Network Industry Classifications and Peer Firms*

To identify a firm's competing peers in the same product market, we employ Hoberg and Phillips Text-based Network Industry Classifications (TNIC) which are based on firm pairwise similarity scores from a textual analysis of product descriptions in firm 10-K annual filings. Based on the notion that firms operating in the same product market use many similar words to describe their products, this industry classification method provides firm-by-firm pairwise word similarity scores in a given year and then identifies competing peers of each firm using the similarity scores. Since firms update their 10-K filings on an annual basis, TNIC is time-varying and is updated as firms change their products. This is one of the major features that distinguishes TNIC from the traditional industry classifications, such as SIC and NAICS, which do not reflect in a timely manner when firms change their products over time (Hoberg and Phillips, 2016). Since our hypothesis concerns peer firms in the same product market, TNIC is more suitable for our empirical analysis.

We obtain TNIC data from the Hoberg-Phillips Data Library and use the TNIC3 classification to identify a firm's direct competing peers.[22] TNIC3 requires peer firms to have pairwise similarity scores with a given firm to be above a certain threshold, which

[22] The data are available at http://hobergphillips.tuck.dartmouth.edu/. We thank the authors for making their data available.

is calibrated to approximate three-digit SIC codes (Hoberg and Phillips, 2010, 2016). We also employ the TNIC2 classification, which is constructed to match the level of the coarseness of the two-digit SIC classification. Given the low similarity between firms in the same TNIC2 product market, firm pairs identified as the same TNIC2 but different TNIC3 product markets are deemed to be non-peers. Only firm pairs operating in the same TNIC3 product market are identified as competing peers.

2.6. *Sample and Summary Statistics*

After combining TRI data, NETS data, enforcement actions data, and TNIC data, for each plant, we identify its nearby TNIC3-peer plants that are located within a radius of 100 miles. In a given year, we identify a plant as a treated plant if the EPA takes an enforcement action against any of its nearby (i.e., within 100 miles) peer plants during the year. Since a treated plant's own environmental violation can confound the effect of its peer's violation, we remove plant-year observations if in the event year and the three years after the enforcement action, the EPA takes enforcement action against the treated plant itself. To construct a control group of plants whose products are reasonably related to those of the treated plant and the violating peer plant, we drop plants of firms that are not in the same TNIC2 product market. We also require plants to have available toxic releases information, location data, and non-missing firm control variables. After constructing cohorts of treated and control plants for the stacked difference-in-differences (DiD) framework, we obtain our final sample which contains 158,211 plant-year observations between 1990 and 2015. Section 3.1 describes the construction of the stacked DiD cohorts.

Table 1 Panel A reports the summary statistics of the key variables used in the baseline analysis. *Toxic* has a mean of 0 and a standard deviation of 1 as the measure is standardized using the industry mean and standard deviation. An average firm in our sample has a market capitalization of $2.54 billion, a *Book-to-Market* ratio of 0.49, a *Return on Assets* ratio of 0.14, *Ln(Sale)* of 8.08, and a *Leverage* ratio of 0.20.

[Insert Table 1 About Here]

3. Empirical Results

Our analysis focuses on non-target plants defined as those that do not experience an EPA enforcement action over the past three years. The first hypothesis we examine in this study is that, in the presence of compliance slack, non-target plants respond to an EPA enforcement action against a nearby TNIC3-peer plant by reducing harmful toxic releases. To motivate the use of Hoberg and Phillips TNIC3 classification, in Appendix Table B2, we examine whether plant pairs operating in the same TNIC3 product market release similar chemicals that are harmful to human health. Using a plant-pair level measure of correlations of toxic releases between TNIC plant-pairs and a firm-pair level measure of technological proximity between TNIC firm-pairs, we find that these correlations are stronger among TNIC3 peers than non-TNIC3 peers (including those peers in the same TNIC2 but outside TNIC3 classification). These results suggest that TNIC3 reasonably reflects the similarity of harmful toxic releases as well as the similarity of technology between peer firms.

3.1. Non-Target Plants' Responses to Nearby Enforcement Actions

Having shown that peer plants in the same TNIC3 tend to release similar harmful chemicals than non-peer plants, we now examine whether non-target plants reduce their toxic releases after the EPA takes an enforcement action against a peer plant in close proximity. We argue that following an enforcement action against a peer plant, nearby plants from the same industry may anticipate being under increased regulatory scrutiny (we show in Section 4.1 that inspections indeed become more frequent for local plants). As a result, they will step up compliance and toxic emissions will decrease. The reasons why the threat of inspections can lower emissions are twofold. First, penalties could be lower if emissions are not excessive. Second, the plant could be in violation of EPA guidelines, and invest in abatement measures that make them more compliant and at the same time lower emissions.[23] In Appendix A, we outline a model which generates this and some of the other testable implications that follow from this setting.

Specifically, we use the stacked difference-in-differences (DiD) framework to compare changes in toxic releases of treated plants and control plants around the time of EPA enforcement actions. Following Gormley and Matsa (2011), for each year that has enforcement actions, we construct a sample (cohort) of treated plants and control plants using plant-year observations for the three years before and the three years after an enforcement event. We remove the event year from the sample. Treated plants are those that are not targeted by the EPA but are located within 100-mile radius of a violating TNIC3-peer plant.[24] Control plants include other plants of the same parent firm as a treated plant but located outside 100 miles radius of the violating peer plant (irrespective of their proximity to treated plants), plants of other TNIC3-peer firms located outside 100-mile radius of the violating peer plant, and plants of firms that are outside TNIC3 but in the same TNIC2 product market as treated plants (irrespective of their proximity to the target plant). We remove plants of firms that are outside the TNIC2 network of a treated plant's parent firm. To avoid any contamination of our control group, we require that control plants in each cohort have not been treated in a past cohort and will not become treated in the six years after an enforcement event (Baker, Larcker, and Wang, 2021). This procedure results in a total of 20 cohorts over our sample period, each representing a year that has enforcement actions.[25] In Table 1 Panel B, we report the number of treated plants and the number of control plants in each event year (cohort).

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[23] In Section 4.5, we provide evidence that plants step up investment in abatement measures.

[24] Our results are not affected if we include or exclude treated plants that become treated again (i.e. being close to another enforcement action against a violating peer plant) during the post-event window.

[25] While the identification of treated plants and control plants is based on proximity to an enforcement event, following Gormley and Matsa (2011) we pool all events in the same event year as one cohort. This approach also accounts for cases where a plant can be close to multiple violating peer plants in a given year. The first cohort is in 1993 (three years after the beginning of our sample) because the pre-event window uses plant-year observations in the three years before each event. Similarly, the last cohort is in 2012 (not 2015) because the post-event window uses plant-year observations in the three years after each event.

On average, a cohort contains 313 treated plants and 2,206 control plants. We stack these cohorts across all years and estimate the following plant-year panel regression:

$$Toxic_{p,c,t} = \beta_0 + \beta_1\, Post\ ClosePeerEA_{p,c,t} + \varphi + \tau + \mu + \varepsilon_{p,c,t} \qquad (1)$$

where $Toxic_{p,c,t}$ is the total on-site harmful chemical releases of (non-target) treated plant p of cohort c standardized to have zero mean and unit standard deviation using the industry mean and standard deviation in each year t. *Post ClosePeerEA* is a dummy variable that is equal to 1 for treated plant-year observations in the three years after the EPA takes an enforcement action against a peer plant located in close proximity and 0 otherwise.[26] φ, τ, and μ are vectors for the plant × cohort, year × cohort, and county × cohort fixed effects , respectively.[27] Following Gormley and Matsa (2011, 2016), we do not include control variables in this baseline regression to avoid the issues of bad controls that potentially bias the estimate of β_1 (Angrist and Pischke, 2009). Nevertheless, we confirm that none of our conclusions change when we include standard control variables such as size, book-to-market, return on assets, sales, and leverage. It is also useful to note that our stacked DiD approach differs from the traditional generalized DiD method in which estimation bias may arise as the control group comprises of previously treated plants (Goodman-Bacon, 2021; Sun and Abraham, 2021). As shown in recent studies (Gormley and Matsa, 2011, 2016; Baker, Larcker, and Wang, 2021; Goodman-Bacon, 2021), the stacked DiD method is superior to the generalized DiD approach because the construction of each cohort removes all control plants that were already treated in the past cohorts. Nevertheless, we also confirm that all of our results continue to hold when

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[26] For each enforcement action, we use the year of case conclusion as event year when the EPA finalizes the total penalty and the number of violations. We confirm that our findings do not qualitatively change when we use the initiation year of an enforcement action or when we require that the duration between conclusion date and initiation date is less than one year. These results are expected given that the median duration between initiation and conclusion dates is 29 days.

[27] County × cohort fixed effects control for time-invariant unobservable characteristics of individual counties in each cohort. These fixed effects can be estimated together with plant × cohort fixed effects because plants may relocate. Since the NETS database is survivorship-bias free, it can identify those relocations (Addoum, Ng, and Ortiz-Bobea, 2020; Chen, Dasgupta, Huynh, and Xia, 2021; Huynh and Xia, 2021).

we use the generalized DiD approach, although the economic magnitudes of the estimated treatment effects are larger in the generalized DiD setting.

Table 2 presents the estimation results. Column 1 displays the regression specification with plant × cohort and year × cohort fixed effects, and the regression in Column 2 includes plant × cohort, year × cohort, and county × cohort fixed effects fixed effects. In both specifications, we do not include control variables. In Columns 3 and 4, we repeat the regressions in the first two columns but include a set of standard control variables, namely the natural logarithm of market capitalization, book-to-market ratios, return on asset, the natural logarithm of sales, and book leverage. In all specifications, the coefficients on *Post ClosePeerEA* are negative and statistically significant at the 1% level, suggesting that treated plants' toxic releases are lower following an EPA enforcement action against a nearby peer plant. The effect is also economically significant. For instance, as the dependent variable is standardized to have unit standard deviation, the coefficient on *Post ClosePeerEA* in Column 2 indicates that treated plants reduce harmful chemical releases by 0.026 unit after an environmental enforcement action against a nearby peer plant. This reduction is equivalent to drop in toxic releases from the 60th percentile level to the median level of the sample distribution.

[Insert Table 2 About Here]

Treated plant could have local knowledge of its peer's risk of enforcement action and thus, take precautionary action to avoid being the next target. In this case, we expect to observe that the difference in toxic releases between treated plants and control plants exists prior to the enforcement action. To examine this possibility, we repeat regression (1) but add two dummy variables, *Pre1 ClosePeerEA* and *Pre2 ClosePeerEA*, which, respectively, take a value of 1 for one year and two years before an enforcement action and zero otherwise (the third year before the enforcement action occurs thus serves as the baseline). Panel B of Table 2 reports the estimation results. None of the coefficients on these pre-event dummy variables are significant, whereas the coefficient on the post-event dummy variable, *Post ClosePeerEA*, remains negative and significant.

Figure 1 depicts the trends in the differences of toxic releases between treated and control plants over the [-3, 3] window of an enforcement action. Consistently, we observe that, in the pre-event years, the differences are stable and statistically insignificant, suggesting that there were no pre-trends. Following an enforcement action against a nearby peer plant, the differences between the two groups become negative and statistically significant.

[Insert Figure 1 About Here]

3.2. *Is the Reduction in Toxic Releases Driven by the Self-Reported Bias?*

Since emission levels are self-reported, there could be concern that treated plants under-report emissions in response to the enforcement action to avoid attracting the EPA's attention. However, as noted before, plants that misreport their emissions can face civil penalties or criminal charges (Greenstone, 2003; Xu and Kim, 2021). Moreover, in our context, an enforcement action against a peer firm could indicate that the EPA's attention has been shifted to the area, heightening the risk of scrutiny for other plants in close proximity. Thus, to the extent that compliance slack is widespread, these close plants could have stronger incentives to report correctly following a nearby enforcement action to avoid potential penalties for misreporting.

As an alternative estimate of pollution levels, we use air quality index (*AQI*) computed using data from monitoring stations located within one-mile radius from a plant. We repeat regression (1) but replace the dependent variable with average annual *AQI*. Appendix Table B3 reports the estimation results. We find that the coefficient on *Post ClosePeerEA* remains negative and statistically significant, suggesting that air quality index around a plant improves after the EPA takes an enforcement action against a nearby peer plant.[28]

[28] We confirm that our results are robust to using individual components of air quality indexes that are computed based on individual criteria pollutants, namely, ozone, particulate matter smaller than 2.5 micrometres, sulfur dioxide, carbon monoxide, and nitrogen.

3.3. *Decaying Effects of Enforcement Actions and Proximity to Peer Plant*

Our next analysis examines whether the spillover effects of enforcement actions depend on the proximity between a treated plant and the violating peer plant. We do so by re-estimating regression (1) but including two additional dummy variables for plant *p*, *Post PeerEA*$_{(100,\ 200)}$ and *Post PeerEA*$_{(>200)}$, which are equal to 1 for the three years after the EPA takes an enforcement action against its violating peer plant that is located between 100 miles and 200 miles and greater than 200 miles, respectively, and zero for plants that are located outside these distance ranges of an enforcement action and other control plants as defined in Equation (1). Appendix Table B4 displays the estimation results. We observe decaying effects of a peer enforcement action on a plant's toxic releases as its proximity to the violating peer plant increases. Specifically, the coefficient on our main variable, *Post ClosePeerEA*, remains negative and statistically significant at the 1% level, whereas the coefficient on *Post PeerEA*$_{(100,\ 200)}$ is smaller in magnitude and it becomes insignificant for *Post PeerEA*$_{(>200)}$.[29] This result is consistent with the notion that enforcement threat is local and its effect on plant emissions decreases with proximity.

3.4. *Severity of Peer Plants' Violations, Historical Exposure to Enforcement Actions, and Treated Plant's Response*

If the non-target plant is concerned about ex-ante regulatory threats coming from an enforcement action against a nearby peer plant, we expect that its response would be more pronounced when the peer's violation is more severe. To examine this prediction, we conduct two tests using two alternative proxies for the severity of the peer plant's violation. In the first test, we employ the total penalty given to nearby enforcement cases as a proxy for severity. The total penalty for each case is computed as the sum of state and/or local penalty, the total compliance costs (e.g. the dollar values of injunctive relief and the physical or nonphysical costs of returning the facility to compliance), and the cost

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[29] Formal statistical tests show that the differences in the coefficients between *Post ClosePeerEA* and *Post PeerEA*$_{(>200)}$ are statistically significant at the 1% level, while the differences in the coefficients between *Post ClosePeerEA* and *Post PeerEA*$_{(100,200)}$ are not significant at the conventional levels.

that the defendant agrees to undertake in settlement of an enforcement action to clean up the environment (if any). We then create a dummy variable, *HighCost*, that is equal to 1 if the total penalty is above the sample median and zero otherwise.

In the second test, we obtain data on the type of each violation from the EPA. There are approximately 220 types of violations ranging from violations of a specific environmental law to failures to comply with reporting requirements. Based on these violation charges, we create a dummy variable, *MajorViolation*, that is equal to 1 if an enforcement action involves major violations such as violation of an environmental law, violation of environmental safety standards, violation of chemical discharge permit, or illegal dumping of chemicals and zero for other violation types (e.g. failure to maintain records, failure to file reports, or refusal to allow inspection or sampling).

We then re-estimate regression (1) but include an additional interaction term between *Post ClosePeerEA* and either *HighCost* or *MajorViolation*. Results reported in Appendix Table B5 show that the coefficient on the interaction term between *Post ClosePeerEA* and the indicator of violation severity is negative and statistically significant, suggesting that a treated plant's reduction of toxic releases is more pronounced when the peer plant's violation is more severe. These results are consistent with the notion that a more serious violation by the target plant is likely to invite more intensive monitoring of the plant by the regulators, and hence the likelihood of nearby plants being inspected by the regulators is higher. As a result, nearby plants step up their compliance and emissions decrease further when the violation is of a more serious nature.

A plant's response to a nearby peer EPA enforcement action may be weaker if its local peer plants experienced EPA enforcement in the past. By contrast, a plant that is located in an area where its local peers have not experienced a recent enforcement action may respond more strongly, possibly because compliance slack is higher. In Appendix Table B6, we repeat the baseline regression in two samples: Group 1 contains treated plants whose close peers have not experienced any enforcement action over the past 5 years and Group 2 consists of treated plants that observe at least one EPA enforcement action taken against a local peer plant over the past 5 years. The regression for Group 1 shows that the coefficient on *Post ClosePeerEA* is -0.034, which is statistically significant at the 1% level, whereas the regression for Group 2 has the coefficient on *Post ClosePeerEA* of -0.012, which is significant at the 10% level. Consistent with the prediction of compliance slack, these results suggest that the spillover effects are more pronounced when the EPA was historically less active.[30]

4. Mechanisms

While non-target treated plants could be conscious of heightened regulatory risk, the extent to which they take actions to reduce emissions could be limited because changes to the production process are costly. In this section, we examine the roles of SRMFs and firm operational flexibility in explaining why plants have the incentive to reduce toxic releases and how they can plausibly do so.

First, a contemporary literature shows that SRIs have non-pecuniary motives when making investment decisions and they are willing to sacrifice returns for social impact (Baker, Bergstresser, Serafeim, and Wurgler, 2018; Hartzmark and Sussman, 2019; Barber, Morse, and Yasuda, 2021). Another strand of literature shows that SRIs engage with portfolio firms and improve their ESG performance (Dyck, Lins, Roth, and Wagner, 2019; Dimson, Karacaş, and Li, 2021). However, other studies find no causal evidence (Heath, Macciocchi, Michaely, and Ringgenberg, 2021), and some argue that SRIs engage in greenwashing (Liang, Sun, and Teo, 2021). In particular, U.S.-based SRIs, in comparison with SRIs from countries with higher social norms, are found to deviate from their stated pro-E&S positions (Gibson Brandon, Glossner, Krueger, Matos, and Steffen, 2021).

We investigate whether the local presence of an SRMF has a material impact on the emissions of investees' local treated plants following a nearby EPA enforcement action. We do not directly observe monitoring by SRMFs. However, we argue that if monitoring is an objective, SRMFs would prefer to invest in firms located in close proximity because it is easier and less costly for them to monitor local firms. In Appendix Table B7, we show

[30] By construction, treated plants do not experience an enforcement action themselves over the future 3 years.

that SRMFs' holdings of local firms with good environmental ratings are significantly larger than their holdings of distant firms with the same environmental profile. We, however, do not find a corresponding result for mutual funds that are not classified as socially responsible. These results suggest that local SRMFs have superior local knowledge about local plants' operating practice. Knowing that the treated plant and the peer violator have similar toxic releases, a nearby EPA enforcement action could prompt these local SRMFs to exert pressure on the parent firm (whose shares they hold) to cut toxic releases at the local treated plant.

Second, we contend that a firm's ability to respond to heightened local regulatory risk depends on its operational flexibility. Operational flexibility concerns a firm's ability to respond to shocks to business conditions by making functional changes in the production process, using substitute raw materials, or shifting production between manufacturing plants located in different counties (Slack, 1983; Gerwin, 1986; Kogut and Kulatilaka, 1994; Gu, Hackbarth, and Johnson, 2018). As such, we posit that operational flexibility is a plausible determinant of a firm's ability to respond to a nearby enforcement action against a violating peer plant. In what follows, we explore these two potential channels.[31]

4.1. The Impact of Close Socially Responsible Mutual Funds

Examining the role of SRMFs requires data obtained from three sources. First, we collect data on actively managed, open-ended U.S. equity mutual funds from CRSP Survivor-Bias-free Mutual Fund database. The information on fund locations is available starting from 2000. Second, for each fund in the CRSP dataset, we obtain its stock holdings from Thomson Reuters Mutual Fund Holdings database.[32] To ensure that fund managers have sufficient interests in a firm, we require that a fund holds at least 0.5% of the firm's total number of shares outstanding. We ensure that our results remain robust when we

[31] The model outlined in Appendix A spells out some details of these mechanisms.
[32] We eliminate index funds using CRSP-defined style indicators and fund names. We further exclude international funds, municipal bonds funds, and bond funds using Thomson objective code.

vary this threshold from 0.1% to 1%.[33] Last, for each firm in a fund portfolio, we collect data on its environmental scores from MSCI KLD ESG database, which provides evaluations of various aspects of environmental performance, such as the adoption of waste management and greater use of renewable energy (Engle, Giglio, Kelly, Lee, and Stroebel, 2020). Following prior research, we compute the environmental score, *EScore*, for each firm in a given year as the difference between environmental strengths and concerns.

We follow Hwang, Titman, and Wang (2018) and Cao, Titman, Zhan, and Zhang (2021) to identify socially responsible financial institutions. In each quarter, we sort funds in our sample into two groups, based on the average environmental score of firms in their portfolio holdings, where the top group contains institutions with a high average portfolio *EScore* and the bottom group consists of institutions with a low average portfolio *EScore*. Financial institutions in the top group are deemed socially responsible.[34] Note that we determine the SRMF designation using a fund's holdings as of the year before an EPA enforcement event. Thus, the identification of SRMFs is not affected by an investee's ex-post response to an enforcement action.

After combining the fund location information, the fund holdings of each parent firm, and the parent firm's plant locations, we create a dummy variable, *CloseSRMF*, which is equal to 1 if there is a socially responsible mutual fund, which holds shares in the parent firm to which a non-target treated plant belongs, located within 100 miles from the treated plant and within 100 miles from the violating peer plant. We then re-estimate regression (1) but include an additional interaction term between *Post ClosePeerEA* and *CloseSRMF*.

[33] This 0.5% threshold is equivalent to the 90th percentile value in our sample (the mean, median, the 25th percentile, and the 95th percentile are, respectively, 0.35%, 0.03%, 0.01%, and 1.16%, with a standard deviation of 2.92%). Note that these statistics are seemingly small because they are computed for a single fund's holding of a stock. When we aggregate all *SRMF* holdings in a stock, the average value is 5.1% of the total number of shares outstanding with a standard deviation of 7%.

[34] This method better reflects the true sustainability orientation of a fund, as compared to a fund's self-declared objectives. Chen, Cohen, and Gurun (2021) find that funds misclassify their styles into a different category than they should be if their actual holdings were used. MorningStar also uses fund holdings to classify funds as socially responsible (Hartzmark and Sussman, 2019). We confirm that our results are robust to alternative definitions of SRMF such as sorting funds into three or five groups based on *EScore* and identifying funds in the top group as socially responsible funds.

Columns 1 and 2 of Table 3 Panel A report the estimation results. We observe a negative and significant coefficient on *Post ClosePeerEA* × *CloseSRMF*, suggesting that treated plants, whose SRMFs are located in close proximity, reduce toxic releases more than other treated plants.

The local advantages of SRMFs imply that the impact of these funds depends on their proximity to the enforcement action (Coval and Moskowitz, 2001). To examine this prediction, for each treated plant, we create two dummy variables, $SRMF_{(100,\ 200)}$ and $SRMF_{(>200)}$, which are equal to 1 if the distance from both the treated plant and the violating peer plant to the nearest SRMF, which holds shares of the treated plant's parent firm, is between 100 miles and 200 miles, and greater than 200 miles, respectively. We then repeat the regressions in Columns 1 and 2 but include the interaction term between each of these dummy variables and *Post ClosePeerEA*. Columns 3 and 4 of Table 3 Panel A present the estimation results. We observe decaying effects of SRMF as the distance is larger. Specifically, in Column 4, the coefficient on *Post ClosePeerEA* × *CloseSRMF* is -0.030, which is statistically significant at the 1% level. The coefficient on *Post ClosePeerEA* × $SRMF_{(100,\ 200)}$ is -0.016 and the coefficient estimate on *Post ClosePeerEA* × $SRMF_{(>200)}$ is 0.007.[35] These results suggest that the influence of local SRMFs on treated plants is stronger than distant SRMFs.

[Insert Table 3 About Here]

Pre-Event Trends and Local SRMFs

To examine the differential emissions between treated plants that are close to an SRMF and other treated plants before enforcement actions, we interact each of the pre-event year dummy variables with *CloseSRMF*. In Panel B of Table 3, we find that the coefficients on these interaction terms are insignificant, suggesting that during the pre-event period, emissions between treated plants close to an SRMF and other treated plants

[35] Formal statistical tests for the differences in the coefficients between *Post ClosePeerEA* × *CloseSRMF* and *Post ClosePeerEA* × $SRMF_{(>200)}$ yield an *F*-statistic of 3.79 (*p*-value = 0.056) for Column 3 and an *F*-statistic of 4.10 (*p*-value = 0.047) for Column 4, which are both statistically significant. *F*-statistics for the differences in the coefficients between *Post ClosePeerEA* × *CloseSRMF* and *Post ClosePeerEA* × $SRMF_{(100,\ 200)}$ are 0.39 (*p*-value = 0.533) for Column 3 and 0.83 (*p*-value = 0.366) for Column 4.

do not differ from each other. The results indicate that signals about compliance slack are not precise enough for SRMFs to incur the monitoring costs when the regulatory threat is low; however, a nearby enforcement action elevates the regulatory risk and monitoring occurs. These insignificant pre-event trends are also consistent with findings documented in recent studies that ownership by socially responsible institutions does not, *on average*, affect a firm's environmental performance (Gibson Brandon, Glossner, Krueger, Matos, and Steffen, 2021; Heath, Macciocchi, Michaely, and Ringgenberg, 2021; Liang, Sun, and Teo, 2021). However, a nearby enforcement action can alert local SRMFs about compliance slack in the area, prompting them to elevate their monitoring of local treated plants.

The "Self-Reaction" Hypothesis

Another potential concern regarding the role of local SRMFs is that firms held by these institutions have good environmental performance and thus, these firms may choose to reduce emissions even in the absence of local SRMF influence. This is particularly an issue because our method to identify SRMFs is based on fund holdings of firms with good environmental performance. We call this the "self-reaction" hypothesis. This hypothesis predicts that toxic releases should be lower across all plants of the firm, not just at the plant in close proximity to the violating peer plant. As we show in the next section, at least for firms with high operational flexibility, toxic releases increase at distant plants that are located beyond the 100-mile from the enforcement action, suggesting that our results are unlikely to be driven by this alternative explanation.[36]

As an alternative approach to rule out the self-reaction hypothesis, we re-examine the effects of SRMFs using two samples of firms that are matched based on environmental scores (*EScore)*. To construct the first matched sample, for each treated plant that is located close to an SRMF (i.e. within 100 miles), we find a matched treated plant that is

[36] In untabulated analysis, we repeat this test using the total mutual fund ownership (i.e. aggregating both socially responsible and non-socially responsible institutions) and find that the effects are nonsignificant. We also confirm that our results are not driven by common owners of both treated firm and the violating peer firm.

located between 100 miles and 200 miles from its nearest SRMFs and whose parent firm has the same *EScore*. We remove treated plants that cannot be matched. We repeat this matching procedure based on parent firms' *EScore* to find a match between the matched treated plants located within 100-mile radius of an SRMF with treated plants located more than 200 miles from the nearest SRMFs. This matching procedure ensures that we compare the toxic releases between treated plants owned by firms with the same environment performance as judged by an independent rating agency, i.e. MSCI.[37] To construct the second alternative matched sample, in addition to the matching procedure for all the treated plants, we also find matched plants of control firms in the same TNIC2 network that have the same *EScore* as the treated firms. This matching procedure further ensures that we not only compare the toxic releases among treated plants – whose parents have the same environmental performance – but also compare the toxic releases of treated plants with those of control plants owned by firms with the same environmental performance.

We re-estimate the regression of Table 3 Panel A using the matched samples and report the results in Table 3 Panel C. Consistent with the results shown in Table 3 Panel A, we observe that the effects of SRMFs on local treated plants' toxic emissions decay as proximity increases. In particular, the coefficient on *Post ClosePeerEA* × *CloseSRMF* remains negative and significant, suggesting that our results are unlikely to be explained by the self-reaction of firms with good environmental performance.

Another alternative but related hypothesis is that SRMFs invest in firms that do not have bona fide environmental motives, but these firms have the ability to engage in window-dressing activities in response to a nearby peer enforcement action. We term this

[37] For example, if a treated plant P1 that is located within 100-mile radius of an SRMF and whose parent Firm 1's *EScore* is equal to 2 can be matched to a treated plant P2 (located within [100miles, 200 miles] from its nearest SRMF), whose parent Firm 2's *EScore* is also equal to 2, and a treated plant P3 (located more than 200 miles from its nearest SRMF), whose parent Firm 3's *EScore* is also 2, then we keep all the three plants P1, P2, and P3 in the treated group. If another treated plant B1 (with a close SRMF), whose parent firm has an *EScore* of 3, can be matched to a treated plant B2 whose parent firm has an *EScore* equal to 3 (but located between [100, 200] miles from the nearest SRMF) as well as a treated plant B3 whose parent firm has an *EScore* equal to 3 (but located more than 200 miles from the nearest SRMF), then we also keep all of these treated plants B1, B2, and B3.

the window-dressing hypothesis. Several results from our channel tests presented in the next sections suggest that the window-dressing hypothesis is unlikely to be the explanation. We elaborate on this issue in Section 4.6.

EPA Inspections and Local SRMFs

One of the main premises of our arguments is that the nearby peer plants face higher risk of inspection following an enforcement action. We now provide evidence in support of this premise. We also show that the additional emission reduction that we attribute to the local SRMFs is not driven by the possibility that the EPA inspects treated plants located close to an SRFM more frequently than other treated plants (recall that the emission reductions of treated plants located close to an SRMF are twice as large as those treated plants that are not close to an SRMF).

We obtain data on inspections conducted by the EPA or local authorities from EPA's ICIS database. We then estimate the stacked DiD regression of Table 3 Panel A but replace the dependent variable with *Ln(Inspections)*, which is the natural logarithm of one plus the number of inspections of a plant in a given year. Appendix Table B8 reports the estimation results. We find that the coefficient on *Post ClosePeerEA* is positive and statistically significant. This result indicates that, following a nearby enforcement action against a peer plant, treated plants indeed experience an increase in the frequency of inspections by either the EPA or local authorities. This result supports our hypothesis that the nearby peer plants face higher risk of inspection following an enforcement action. However, the coefficient on *Post ClosePeerEA* × *CloseSRMF* is small and statistically insignificant, suggesting that there is no difference in inspection frequency between treated plants close to an SRMF and other treated plants. As such, our findings in Table 3 Panel A are unlikely to be driven by more frequent inspections for treated plants that are located close to an SRMF.

4.2. The Role of Firm Operational Flexibility

In the literature, different measures are typically used to capture various dimensions of operational flexibility. We use three alternative proxies for operational flexibility. As firms with high inventory levels have higher ability to weather shocks to production, our first measure is the firm inventory level. For the second proxy, we follow prior research (Fischer, Heinkel, and Zechner, 1989; Gu, Hackbarth, and Johnson, 2018) and measure firm operational inflexibility as the historical range (maximum minus minimum) of operating costs-to-sales ratio, scaled by the volatility of the firm's sales growth. Firms with less flexible operations will require larger variation in sales relative to operating costs to alter it's the scale of operations, and therefore, will have a larger range. Our last proxy for operational flexibility is the number of plants a firm has in its operations. Intuitively, firms with more plants operating throughout the U.S. have higher ability to adjust production of one plant by, for example, shifting some of the production to other plants.

We split the sample into two groups based on the median of each operational flexibility measure calculated in each enforcement event year.[38] We then estimate regression (1) using each subsample and report the results in Table 4 Panel A. Consistent across all measures, we find that the effects of a nearby enforcement action on local non-target plants are insignificant in the subsample of plants whose parent firms have low operational flexibility. In contrast, these effects are negative and significant in the subsample of parent firms with high operational flexibility (i.e. those with high inventory, low operating inflexibility, and more plants). These results are consistent with the prediction that operational flexibility is an important determinant of a firm's ability to reduce toxic releases at a local plant when it faces heightened regulatory risk.

In Table 4 Panel B, we examine the joint effects of local SRMF and operational flexibility on the toxic releases of local non-target treated plants. We find that the coefficient on *Post ClosePeerEA* × *CloseSRMF* is negative and significant among plants whose parent firms have high operational flexibility. For parent firms with low flexibility, while the coefficient is negative in all regressions, it is statistically insignificant and smaller in magnitude. These results suggest that both local SRMF and operational

[38] Our results remain robust when we use a firm's operational flexibility measured in year *t*-1 and partition plants based on the sample median value.

flexibility are important factors that affect a plant's response to a nearby enforcement action.

[Insert Table 4 About Here]

4.3. *How Do Firms Respond to Nearby Enforcement Actions?*

We next look inside the parent firm and examine how it reduces emissions at the local treated plant. Reducing toxic releases at the treated plant may require both investment in costly abatement measures as well as cutting down on production at the plant. We provide evidence of investment in abatement in Section 4.5 below. To reduce production at the local plant and still meet current demand, we conjecture that firms with high inventory levels would tap into their inventory. As such, we expect that these firms' inventory levels will decrease following an enforcement action against a peer firm. Another tactic a firm could use to reduce its exposure to the local regulatory threat is to shift emissions to plants located in other regions—an approach that is aided by the firm's operational flexibility. We therefore posit that, for firms with high operational flexibility, toxic releases are higher at plants that are remote from violating peer plant. We test these predictions below.

4.3.1. *Effect of Peer Enforcement Action on Non-Target Firm Inventory*

To examine firm inventory changes following an enforcement action against a peer plant, we construct a stacked DiD sample at the firm level. For each event year, we construct a cohort of treated firms and control firms using firm-year observations during the [-3, 3] window around an EPA enforcement event action against a nearby peer plant. We identify treated firms as those that have at least one plant located within 100 miles from a violating TNIC3-peer plant. Control firms are those that operate in the same TNIC2 product market as the treated firm and do not have plants located within 100 miles from the violating peer plant. We also require that control firms do not have plants treated in past cohorts and will not have plants treated in the next 6 years. We then pool all cohorts across years and estimate the following firm-level regression:

$$\Delta Inventory_{i,c,t} = \beta_0 + \beta_1\ Post\ Treatfirm_{i,c,t} + \varphi + \tau + \varepsilon_{i,c,t} \qquad (2)$$

Where $\Delta Inventory_{i,c,t}$ is the change of inventory levels from year t-1 to year t+1 calculated as $Ln(Inventory)_{i,c,t+1} - Ln(Inventory)_{i,c,t-1}$, for firm i of cohort *c*. *Post Treatfirm* is a dummy variable that is equal to 1 for treated firms in the three years after the EPA takes an enforcement action against a violating peer firm and 0 otherwise. φ and τ are vectors for firm × cohort and year × cohort fixed effects, respectively. We compute standard errors clustered at the firm and year level.

Table 5 presents the estimation results. In Columns 1 and 2, the sample is divided into high- and low-inventory groups based on the median value of inventory level measured in year t-1. In Columns 3 and 4, the sample is divided into high- and low-inventory groups based on the median value of inventory level measured in year t-2. Regardless of how we split the sample, we observe that the coefficient on *Post Treatfirm* is negative and significant in the subsample of high-inventory firms, whereas it is positive but insignificant in the low-inventory group.[39] These results are consistent with the prediction that high-inventory firms use up their inventory at a faster rate after observing an enforcement action against a peer firm than during normal periods

[Insert Table 5 About Here]

4.3.2. The Transfer of Toxic Releases, Operational Flexibility, and Local SRMFs

We next examine whether firms shift toxic releases from treated plants, which are located close to an enforcement action, to distant plants (which would involve reallocating production from the local to the distant plants). We do so by constructing a stacked DiD sample of distant plants only (i.e. we remove treated plants located within 100 miles of the violating peer plant) as follows. First, we identify a treated firm that owns

[39] A potential concern is that our results could be driven by the mean reversion of inventory levels. In untabulated analysis, we control for this effect using the lagged value of inventory levels in these regressions and find similar results. Moreover, mean reversion should affect both the high- and low-inventory subsample, whereby inventory in the high subsample becomes lower and that in the low subsample becomes higher. We, however, find that the effects are not statistically significant in the low-inventory subsample, suggesting that mean reversion is unlikely to bias our results.

at least one treated plant located within 100 miles of a violating peer plant and also owns distant plants located outside the 100-mile radius. Second, for each event year, we construct a cohort of treated distant plants and control plants. Treated distant plants are those that belong to treated firms. Control plants are those that belong to other TNIC3-peer firms (which do not own any treated plants) or those that belong to firms operating outside TNIC3 but in the same TNIC2 product market as the treated firms. We also require that control plants' parent firms do not have treated plants in a past event and will not have treated plants in the next 6 years. We then estimate the following plant-level regression:

$$Toxic_{p,c,t} = \beta_1 \, Post\ TreatDistant_{p,c,t} + \varphi + \tau + \mu + \varepsilon_{p,c,t} \qquad (3)$$

where *Post TreatDistant* is equal to 1 for treated distant plants in the three years after the EPA takes an enforcement action against a violating peer plant and zero otherwise. φ, τ, and μ are defined in regression (1).

We report the estimation results for regression (3) in Table 6 Panel A. The coefficient on *Post TreatDistant* is positive but statistically insignificant, indicating that, on average, there is no association between an enforcement action against a peer plant and toxic releases at the distant plants of a typical treated firm.

[Insert Table 6 About Here]

The picture, however, changes when we focus on firms with high operational flexibility. In Table 6 Panel B, we estimate regression (3) using subsamples that are split based on the median of each operational flexibility measure calculated at the time of enforcement event. We find that the coefficient on *Post TreatDistant* is positive and significant in the subsample of high-flexibility firms (i.e. those with high inventory, low inflexibility, and more plants), whereas it is insignificant in the group of low-flexibility firms. These results suggest that, for treated firms with high operational flexibility, toxic releases at distant plants are significantly higher following an enforcement action against a local peer plant. They are also consistent with the notion that operational flexibility enables firms to shift emissions from the local plant to plants in other regions, thereby reducing the local plant's exposure to local regulatory risk. Given that treated firms shift emissions to distant plants, one may ask whether the net emissions at the aggregate firm level are lower. We will visit this question in Section 4.9 after we discuss the long-run emissions at the treated plant level.

In Table 6 Panel C, we examine whether such transfer of emissions occurs in the presence of local SRMF. We find that, while the coefficient on *Post TreatDistant* remains positive, the coefficient on *Post TreatDistant* × *CloseSRMF* is negative and statistically significant in the subsamples of firms with high operationally flexibility. For example, when we measure operational flexibility with the number of plants, the coefficient on *Post TreatDistant* × *CloseSRMF* is -0.038 (*t*-statistics = -3.62), which is larger than the coefficient on *Post TreatDistant* of 0.035 (*t*-statistics = 1.92). These results suggest that parent firms do not shift emissions to distant plants when local SRMFs are located close to the treated plants. A possible reason for this could be that when there is a local SRMF owning the parent firm, the treated firm invests more in abatement measures, making it possible to maintain local production without transferring it to distant plants.

A plant in TRI is also required to report the amounts of chemicals that are transferred to an off-site facility for treatment before releasing to the environment. In Appendix Table B9 we examine whether treated plants change their off-site toxic releases as reported in TRI following a nearby enforcement action against peer plants.[40] We do so by replacing the dependent variable in regression (1) with standardized off-site releases of harmful chemicals. We find that treated plants' off-site toxic releases do not change after observing a nearby enforcement action. This result is expected if investing in an off-site waste treatment facility is time-consuming and costly or if treated plants are aware that a potential EPA scrutiny is likely to be thorough. Thus, plants cannot simply avoid it by changing the way they disclose toxic releases because these off-site releases are still tied to the local treated plants. Flexible plants could, however, have the ability to shift production to regions where the local EPA region is not specialized in their industries,

[40] TRI does not specify the locations of these off-site facilities.

thereby helping them to release more harmful chemicals. We show this emissions transfer in the next section.

4.4. *Where Do Parent Firms Shift Emissions To?*

Given finite resources, one of the enforcement approaches adopted by the EPA is to allow each regional office to concentrate resources in industries that pose the greatest risk to the environment (Gunningham, 2011). Thus, plants of certain industries in which an EPA regional office focuses its resources potentially face higher regulatory risk than other industries in the same region. To the extent that a parent firm is aware of an EPA region's concentration, we contend that, when the firm faces enhanced regulatory risk in one region, it could transfer emissions to other regions where the EPA regional office does not concentrate resources in that industry. To examine this conjecture, we estimate the following plant-level regression using a subsample of distant plants that are located outside the 100-mile radius of the violating peer plant.

$$
\begin{aligned}
Toxic_{p,c,t} = \beta_0 + \beta_1\, Post\ TreatDistant_{p,c,t} \times OutsideTop3_{pc,,t} + \\
\beta_2\, Post\ TreatDistant_{p,c,t} + \varphi + \tau + \mu + \varepsilon_{p,c,t}, \qquad (4)
\end{aligned}
$$

where *OutsideTop3* is a dummy variable that is equal to 1 if the distant plant's industry is *not* one of the EPA regional office's Top 3 industries by enforcement actions and zero if it is the same. We identify an EPA region's Top 3 industries by first ranking industries in the region based on the number of enforcement actions against firms in each industry over the past 3 or the past 5 years. We then select the Top 3 industries with the highest number of enforcement actions. Other variables are defined as in regression (3). As an alternative definition of EPA regional office's concentration, we also replace Top 3 industries with Top 5 industries.

Table 7 reports the estimation results. We find that the coefficients on *Post TreatDistant* × *OutsideTop3* and *Post TreatDistant* × *OutsideTop5* are positive and statistically significant, while the coefficient on *Post TreatDistant* is insignificant. These results suggest that the parent firm shifts emissions to distant plants where the EPA regional office in charge does not concentrate in its industry.

[Insert Table 7 About Here]

4.5. Pollution Abatement, Local SRMFs, and Operational flexibility

The previous section shows that flexible firms shift emissions to distant plants to reduce exposure to heightened regulatory risk in the area. To provide evidence that the emission reductions at the local plants are not entirely achieved at the expense of transferring emissions to distant plants when SRMFs are located near these plants, we conduct a number of tests. First, in this section, we show that treated plants with close SRMFs invest in abatement measures following nearby enforcement. In sections 4.6-4.8, we further provide results, which together suggest that, while the transfers are presumably motivated to reduce the immediate regulatory risk at the local plant, the enforcement action triggers enhanced scrutiny and engagement by the local SRMFs. Finally, we show in Section 4.9 that aggregate firm-level emissions decrease for the treated firms, further suggesting that these transfers do not entirely offset local emission reductions in the presence of SRMFs.

We measure abatement activities at the plant level using data from the EPA's Pollution Prevention (P2) database. As part of the TRI reporting process, plants are required to report any activities undertaken to limit the amount of harmful chemicals released to the environment. Following Akey and Appel (2021), we classify these activities into two categories: improvements on production process and changes in operating practices. Process improvements entail activities such as optimizing chemical reaction conditions, modifying equipment, and other process modifications. Good operating practices involve activities such as improving maintenance scheduling, record keeping, and quality control.[41]

[41] According to the EPA, an example of a process modification is when a chemical manufacturing facility replaced equipment identified during the Leak Detection and Repair (LDAR) program as contributing to leaks and fugitive emissions of methanol. An example of operating practice is when a coating manufacturer

In Table 8 Panel A, we examine whether the presence of a local SRMF is associated with changes in abatement activities at local treated plants following a nearby peer's enforcement action. In the regression of Column 1, the dependent variable is *Process*, which is a dummy variable indicating abatement related to process improvement, and the dependent variable of the regression reported in Column 2 is *Practice*, which is an indicator for abatement related to operating practices. We find that the coefficient on the interaction term between *Post ClosePeerEA*× *CloseSRMF* is positive and statistically significant at the 1% level in Column 1, while this coefficient is insignificant in Column 2. Consistent with the monitoring role of local SRMFs, these results suggest that treated plants with a close SRMF are more likely to engage in abatement activities related to the production process, rather than mere changes in operating practices, after observing a nearby enforcement action against a peer plant.

[Insert Table 8 About Here]

In Table 8 Panel B, we repeat the regression of Column 1 Panel A using subsamples that are split based on the median value of each operational flexibility measure. We find that the influence of SRMFs on abatement investment is concentrated among firms with high operational flexibility. This result may appear counterintuitive since the flexible firms would appear to have a way to reduce their exposure to local regulatory threats by transferring emissions to distant plants, which might make investment in abatement less urgent. However, if local SRMFs do not have the capacity to monitor distant plants, which might be vulnerable to future scrutiny by the regulators, then they can insist on abatement measures at the local plant.[42]

In untabulated analysis, we repeat Table 8 Panel B using *Practice* as the dependent variable and find that none of the coefficients in the subsamples of operating flexibility measures is significant. These results are consistent with our conclusions in Table 8 Panel

implemented production scheduling rules to minimize changeovers between products and cleaning of equipment, reducing usage of xylenes. See EPA website for more examples.

[42] In the next section, we provide evidence consistent with the idea that the additional monitoring of the local plant generates firm-specific information about compliance to the local SRMF. When the local firm is non-complaint, the SRMF not only insists on immediate abatement measures at the local plant, but also at distant plants with some time lag.

A that SRMFs demand real abatement activities that help limit emissions rather than simple adjustments of operating practices.

4.6. *Discussion on the Role of Local Socially Responsible Institutions*

How do SRMFs influence their treated investee firms to be more environmentally friendly? Our results thus far suggest that SRMFs influence local treated plants to adopt abatement measures to mitigate emissions in the three years after a nearby peer enforcement action. To the extent that SRMFs are concerned about firm-level non-compliance and the environmental performance of portfolio firms—be it because they have sustainability motives or other reasons—we expect that they should engage with the treated investee firms to make abatement investments not only at the local treated plant but also at all plants. Yet abatement activities, by their nature, are costly and take several years to implement. It is thus plausible that SRMFs allow treated firms to invest in abatement measures in a staggered manner across the plants, starting with the local treated plant because it faces immediate regulatory threat.

To examine this conjecture, we repeat the regression of Table 8 Panel A but use a sample of distant plants only. Table 9 reports the estimation results. We find that in the three years after a nearby peer enforcement action, the presence of local SRMFs has insignificant effects on process-related abatement at treated firms' distant plants (Columns 1 and 2). However, when we examine the abatement activities at these distant plants during the period [4, 10] years after an enforcement action, we find that the presence of a close SRMF is associated with higher likelihood of implementing abatement measures related to production process, but not operating practice (Columns 3 and 4).[43] Consistent with our prediction, these results suggest that SRMF's strategy is to allow treated firms to respond to a nearby enforcement action by reducing emissions at local

[43] To avoid confounding effects of enforcement actions during the [4, 10] period, we remove from the sample distant plants that are close to an enforcement action against their peer plants during the [4, 10] period. We also remove the first three years after an EPA enforcement action for distant plants owned by treated firms.

treated plants in the short term, and then gradually implementing abatement measures to reduce emissions at other distant plants in the long term.

[Insert Table 9 About Here]

Alternative Hypotheses for the Role of SRMFs

As we have discussed in Section 4.1, there are two potential alternative hypotheses that could explain our results, i.e. the self-reaction hypothesis and the window-dressing hypothesis. The evidence from matched samples based on firm environmental performance reported in Section 4.1 suggests that the self-reaction of environmentally friendly firms is unlikely to confound our results. Here, we note several other results in our study that also help rule out the alternative hypotheses, particularly the window-dressing explanation. First, these alternative hypotheses predict that local treated plants will respond to a nearby peer enforcement action by reducing toxic emissions and this response is irrespective of their proximity to the nearest SRMF. But Section 3.3 shows that the reduction of toxic releases is lower as the proximity to the nearest SRMF decreases – a result that is inconsistent with both the self-reaction hypothesis and the window-dressing hypothesis. Second, window-dressing firms will reduce emissions at the local treated plants only but will not implement abatement measures at distant plants even in the long run. The fact that treated firms gradually invest in abatement across plants, not just the local treated plants, suggests that window-dressing is unlikely to be the explanation. Last, as we show in Section 4.8, local treated plants increase their emissions level again during the period from 4 years to 10 years after a nearby peer enforcement action. These long-run reversals are, however, prevented when local treated plants are located close to an SRMF. In Section 4.9, we show further that the effects of SRMFs on the long-run emissions at the aggregate firm level decay as proximity to the nearest SRMFs increases. These results are again inconsistent with the window-dressing hypothesis and the self-reaction hypothesis.

4.7. Non-Responding Firms and Changes in Holdings of SRMFs

The threat of exit is a potential mechanism through which socially responsible institutions incentivize firms to make real changes in their production to reduce toxic releases. Thus, our next analysis examines whether SRMFs sell a firm's shares if its plants do not reduce toxic releases following a nearby enforcement action.[44] Specifically, we estimate the following regression at the firm-fund-year level.

$$\Delta Weight_{i,f,t+1} = \beta_1 Treatfirm_{i,t} \times CloseSRMF_{i,f,t} \times NonRespond_{i,t} + \beta_2 Treatfirm_{i,t} \times NonRespond_{i,t} + \beta_3 Treatfirm_{i,t} \times CloseSRMF_{i,f,t} + \beta_4 Treatfirm_{i,t} + \gamma' Y_{f,t} + \varphi + \mu + \tau + \varepsilon_{i,f,t}, \quad (5)$$

where $\Delta Weight_{i,f,t+1}$ is the difference between stock i's weight in mutual fund f's portfolio in the first quarter of year t+1 and its weight in the first quarter of year t-1. $Treatfirm_{i,t}$ is a dummy variable that is equal to 1 if firm i has at least one plant located in close proximity to an EPA enforcement action against a violating peer plant in year t and zero otherwise. $CloseSRMF_{i,f,t}$ is a dummy variable that is equal to 1 if a socially responsible mutual fund f, which holds stock i, is located within 100 miles from the violating peer plant and firm i's treated plant and zero otherwise. $NonRespond_{i,t}$ is a dummy variable that is equal to 1 if firm i does not reduce toxic releases at its treated plants in the year after the enforcement action against a local peer plant and zero otherwise. $Y_{f,t}$ is a set of fund-level control variables (fund size, fund expense ratio, turnover ratio, fund returns, and fund flows). φ, μ, and τ represent fund fixed effects, firm/industry fixed effects, and year fixed effects, respectively.

We report the estimation results in Table 10. The coefficients β_1 and β_2 are both negative and statistically significant, suggesting that SRMFs reduce their holdings in non-responding firms after an enforcement action against a local plant, and these decreases in holdings are more pronounced among funds located in close proximity. The coefficient β_3 is positive, indicating that, compared to distant SRMFs, local SRMFs have a stronger

[44] As we show in the previous section, a plausible reason why these firms do not respond to a peer enforcement action is due to their operational inflexibility. Even for firms with high operational flexibility, however, compliance costs can outweigh the benefits of investing in abatement measures, as evidenced by their engagement in opportunistic tactics such as shifting emissions to distant plants.

preference for local firms that respond to a nearby enforcement action. We also observe a positive coefficient β_4, suggesting that distant SRMFs also increase their holdings in responding firms.[45] Taken together, these results support the notion that socially responsible institutions are willing to divest from firms that do not take actions to limit emissions in response to heightened regulatory risk, thereby acting as an external monitor that complements the EPA's role in a region.

[Insert Table 10 About Here]

4.8. Long-Run Toxic Releases at Local Non-Target Plants

We have shown in the previous sections that firms with high operational flexibility reduce toxic releases at local plants that face heightened regulatory risk by shifting emissions to distant plants. To the extent that local regulatory risk is transitory (e.g. the EPA's focus may shift to a different industry or a different area due to media attention or political influence), we conjecture that the parent firm could increase emissions at these treated plants again in the long run after the EPA activity becomes less active in the area. At the same time, the presence of SRMFs in the area could serve as a continuing monitoring role even when regulatory risk arising from a possible EPA spillover investigation subsides. Thus, we predict that the reversals of emissions in the long run could be prevented when there is a local SRMF in close proximity. To examine these predictions, we construct cohorts of treated and control plants using plant-year observations for the three years before and the [4, 10] years after each event year. We remove from the sample the first three years after each event as well as events where there are confounding enforcement actions during the [4, 10] period. We further require that control plants have not been treated in a past event and will not become treated in the next 10 years. We then estimate the following plant-level regression:

[45] In an untabulated analysis that examines the portfolio holdings of non-SRMFs, we do not find similar results. That is, non-SRMFs do not change their holdings in treated firms following a nearby enforcement action regardless of their proximity to the treated plants or whether the treated firms respond to the enforcement actions.

$$Toxic_{p,c,t} = \beta_0 + \beta_1\ Post\ ClosePeerEA[4,10]_{p,c,t} + \varphi + \tau + \varepsilon_{p,c,t}, \tag{6}$$

where $Post\ ClosePeerEA[4,10]_{p,c,t}$ is equal to 1 for treated plant p from years t+4 to t+10 and zero otherwise. All other variables are defined as in regression (1).

Table 11 Panel A reports the estimation results. We find that the coefficient on *Post ClosePeerEA[4, 10]* is positive and statistically significant at least at the 1% level, suggesting that emissions at treated plants increase again in the long run. The effect is also economically significant. For example, in Column 2 the coefficient estimate on *Post ClosePeerEA[4, 10]* is 0.028, which indicates that, in the long run, emissions at treated plants recover back 100% of the emissions reduction that occurred in the immediate three years after the enforcement action.[46] The coefficient on *Post ClosePeerEA[4, 10]* × *CloseSRMF* is -0.048, suggesting that treated plants that are located close to an SRMF do not revert their emissions, but rather they continue to reduce emissions in the long run.

[Insert Table 11 About Here]

The previous section also shows that SRMFs divest from non-responding firms that do not reduce toxic releases in light of heightened regulatory risk. Such divestment can also serve as a warning sign for other treated plants such that it deters these plants from increasing emissions in the long run. In Table 10 Panel B, we examine this prediction. In Column 1, we regress plant-level toxic releases on *Post ClosePeerEA[4, 10]* × *Local_NonRespond*, *Post ClosePeerEA[4, 10]*, and fixed effects, where *Local_NonRespond* is a dummy variable that is equal to 1 if the treated plant is located close to a non-responding plant and zero otherwise. We find that the coefficient on *Post ClosePeerEA[4, 10]* × *Local_NonRespond* is negative and significant, suggesting that long-run toxic releases at treated plants continue to be lower when there is a local non-responding plant, which did not reduce toxic releases even after observing a nearby enforcement action. In Column 2, we repeat this regression but additionally include the interaction term *Post ClosePeerEA[4, 10]* × *Local_NonRespond* × *$CloseSRMF_{NR}$*, where *$CloseSRMF_{NR}$* equals 1 if a local non-responding plant is located within 100 miles from an SRMF, which holds the shares of

[46] This is a comparison between the coefficient estimate on *Post ClosePeerEA[4, 10]* and the coefficient estimate on *Post ClosePeerEA* of 0.027 reported in Table 2 Column 1.

non-responding plant's parent firm, and 0 otherwise. Consistently, we find that the coefficient on this interaction term is negative and statistically significant at the 1% level, suggesting that long-run toxic releases at treated plants are lower when these plants are located close to a non-responding plant, which is, in turn, located close to its SRMFs. These results are again consistent with the disciplinary role of local socially responsible institutions: as SRMFs potentially sell shares of non-responding firms, such threat of exit helps keep the emissions level at local treated plants lower in the long run.

4.9. Firm-level Evidence

The plant-level results show that treated firms reduce toxic emissions at local treated plants, while transferring some of the emissions to distant plants. A natural question arises as to whether a treated firm's overall toxic emissions are lower after an enforcement action. To explore this question, we employ a firm-level stacked DiD setting similar to the one used in Section 4.3.1 in which a firm is considered treated firm if one of its plants is located close to a violating peer plant. We compute firm-level total emissions, *Firm Toxic,* by aggregating toxic releases across plants owned by a firm in a given year and use it as the dependent variable in the following firm-level regression:

$$
\begin{aligned}
Firm\,Toxic_{i,c,t} &= \beta_0 + \beta_1\, Post\,TreatFirm_{i,c,t} + \beta_2 Post\,TreatFirm_{i,c,t} \times CloseSRMF_{i,c,t} + \sigma_i \\
&\quad + \tau_t + \varepsilon_{i,c,t}, \qquad (7)
\end{aligned}
$$

where $Post\,TreatFirm_{i,c,t}$ is equal to 1 for treated firm-year observations in the three years after the EPA takes an enforcement action against the violating peer plant located within 100 miles of the treated firm's plants, and 0 otherwise. $CloseSRMF_{i,c,t}$ is equal to 1 if an SRMF, which holds the treated firm's stock, is located within 100 miles from one of the treated firm's treated plants and within 100 miles from the violating peer plants. σ_i and τ_t represent the vectors of firm × cohort and year × cohort fixed effects, respectively. We also examine the long-run toxic releases at the firm level over the period from t+4 to t+10 after events andreplace *Post TreatFirm* with *Post TreatFirm[4, 10]*.

Table 12 report the estimation results. Columns 1, 2, and 3 display the results for the short-run toxic releases. We find that the coefficients on *Post TreatFirm* and *Post TreatFirm* × *CloseSRMF* are negative and significant. These results suggest that the net toxic reductions at treated firms are lower and the effects are stronger when treated firms have a close SRMF. These reductions, however, revert back during the [4, 10] period after an enforcement action as evidenced by the positive coefficient on *Post TreatFirm[4, 10]* in Column 3. Column 4 shows that the coefficient on *Post TreatFirm[4, 10]* × *CloseSRMF* is −0.086, while the coefficient on *Post TreatFirm[4, 10]* is 0.048. Consistent with the plant-level results, the presence of an SRMF in close proximity also helps prevent the emissions reversals at the firm level.

[Insert Table 12 About Here]

To complete our analysis, we repeat the firm-level regression using subsamples split based on the median value of each operational flexibility measure. Consistently, the results reported in Appendix Table B10 show that the effects are concentrated among firms with high operational flexibility.

5. Conclusion

In this study, we examine whether and how local SRMFs complement the EPA in monitoring local plants' environmental behavior. We exploit a unique setting in which the EPA first takes an enforcement action against a peer firm, which alerts other local firms operating in the same product market as well as local SRMFs about heightened environmental regulatory risk in the area. This setting allows us to identify the causal role of socially responsible institutions in influencing the emissions levels of local plants that are not targeted by the EPA. We argue and show that, due to compliance slack, a firm reduces its toxic emissions at a local plant (treated plant) after observing an EPA enforcement action against its peer firm's violating plant that is located in close proximity. These spillover effects are more pronounced when the plant is located close to an SRMF and decay monotonically as the distance to the SRMF increases.

We find that, possibly due to high compliance costs, only treated plants that belong to firms with high operational flexibility respond to a nearby enforcement action against a peer plant. However, the way they respond depends on the presence of local SRMFs. Treated plants that are not close to an SRMF respond by engaging in short-term opportunistic tactics such as selling from inventory or shifting emissions to other distant plants possibly to temporarily reduce their exposure to heightened local regulatory risk. In the long run, these plants revert their emissions back by 100% of the short-run reduction amount. In contrast, for treated plants located close to an SRMF, we find that they do not engage in these tactics. Rather, following nearby enforcement actions against peer firms, these plants implement real abatement measures related to production process to prevent emissions and thus, their long-run reversals of emissions are prevented.

Further investigation into the role of local SRMFs shows that their threats of exit serve as a disciplinary tool to influence investees' responses. Specifically, we find that SRMFs reduce holdings in firms whose treated plants do not respond to a nearby enforcement action and increase holdings in responding firms. We further find that SRMFs' selling of non-responders' shares serves as a threat of exit for other local treated plants such that it deters these plants from increasing emissions in the long run.

These findings highlight the role of U.S.-based SRMFs in complementing EPA enforcement to ensure environmental compliance of local plants. In particular, the spillover effects of EPA enforcement actions suggest that the EPA's punishment of one firm triggers increased monitoring by local SRMFs and helps raise the environmental compliance levels of other peer firms in the region. Yet, it is the local SRMFs who ensure that local plants' emissions remain low in the long run. Our findings based on this unique setting suggest socially responsible investors do not "walk the talk"; rather, they do change firm behavior if being prompted by an EPA enforcement action.

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Figure 1: Differences of Toxic Releases Between Treated and Control Plants

The figure shows the average differences of toxic releases between treated and control plants over the [-3, 3] window of a nearby peer enforcement action, together with the 95% confidence intervals. We use the stacked difference-in-differences (DiD) framework. Specifically, for each event year, we construct a cohort of treated plants and control plants using plant-year observations for the three years before and the three years after an EPA enforcement event action against the peer plant. We remove the event year from the sample. Treated plants are those that are not targeted by the EPA but are located within 100-mile radius of a violating TNIC3-peer plant. Control plants are other plants of the same parent firm as a treated plant but located outside 100 miles radius of the violating peer plant, plants of other TNIC3-peer firms located outside 100-mile radius of the violating peer plant, and plants of firms that are outside TNIC3 but in the same TNIC2 product market as treated plants. We require that control plants have not been treated in a past event and will not become treated in the next 6 years. The average differences between treated and control plants are the coefficients obtained from the plant-year level regression:

$$Toxic_{p,c,t} = \beta_0 + \beta_1\, Pre1\ ClosePeerEA_{p,c,t} + \beta_2 Pre2\ ClosePeerEA_{p,c,t} + \beta_3 Post1\ ClosePeerEA_{p,c,t} + \beta_4 Post2\ ClosePeerEA_{p,c,t} + \beta_5 Post3\ ClosePeerEA_{p,c,t} + \varphi + \tau + \mu + \varepsilon_{p,c,t}$$

where $Toxic_{p,c,t}$ is the total on-site harmful chemical releases of plant p of cohort c standardized using the industry mean and standard deviation in each year t. $Pre1\ ClosePeerEA_{p,c,t}$ and $Pre2\ ClosePeerEA_{p,c,t}$ are dummy variables that are, respectively, equal to 1 for treated plant p of cohort c for the first year and the second year before an EPA enforcement action taken against a nearby peer plant and zero otherwise. $Post1\ ClosePeerEA_{p,c,t}$, $Post2\ ClosePeerEA_{p,c,t}$, and $Post3\ ClosePeerEA_{p,c,t}$ are dummy variables that are, respectively, equal to 1 for treated plant p of cohort c for the first year, the second year, and the third year after an EPA enforcement action taken against a nearby peer plant and zero otherwise. φ, τ, and μ are vectors for the plant, county-year, and industry-year fixed effects, respectively.

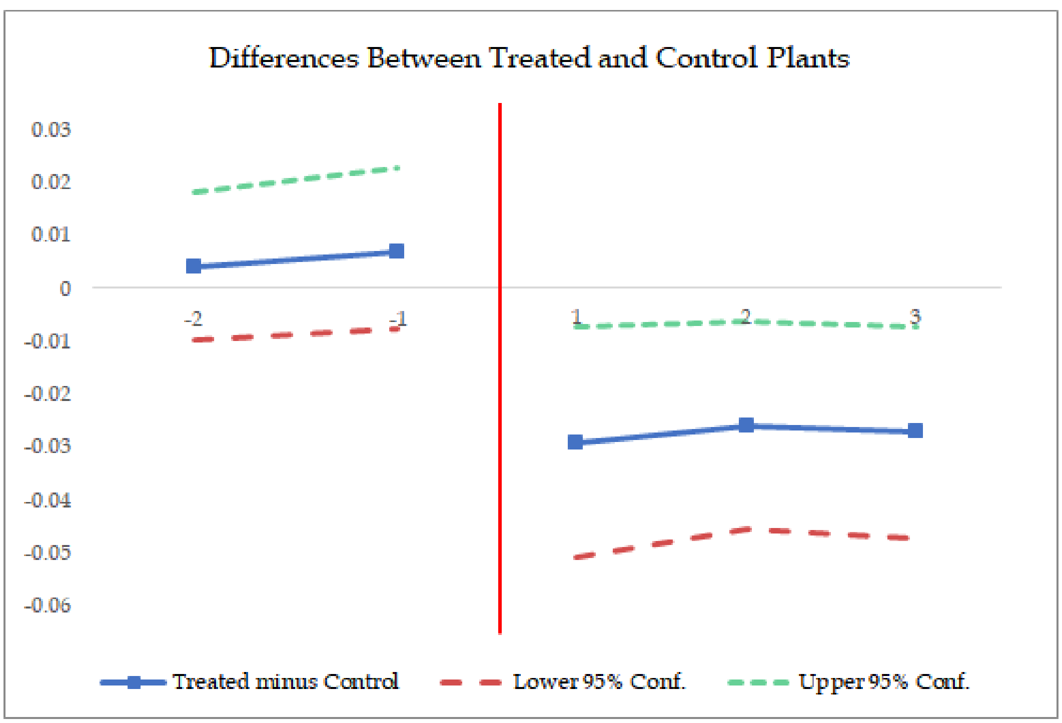

Table 1: Summary Statistics

In Panel A, the summary statistics include the sample mean, 5th, 40th, median, 60th, 95th, and standard deviation of the key variables used in this study. These variables are defined in Appendix Table B1. The sample contains 158,211 plant-year observations between 1990 and 2015. Panel B reports the number of treated plants and the number of control plants in each event year (cohort). The construction of each cohort is described in Section 3.1. The first cohort is in 1993 (three years after the beginning of our sample) because the pre-event window uses plant-year observations in the three years before each event. Similarly, the last cohort is in 2012 because the post-event window uses plant-year observations in the three years after each event.

Panel A: Summary Statistics for the Key Variables

Variable	Mean	5th	40th	Median	60th	95th	Std. Dev.
Toxic	0.000	-0.503	-0.247	-0.210	-0.184	1.334	1.000
Post ClosePeerEA	0.100	0.000	0.000	0.000	0.000	1.000	0.299
Size	7.573	4.258	7.056	7.524	8.011	10.888	1.971
Book-to-Market	0.493	0.058	0.353	0.423	0.497	1.227	0.412
Return on Asset	0.146	0.044	0.125	0.140	0.158	0.269	0.069
Ln(Sale)	7.820	4.903	7.490	7.861	8.238	10.374	1.650
Leverage	0.197	0.003	0.134	0.170	0.211	0.485	0.146

Panel B: The Number of Treated Plants and Control Plants in Each Event Year

Event Year / Cohort	Number of Treated Plants	Number of Control Plants
1993	209	3,003
1994	129	2,823
1995	209	2,714
1996	219	2,534
1997	243	2,440
1998	446	2,420
1999	377	2,341
2000	443	2,267
2001	438	2,203
2002	384	2,025
2003	350	1,953
2004	326	1,837
2005	364	1,727
2006	274	1,632
2007	334	1,561
2008	331	1,505
2009	324	1,439
2010	279	1,420
2011	348	1,369
2012	243	1,313
Average	313.5	2,206.3

Table 2: Spillover Effects of EPA Enforcement Actions

This table reports the results from the regressions that examine toxic releases at plants located in close proximity to an EPA enforcement action. We use the stacked difference-in-differences (DiD) framework. Specifically, for each event year, we construct a cohort of treated plants and control plants using plant-year observations for the three years before and the three years after an EPA enforcement event action against the peer plant. We remove the event year from the sample. Treated plants are those that are not targeted by the EPA but are located within 100-mile radius of a violating TNIC3-peer plant. Control plants are other plants of the same parent firm as a treated plant but located outside 100 miles radius of the violating peer plant, plants of other TNIC3-peer firms located outside 100-mile radius of the violating peer plant, and plants of firms that are outside TNIC3 but in the same TNIC2 product market as treated plants. We require that control plants have not been treated in a past event and will not become treated in the next 6 years. We estimate the following plant-level regression:

$$Toxic_{p,c,t} = \beta_0 + \beta_1\ Post\ ClosePeerEA_{p,c,t} + \varphi + \tau + \mu + \varepsilon_{p,c,t},$$

where $Toxic_{p,c,t}$ is the total on-site harmful chemical releases of plant p of cohort c standardized using the industry mean and standard deviation in each year t. *Post ClosePeerEA* is a dummy variable that is equal to 1 for treated plants in the three years after the EPA takes an enforcement action against the peer plants located in close proximity and 0 otherwise. φ,τ, and μ are vectors for the plant × cohort, year × cohort, and county × cohort fixed effects, respectively. In Panel B, *Pre1 ClosePeerEA* (*Pre2 ClosePeerEA*) is a dummy variable that is equal to 1 for the first year (second year) before an EPA enforcement action and zero otherwise. Standard errors are double clustered at the plant and year level. t-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. The variables are defined in Appendix Table B1.

Panel A: Peer's EPA Enforcement Actions and Toxic Releases

	Dependent Variable: *Toxic*			
Variable	(1)	(2)	(3)	(4)
Post ClosePeerEA	-0.027***	-0.026***	-0.027***	-0.025***
	(-4.248)	(-4.003)	(-3.906)	(-3.614)
Size			0.006	0.006
			(0.948)	(0.970)
Book-to-Market			-0.011	-0.011
			(-1.297)	(-1.191)
Return on Asset			0.166**	0.168**
			(2.116)	(2.061)
Ln(Sale)			0.026**	0.018**
			(2.442)	(2.104)
Leverage			0.027	0.031
			(0.826)	(0.997)
Plant × Cohort FEs	Yes	Yes	Yes	Yes
Year × Cohort FEs	Yes	Yes	Yes	Yes
County × Cohort FEs	No	Yes	No	Yes
Number of Obs	158,211	158,211	157,906	157,906
Adj. R-squared	0.830	0.840	0.833	0.843

Table 2: continued

Panel B: Pre-Trend Tests

	Dependent Variable: *Toxic*			
Variable	(1)	(2)	(5)	(6)
Post ClosePeerEA	-0.030***	-0.027***	-0.029***	-0.025**
	(-3.105)	(-2.855)	(-2.672)	(-2.464)
Pre1 ClosePeerEA	0.004	0.008	0.002	0.005
	(0.550)	(1.041)	(0.228)	(0.673)
Pre2 ClosePeerEA	0.003	0.004	0.002	0.003
	(0.378)	(0.627)	(0.221)	(0.444)
Size			0.006	0.006
			(0.941)	(0.919)
Book-to-Market			-0.011	-0.010
			(-1.307)	(-1.203)
Return on Asset			0.167**	0.166**
			(2.112)	(2.033)
Ln(Sale)			0.026**	0.018**
			(2.438)	(2.097)
Leverage			0.029	0.031
			(0.872)	(1.006)
Plant × Cohort FEs	Yes	Yes	Yes	Yes
Year × Cohort FEs	Yes	Yes	Yes	Yes
County × Cohort FEs	No	Yes	No	Yes
Number of Obs	158,211	158,211	157,906	157,906
Adj. R-squared	0.830	0.840	0.834	0.844

Table 3: The Role of Socially Responsible Mutual Funds

This table reports the results from the regressions that examine the role of socially responsible mutual funds in influencing a firm's response to a nearby EPA enforcement action. The sample starts from 2000 due to the availability of fund-level data. We use the same stacked difference-in-differences (DiD) framework as in Table 2 except that the regressions of this table incorporate interaction terms with close socially responsible mutual funds (SRMF). Specifically, Panel A presents the results for the following plant-level regression:

$$Toxic_{p,c,t} = \beta_1\ Post\ ClosePeerEA_{p,c,t} \times CloseSRMF_{p,c,t} + \beta_2\ Post\ ClosePeerEA_{p,t} + \varphi + \tau + \mu + \varepsilon_{p,c,t}$$

where *CloseSRMF* is a dummy variable equal to 1 if a socially responsible mutual fund, which holds the treated plant's parent firm's stock, is located within 100 miles from the treated plant and within 100 miles from the violating peer plant. Other variables are defined as in Table 2. In Columns 3 and 4 of Panel A, $SRMF_{(100,\ 200)}$ (or $SRMF_{(>200)}$) is a dummy variable equal to 1 if a socially responsible mutual fund is located between 100 miles and 200 miles (or greater than 200 miles) from both the treated plant and the violating plant. *F*-statistics for the differences in the coefficients between *Post ClosePeerEA* × *CloseSRMF* and *Post ClosePeerEA* × $SRMF_{(>200)}$ are 3.79 (p-value = 0.056) for Column 3 and 4.10 (p-value = 0.047) for Column 4. *F*-statistics for the differences in the coefficients between *Post ClosePeerEA* × *CloseSRMF* and *Post ClosePeerEA* × $SRMF_{(100,\ 200)}$ are 0.39 (p-value = 0.533) for Column 3 and 0.83 (p-value = 0.366) for Column 4. Panel B reports the regression in Panel A but add pre-event dummies, *Pre1 ClosePeerEA* and *Pre2 ClosePeerEA*, and the interactions term between each pre-event dummy and *CloseSRMF*. Panel C reports the regression in Panel A Column 4 but uses matched samples. To construct the matched sample in Column 1, we require that the parent firms of treated plants located within 100-mile radius of an SRMF can be matched to the parent firms that have the same *EScore* and whose treated plants are located more than 100 miles from the nearest SRMFs. We remove treated plants that cannot be matched. We repeat this matching procedure to find a match between the matched treated plants within 100-mile radius of an SRMF with treated plants that are located more than 200 miles from the nearest SRMFs. In Column 2, in addition to the matching procedure between treated plants depending on their proximity to SRMF, we also find matched plants of control firms in the same TNIC2 network that have the same *EScore* as the treated firms. Standard errors are double clustered at the plant and year level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. The variables are defined in Appendix Table B1.

Panel A: The Role of Nearby Socially Responsible Mutual Funds

	Dependent Variable: *Toxic*			
Variable	(1)	(2)	(3)	(4)
Post ClosePeerEA × *CloseSRMF*	-0.026**	-0.027**	-0.029***	-0.030***
	(-2.341)	(-2.446)	(-2.612)	(-2.775)
Post ClosePeerEA × $SRMF_{(100,\ 200)}$			-0.018	-0.016
			(-1.031)	(-1.040)
Post ClosePeerEA × $SRMF_{(>200)}$			-0.002	-0.003
			(-0.247)	(-0.376)
Post ClosePeerEA	-0.022**	-0.023**	-0.022**	-0.022**
	(-2.348)	(-2.352)	(-2.341)	(-2.352)

Plant × Cohort FEs	Yes	Yes	Yes	Yes
Year × Cohort FEs	Yes	Yes	Yes	Yes
County × Cohort FEs	No	Yes	No	Yes
Number of Obs	68,509	68,509	68,509	68,509
Adj. R-squared	0.875	0.879	0.875	0.879

Panel B: Pre-Trend Tests

	Dependent Variable: *Toxic*	
Variable	(1)	(2)
Post ClosePeerEA × CloseSRMF	-0.033***	-0.034***
	(-3.090)	(-3.084)
Post ClosePeerEA	-0.022**	-0.021**
	(-2.339)	(-2.105)
Pre1 ClosePeerEA × CloseSRMF	-0.002	0.001
	(-0.101)	(0.073)
Pre2 ClosePeerEA × CloseSRMF	-0.008	-0.008
	(-0.295)	(-0.333)
Pre1 ClosePeerEA	-0.003	-0.001
	(-0.583)	(-0.162)
Pre2 ClosePeerEA	-0.002	-0.001
	(-0.517)	(-0.198)
Plant × Cohort FEs	Yes	Yes
Year × Cohort FEs	Yes	Yes
County × Cohort FEs	No	Yes
Number of Obs	68,509	68,509
Adj. R-squared	0.877	0.880

Panel C: Matched Treated and Control Groups Based on EScore

	Dependent Variable: *Toxic*	
Variable	(1)	(2)
Post ClosePeerEA × CloseSRMF	-0.052**	-0.054**
	(-1.990)	(-2.294)
Post ClosePeerEA × $SRMF_{(100, 200)}$	-0.015**	-0.013
	(-2.714)	(-1.422)
Post ClosePeerEA × $SRMF_{(>200)}$	0.006	0.003
	(0.666)	(0.247)
Post ClosePeerEA	-0.015***	-0.032***
	(-3.210)	(-9.210)
Plant × Cohort FEs	Yes	Yes
Year × Cohort FEs	Yes	Yes
County × Cohort FEs	Yes	Yes
Number of Obs	61,683	28,195
Adj. R-squared	0.860	0.893

Table 4: The Role of Operational flexibility

This table reports the results from the subsample tests based on the sample median of different operational flexibility measures. In Columns 1 and 2, the sample is split based on the median value of the firm's inventory level measured in the event year. In Columns 3 and 4, the sample is split based on operational inflexibility calculated as the firm's historical range of operating costs scaled by the volatility of changes in sales over assets, measured in the event year. In Columns 5 and 6, the sample is split based on the number of plants of a firm measured in the event year. Panel A reports the results from the regression of Table 2 using various subsamples. Panel B reports the results from the regression of Table 3 using various subsamples. Standard errors are double clustered at the plant and year level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. The variables are defined in Appendix Table B1.

Panel A: Operational flexibility

	Dependent Variable: *Toxic*					
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Low Inventory	High Inventory	High Inflexibility	Low Inflexibility	Less Plants	More Plants
Post ClosePeerEA	-0.005	-0.030***	-0.011	-0.032***	0.005	-0.027***
	(-0.253)	(-6.042)	(-0.952)	(-5.539)	(0.268)	(-4.549)
Plant × Cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year × Cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes
County × Cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs	76,677	77,108	77,988	74,566	69,951	87,881
Adj. R-squared	0.796	0.857	0.825	0.868	0.816	0.857

Panel B: Socially Responsible Mutual Funds, Operational flexibility, and Toxic Releases

	Dependent Variable: *Toxic*					
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Low Inventory	High Inventory	High Inflexibility	Low Inflexibility	Less Plants	More Plants
Post ClosePeerEA × *CloseSRMF*	-0.010	-0.037**	-0.020	-0.045**	-0.026	-0.047**
	(-0.443)	(-2.109)	(-0.612)	(-2.300)	(-0.916)	(-2.028)
Post ClosePeerEA	0.012	-0.023***	-0.016	-0.016**	0.026	-0.021**
	(0.738)	(-2.887)	(-0.879)	(-2.030)	(1.334)	(-2.405)

Plant × Cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year × Cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes
County × Cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs	32,576	34,099	33,699	32,572	30,835	37,510
Adj. R-squared	0.861	0.885	0.844	0.897	0.859	0.890

Table 5: Change of Inventory Level After A Nearby Enforcement Action

This table reports the results from the firm-year level regressions examining the inventory behavior of high- and low-inventory firms in their responses to a nearby enforcement action. We construct a stacked difference-in-differences (DiD) sample at the firm level. Specifically, for each event year, we construct a cohort of treated firms and control firms using firm-year observations for the three years before and the three years after an EPA enforcement event action against a nearby peer plant. Treated firms have at least one plant located within 100 miles from a violating TNIC3-peer plant. Control firms are those that operate in the same TNIC2 product market as the treated firm and do not have plants located within 100 miles from the violating peer plant. We also require that control firms do not have plants treated in a past event and will not have plants treated in the next 6 years. $\Delta Inventory$ is firm i's change of inventory levels from year t-1 to year t+1 calculated as $Ln(Inventory)_{i,t+1} - Ln(Inventory)_{i,t-1}$. *Post Treatfirm* is a dummy variable that is equal to 1 for the treated firm in the three years after the EPA takes an enforcement action against a violating peer plant, and 0 otherwise. In Columns 1 and 2, the sample is divided into high- and low-inventory groups based on the median value of inventory level measured in year t-1. In Columns 3 and 4, the sample is divided into high- and low-inventory groups based on the median value of inventory level measured in year t-2. Standard errors are double clustered at the firm and year level. t-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. The variables are defined in Appendix Table B1.

	Dependent Variable: $\Delta Inventory$			
	(1)	(2)	(3)	(4)
Variable	High Inventory$_{t-1}$	Low Inventory$_{t-1}$	High Inventory$_{t-2}$	Low Inventory$_{t-2}$
Post Treatfirm	-0.079***	0.006	-0.066***	-0.002
	(-3.784)	(0.203)	(-3.134)	(-0.077)
Firm × Cohort FEs	Yes	Yes	Yes	Yes
Year × Cohort FEs	Yes	Yes	Yes	Yes
Number of Obs	8,488	8,551	8,314	8,388
Adj. R-squared	0.249	0.298	0.236	0.299

Table 6: Transfer of Toxic Releases to Distant Plants

This table reports the results from the regressions examining whether firms transfer toxic releases to distant plants. The sample includes distant plants only (i.e. non-target plants within 100 miles of the violating peer plant are removed). We identify a treated firm that owns at least one plant located within 100 miles of the violating peer plant and also owns distant plants located outside the 100-mile radius. For each event year, we construct a cohort of distant plants that belong to treated firms and control plants using plant-year observations for the three years before and the three years after an EPA enforcement event action against the peer plant. We remove the event year from the sample. Control plants are plants of other TNIC3-peer firms that do not own any treated plants and plants of firms that are outside TNIC3 but in the same TNIC2 product market as treated firms. We require that control plants' parent firms do not have treated plants in a past event and will not have treated plants in the next 6 years. Panel A presents the estimation results for the following plant-level regression:

$$Toxic_{p,c,t} = \beta_1 \; Post\ TreatDistant_{p,c,t} + \varphi + \tau + \mu + \varepsilon_{p,c,t}$$

where *Post TreatDistant* is equal to 1 if a distant plant belongs to a treated firm and for the three years after the EPA takes an enforcement action against the violating peer plant and 0 otherwise. In Column 2 of Panel A, the sample starts from 2000 due to the availability of fund-level data. *CloseSRMF* is a dummy variable equal to 1 if a socially responsible mutual fund, which holds the treated firm's stock, is located within 100 miles from the treated firm's treated plant and within 100 miles from the violating peer plant and zero otherwise. Panel B repeats the regression of Panel A using subsamples that are split based on different operational flexibility measures. In Columns 1 and 2 of Panel B, the sample is split based on the sample median of firms' inventory levels. In Columns 3 and 4 of Panel B, the sample is partitioned based on the median of *Operational Inflexibility*, which is a firm's historical range of operating costs scaled by the volatility of changes in sales over assets. In Columns 5 and 6 of Panel B, the sample is split based on the median of the number of plants per firm. Standard errors are double clustered at the plant and year level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. The variables are defined in Appendix Table B1.

Panel A: Transfer of Toxic Releases

	Dependent Variable: *Toxic*	
Variable	(1)	(2)
Post TreatDistant × *CloseSRMF*		0.002
		(0.095)
Post TreatDistant	0.020	0.018
	(1.081)	(0.779)
Plant × Cohort FEs	Yes	Yes
Year × Cohort FEs	Yes	Yes
County × Cohort FEs	Yes	Yes
Number of Obs	86,917	32,072
Adj. R-squared	0.784	0.821

Table 6: continued

Panel B: The Role of Operational Inflexibility

	Dependent Variable: *Toxic*					
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Low Inventory	High Inventory	High Inflexibility	Low Inflexibility	Less Plants	More Plants
Post TreatDistant	0.004	0.021**	-0.002	0.029**	-0.013	0.039***
	(0.127)	(2.432)	(-0.150)	(2.342)	(-0.417)	(4.400)
Plant × Cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year × Cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes
County × Cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs	41,266	43,081	42,002	39,935	37,181	49,555
Adj. R-squared	0.734	0.822	0.789	0.798	0.750	0.822

Panel C: Socially Responsible Mutual Funds, Operational flexibility, and Transfer of Toxic Releases

	Dependent Variable: *Toxic*					
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Low Inventory	High Inventory	High Inflexibility	Low Inflexibility	Less Plants	More Plants
Post TreatDistant × *CloseSRMF*	0.041	-0.037***	0.022	-0.055**	0.015	-0.038***
	(0.911)	(-3.596)	(1.072)	(-2.397)	(0.306)	(-3.620)
Post TreatDistant	0.018	0.057***	-0.007	0.048*	0.002	0.035*
	(0.550)	(2.607)	(-0.219)	(1.862)	(0.064)	(1.921)
Plant × Cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year × Cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes
County × Cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs	15,094	15,903	15,852	14,806	13,475	18,561
Adj. R-squared	0.789	0.800	0.826	0.832	0.798	0.817

Table 7: Transfer of Toxic Releases and the Industry Concentration of EPA Regions

This table reports the results from the regressions examining whether the transfer of toxic releases to distant plants depends on the industry concentration of EPA regions. The sample includes distant plants only (i.e. plants within 100 miles of the violating peer plant are removed). In Columns 1, we estimate the stacked difference-in-differences regression used in Table 6 but additionally include the interaction terms between *Post TreatDistant* and *OutsideTop3*. *OutsideTop3* is an indicator that is equal to 1 if a distant plant's industry is *not* one of the Top 3 industries that have experienced the most EPA enforcement actions over the past 3 years in the EPA region to which the distant plant belongs and zero if it is the same. We identify an EPA region's Top 3 industries by first ranking industries in the region based on the total number of enforcement actions against firms in each industry over the past 3 years. We then select the Top 3 Industries with the highest number of enforcement actions. In Columns 2, we replace *OutsideTop3* with *OutsideTop5*, which is equal to 1 if a distant plant's industry is *not* a Top 5 industry that have experienced the most EPA enforcement actions over the past 3 years in the EPA region to which the distant plant belongs and zero if it is the same. In Columns 3 and 4, we repeat the regressions in Columns 1 and 2, respectively, except that we use the number of enforcement actions taken against an industry over the past 5 years to identify an EPA region's Top 3 and Top 5 industries. Standard errors are double clustered at the plant and year level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. The variables are defined in Appendix Table B1.

	Dependent Variable: *Toxic*			
Variable	(1)	(2)	(3)	(4)
Post TreatDistant × *OutsideTop3*	0.033***		0.035***	
	(3.095)		(3.393)	
Post TreatDistant × *OutsideTop5*		0.029***		0.035**
		(2.950)		(2.395)
Post TreatDistant	-0.000	0.002	0.001	0.008
	(-0.036)	(0.210)	(0.081)	(0.610)
outsideTop3	-0.014		-0.028	
	(-0.841)		(-1.493)	
outsideTop5		-0.011		-0.026
		(-0.861)		(-1.286)
Plant × Cohort FEs	Yes	Yes	Yes	Yes
Year × Cohort FEs	Yes	Yes	Yes	Yes
County × Cohort FEs	Yes	Yes	Yes	Yes
Number of Obs	86,917	86,917	86,917	86,917
Adj. R-squared	0.787	0.787	0.787	0.782

Table 8: Effects of Socially Responsible Mutual Funds on Pollution Abatement Activities

Panel A reports the results from the regressions examining the role of nearby socially responsible mutual funds in influencing a plant's pollution abatement activities after a nearby EPA enforcement action. We estimate the stacked difference-in-differences regression used in Table 3 except that the dependent variable is different. In Column 1, the dependent variable is *Process*, which is a dummy variable that is equal to 1 in a given year if a plant implements an abatement activity related to its production process including improvements in chemical reaction conditions, modification of equipment, or implementation of better process controls, and zero otherwise. In Column 2, the dependent variable is *Practice*, which is a dummy variable that is equal to 1 in a given year if a plant implements changes to its operating practice such as improvement in maintenance scheduling, record keeping, etc, and zero otherwise. Panel B reports the results from the regression of Panel A that is estimated using various subsamples that are split based on the sample median of different operational flexibility measures. Standard errors are double clustered at the plant and year level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. The variables are defined in Appendix Table B1.

Panel A: Effects of Nearby Socially Responsible Mutual Funds on Pollution Abatement Activities

Variable	*Process* (1)	*Practice* (2)
Post ClosePeerEA × CloseSRMF	0.032***	-0.010
	(3.119)	(-0.627)
Post ClosePeerEA	0.005	-0.004
	(0.924)	(-0.598)
Plant × Cohort FEs	Yes	Yes
Year × Cohort FEs	Yes	Yes
County × Cohort FEs	Yes	Yes
Number of Obs	68,509	68,509
Adj. R-squared	0.666	0.477

Table 8: continued

Panel B: Subsample Tests Based on Flexibility

	Dependent Variable: *Process*					
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Low Inventory	High Inventory	High Inflexibility	Low Inflexibility	Less Plants	More Plants
Post ClosePeerEA × *CloseSRMF*	-0.006	0.033***	-0.013	0.038***	-0.015	0.050**
	(-0.285)	(4.457)	(-0.904)	(3.858)	(-0.853)	(2.523)
Post ClosePeerEA	0.009	0.001	0.006	0.004	0.005	0.005
	(1.063)	(0.225)	(0.701)	(0.916)	(0.604)	(0.722)
Plant × Cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year × Cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes
County × Cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs	32,963	34,003	33,885	32,774	30,974	37,535
Adj. R-squared	0.676	0.664	0.654	0.691	0.620	0.669

Table 9: Effects of Socially Responsible Mutual Funds on Distant Plants' Abatement Activities
Panel A reports the results from the regressions examining the role of nearby socially responsible mutual funds in influencing treated firms' distant plants' pollution abatement activities. The sample includes distant plants only (i.e. non-target plants within 100 miles of the violating peer plant are removed). We estimate the stacked difference-in-differences regression used in Table 6 except that the dependent variable is either *Process* or *Practice*. Columns 1 and 2, *Post TreatDistant* is equal to 1 if a distant plant belongs to a treated firm and for the three years after the EPA takes an enforcement action against the violating peer plant and 0 otherwise. *CloseSRMF* is a dummy variable equal to 1 if a socially responsible mutual fund, which holds the treated firm's stock, is located within 100 miles from the treated firm's treated plant and within 100 miles from the violating peer plant and zero otherwise. In Columns 3 and 4, we use plant-year observations for the three years before and the [4, 10] years after an EPA enforcement event action against the peer plant. We remove from the sample the first three years after the event as well as events where there are treated firms' distant plants' confounding enforcement actions during the [4, 10] period. We require that control plants' parent firms do not have treated plants in a past event and will not have treated plants in the next 10 years. *Post TreatDistant[4, 10]* is equal to 1 if a distant plant belongs to a treated firm and for the [4, 10] years after the EPA takes an enforcement action against the violating peer plant and zero otherwise. In Columns 1 and 3, the dependent is *Process*, which is defined in Table 8. In Columns 2 and 4, the dependent variable is *Practice*, which is defined in Table 8. Standard errors are double clustered at the plant and year level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. The variables are defined in Appendix Table B1.

	Short Run		*Long Run*	
	Process	*Practice*	*Process*	*Practice*
Variable	(1)	(2)	(3)	(4)
Post TreatDistant × *CloseSRMF*	0.006	-0.001		
	(0.618)	(-0.041)		
Post TreatDistant	-0.002	-0.010		
	(-0.238)	(-0.992)		
Post TreatDistant[4, 10] × *CloseSRMF*			0.030***	-0.021
			(4.739)	(-0.997)
Post TreatDistant[4, 10]			0.001	-0.004
			(0.142)	(-0.316)
Plant × Cohort FEs	Yes	Yes	Yes	Yes
Year × Cohort FEs	Yes	Yes	Yes	Yes
County × Cohort FEs	Yes	Yes	Yes	Yes
Number of Obs	32,557	32,557	34,158	34,158
Adj. R-squared	0.678	0.463	0.640	0.422

Table 10: Socially Responsible Mutual Funds' Portfolio Holdings of Non-Responders

This table reports the results from the regressions estimated at the firm-fund-year level that examines changes in an SRMF's holdings of firms after observing a nearby EPA enforcement action. In Columns 1 and 2, the dependent variable, $\Delta Weight_{t+1}$, is calculated as the difference between a stock's weight in a fund's portfolio in the first quarter of year t+1 and its weight in the first quarter of year t-1. In Columns 3 and 4, the dependent variable, $\Delta Weight_{t+2}$, is calculated as the difference between a stock's weight in the first quarter of year t+2 and its weight in the first quarter of year t-1. *Treatfirm* is a dummy variable that is equal to 1 if a firm has at least one plant located in close proximity to EPA's enforcement action against a violating peer plant in year t and 0 otherwise. *CloseSRMF* is a dummy variable that is equal to 1 if an SRMF, who holds the parent firm's stock, is located within 100 miles from the treated plant and within 100 miles from the violating peer plant. *NonRespond* is a dummy variable that is equal to 1 if a firm increases toxic releases at its treated plants in the year after EPA enforcement action and zero otherwise. *Ln(Fund Size)* is the natural logarithm of total net assets (*TNA*) of all share classes of a fund. *Exp Ratio* is a fund's expense ratio. *Turn Ratio* is a fund's turnover ratio. *Fund Return* is the fund's average monthly returns over a quarter. *Fund Flow* over the period t-1 to t is computed as $[TNA_t - (1 + Fund\ Return_t)TNA_{t-1}]/TNA_{t-1}$. Standard errors are double clustered at the fund and year level. t-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. The variables are defined in Appendix Table B1.

	$\Delta Weight_{t+1}$		$\Delta Weight_{t+2}$	
Variable	(1)	(2)	(3)	(4)
Treatfirm × CloseSRMF × NonRespond	-0.225**	-0.230**	-0.193**	-0.198**
	(-2.525)	(-2.453)	(-2.080)	(-1.996)
Treatfirm × NonRespond	-0.032***	-0.033***	-0.043***	-0.044***
	(-3.521)	(-4.130)	(-4.705)	(-5.455)
Treatfirm × CloseSRMF	0.202***	0.181**	0.147	0.177
	(2.824)	(2.419)	(0.638)	(0.783)
Treatfirm	0.011	0.038***	0.035***	0.046***
	(1.229)	(5.336)	(4.155)	(6.572)
Ln(Fund Size)	0.027***	0.026***	0.007	0.005
	(6.440)	(6.017)	(1.621)	(1.272)
Exp Ratio	0.516	0.671	-5.114**	-5.092**
	(0.253)	(0.326)	(-2.471)	(-2.565)
Turn Ratio	-0.024***	-0.026***	0.005	0.003
	(-3.762)	(-4.041)	(0.882)	(0.556)
Fund Return	-0.092	-0.138	0.198*	0.153
	(-0.866)	(-1.322)	(1.925)	(1.492)
Fund Flow	0.254***	0.247***	0.191***	0.187***
	(4.655)	(4.553)	(3.579)	(3.581)
Fund fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	No	Yes	No
Industry fixed effects	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Number of Obs	215,932	215,932	215,932	215,932
Adj. R-squared	0.190	0.179	0.302	0.292

Table 11: Long-Run Responses and the Role of Socially Responsible Mutual Funds

This table reports the results from the stacked difference-in-differences regressions that examine the long-run toxic releases at treated plants over the period from *t*+4 to *t*+10 after an EPA enforcement action against local peer plants in year *t*. For each cohort, we use plant-year observations for the three years before and the [4, 10] years after an EPA enforcement event action against the peer plant. We remove from the sample the first three years after an EPA enforcement action as well as events where there are confounding enforcement actions during the [4, 10] period. We further require that control plants have not been treated in a past event and will not become treated in the next 10 years. Panel A examine the long-run toxic releases at treated plants and the role of the nearby socially responsible mutual fund. *Post ClosePeerEA[4, 10]* is a dummy variable that is equal to 1 for treated plants during the [4, 10] years after the EPA takes an enforcement action against a violating peer plant located in close proximity and zero otherwise. *CloseSRMF* is a dummy variable that is equal to 1 if an SRMF, which holds the parent firm's stock, is located within 100 miles from the treated plant and within 100 miles from the violating peer plant. Panel B examines the role of local non-responders. *Local_NonRespond* is a dummy variable that is equal to 1 if a treated plant is located close to (within 100 miles) a non-responding plant, which does not reduce toxic releases after observing a nearby enforcement action against its peer plant, and zero otherwise. $CloseSRMF_{NR}$ is a dummy variable that is equal to 1 if a local non-responding plant is located within 100 miles from an SRMF that holds the shares of non-responding plant's parent firm, and 0 otherwise. Standard errors are double clustered at the plant and year level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. The variables are defined in Appendix Table B1.

Panel A: Long-Run Responses and the Role of Socially Responsible Mutual Funds

	Dependent Variable: *Toxic*	
Variable	(1)	(2)
Post ClosePeerEA[4, 10] × CloseSRMF		-0.048***
		(-2.716)
Post ClosePeerEA[4, 10]	0.032**	0.028**
	(2.512)	(2.201)
Plant × Cohort FEs	Yes	Yes
Year × Cohort FEs	Yes	Yes
County × Cohort FEs	Yes	Yes
Number of Obs	67,067	67,067
Adj. R-squared	0.860	0.860

Table 11: continued

Panel B: Long-Run Responses and the Role of Local Non-Responders

	Dependent Variable: *Toxic*	
Variable	(1)	(2)
Post ClosePeerEA[4, 10] × Local_NonRespond × CloseSRMF$_{NR}$		-0.025**
		(-2.276)
Post ClosePeerEA[4, 10] × Local_NonRespond	-0.017**	-0.028***
	(-2.194)	(-2.760)
Post ClosePeerEA[4, 10]	0.026**	0.027**
	(2.443)	(2.310)
Plant × Cohort FEs	Yes	Yes
Year × Cohort FEs	Yes	Yes
County × Cohort FEs	Yes	Yes
Number of Obs	67,067	67,067
Adj. R-squared	0.862	0.859

Table 12: Firm-Level Evidence

This table reports the results from the regressions that examine the firm-level total toxic releases. We construct a stacked difference-in-differences (DiD) sample at the firm level. In Columns 1 to 3, for each event year, we construct a cohort of treated firms and control firms using firm-year observations for the three years before and the three years after an EPA enforcement event action against a nearby peer plant. Treated firms have at least one plant located within 100 miles from a violating TNIC3-peer plant. Control firms are those that operate in the same TNIC2 product market as the treated firm and do not have plants located within 100 miles from the violating peer plant. We also require that control firms do not have plants treated in a past event and will not have plants treated in the next 6 years. The dependent variable, *Firm Toxic*, is the total standardized on-site harmful chemical releases of all plants owned by a firm. In Columns 1 and 2, *Post Treatfirm* is a dummy variable that is equal to 1 for the treated firm in the three years after the EPA takes an enforcement action against a violating peer plant, and 0 otherwise. *CloseSRMF* is a dummy variable that is equal to 1 if an SRMF, which holds the treated firm's stock, is located within 100 miles from one of the treated firm's treated plants and within 100 miles from the violating peer plants. Columns 4 and 5 examine the long-run toxic releases at treated firm over the period from *t*+4 to *t*+10 after an EPA enforcement action against local peer plants in year *t*. We remove from the sample the first three years of the treated firms after an EPA enforcement action as well as events where there are confounding enforcement actions during the [4, 10] period. *Post Treatfirm[4, 10]* is a dummy variable that is equal to 1 for treated firms during the [4, 10] years after the EPA takes an enforcement action against a violating peer plant located in close proximity of the treated firm's plants and zero otherwise. Standard errors are double clustered at the firm and year level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. The variables are defined in Appendix Table B1.

	Dependent Variable: *Firm Toxic*				
	Short Run			Long Run	
	(1)	(2)	(3)	(4)	(5)
Variable	1990-2015	2001-2015	2001-2015	2001-2015	2001-2015
Post Treatfirm × CloseSRMF			-0.031**		
			(-2.069)		
Post Treatfirm	-0.026***	-0.026***	-0.025***		
	(-4.116)	(-4.906)	(-4.691)		
Post Treatfirm[4, 10] × CloseSRMF					-0.086***
					(-3.320)
Post Treatfirm[4, 10]				0.047**	0.048*
				(2.143)	(1.908)
Firm × Cohort FEs	Yes	Yes	Yes	Yes	Yes
Year × Cohort FEs	Yes	Yes	Yes	Yes	Yes
Number of Obs	30,564	12,136	12,136	12,623	12,623
Adj. R-squared	0.844	0.857	0.856	0.746	0.747

Appendix A

We set up a model to analyze the effects of an EPA enforcement action on nearby peer plants. The analysis will show how (i) the enforcement action affects emission transfers to other "distant" plants of peers, (ii) transfers are affected by production flexibility, (iii) investment in abatement and emissions by peers are influenced by the presence and actions of local SRMFs, (iv) how distant SRMFs learn from the actions of local SRMFs.

Model Outline

Assume a firm has two plants, denoted 1 and 2. Plant 1 will be "treated" by an enforcement action by the EPA on a nearby plant of a firm in the same industry.

Prior to the enforcement action, the firm produces output levels q_1 and q_2 in the two plants. Assume that production of these output levels creates toxic emissions $e_1 = q_1$ and $e_2 = q_2$, respectively.

Allocation of Production and Emission

The optimal production level in the absence of environmental considerations in plant i is $q_i^*, i = 1, 2$. Assume that resource-constraints limit total production to $\bar{q} = q_1^* + q_2^*$. The firm's decision problem is to allocate production across the two plants to minimize expected penalty from environmental violation.

Let e_1^0 and e_2^0 denote the emission levels in the two plants if the firm followed the environmental guidelines. These are assumed to be firm-specific and verifiable only if the regulator inspects the plants. Thus, even though the emission levels are observable, violation can be determined and penalties imposed only if inspection occurs.

π_R^1 and π_R^2 denote the probabilities of being investigated by the EPA in the two regions (plants). Assume $q_i^* > e_i^0$, so that if each firm is producing the optimal amount in each plant, it is in violation in each plant. Note that even though it may be common knowledge that a plant is in violation, because the regulator cannot inspect all plants, there is only a probability π_R^i that a penalty will be imposed.

$Max\left(p\left(e_i - e_i^0\right), 0\right)$ denotes the expected penalty conditional on being inspected, where p is a per unit excess emission penalty in dollars. Also assume that it is costly to deviate from producing the optimal quantities q_i^* in the two plants, with the cost being given by $c(q_i - q_i^*)^2$. The parameter c captures how costly it is to reallocate production across the plants, i.e., lower c corresponds to more production flexibility.

The firm's problem in the absence of an SRMF is to minimize, with respect to q_1 and q_2:

$$max(p(q_1 - e_1^0), 0)\, \pi_R^1 + max(p(q_2 - e_2^0), 0)\, \pi_R^2 + c(q_1 - q_1^*)^2 + c(q_2 - q_2^*)^2$$

Subject to

$$e_1 = q_1;\ e_2 = q_2;\ q_1 + q_2 = q_1^* + q_2^* = \bar{q}.$$

which can be written as

$$max(p(q_1 - e_1^0), 0)\, \pi_R^1 + max(p(\bar{q} - q_1 - e_2^0), 0)\, \pi_R^2 + c(q_1 - q_1^*)^2 + c(\bar{q} - q_1 - q_2^*)^2.$$

It will be clear that at the optimal solution, $q_i > e_i^0$ as long as π_R^1 and π_R^2 are sufficiently close.

The first-order condition is

$$p\pi_R^1 - p\pi_R^2 + 2c\left(q_1 - q_1^* - (\bar{q} - q_1 - q_2^*)\right) = 0$$

or

$$p(\pi_R^1 - \pi_R^2) + 4c(q_1 - q_1^*) = 0.$$

Hence,

$$q_1 = q_1^* - \frac{p(\pi_R^1 - \pi_R^2)}{4c}. \tag{1.}$$

Thus,

$$e_1 = q_1 \gtreqless q_1^* \ as\ \pi_R^1 - \pi_R^2 \lesseqgtr 0$$

The firm produces higher (lower) than the efficient output in the region where the regulatory threat is lower (higher).

Investment in Abatement

Next, assume that at cost $\tilde{f}$, a plant can invest in emission abatement. If it does so, emission is reduced by $\Delta e_i > 0$.

$\tilde{f}$ can take two values, f_1 or f_2 , with $f_2 > f_1$. Let the probability that $\tilde{f} = f_1$ be $\frac{1}{2}$.

Assume that

(i) the value of $\tilde{f}$ is private information for the firm.

(ii) it is an independent draw for each plant for the same firm (this assumption will be relaxed below).

(iii) for initial values (i.e., pre-EPA enforcement values) of π_R^i, the firm invests in abatement if and only if $\tilde{f} = f_1$. This latter assumption requires a condition that will be provided below.

Enforcement

If EPA enforcement occurs, the probability that plant 1 (which is defined as the local plant) faces inspection by the EPA increases from π_R^1 to $\pi_E^1 > \max(\pi_R^1, \pi_R^2)$. If, after inspection, the plant is found not to have invested in abatement, a lumpsum penalty of t is imposed. Even though this penalty is similar to an enforcement action, to avoid confusion, we call this a "penalty", while referring to the original enforcement action on the target firm as "enforcement".

We will assume that (i) prior to the EPA enforcement, plant 1 will invest in abatement if and only if $\tilde{f} = f_1$ (ii) the increase in regulatory threat is insufficient to make it invest in abatement if $\tilde{f} = f_2$.

It is easy to check that this requires

$$f_1 < \pi_R^1(p\Delta e + t) < \pi_E^1(p\Delta e + t) < f_2$$

which we assume. Thus, while transfers to plant 2 will increase following enforcement (as can be seen from equation (1), if $\tilde{f} = f_2$, there won't be investment in abatement without SRMF action. An analogous condition ensures that plant 2, which is not treated, invests in abatement if and only if $\tilde{f} = f_1$.

The Role of SRMFs

An SRMF receives a noisy binary signal s_i from each plant, which takes a value of 1 with probability ϕ if $\tilde{f} = f_1$ (i.e., the plant i has invested in abatement), and a value of 0 with probability ϕ if $\tilde{f} = f_2$, where $1 > \phi > 1/2$. In other words, the signal is informative about abatement, with a higher value of ϕ corresponding to a more informative signal. We will associate a higher (lower) value of ϕ with a plant that is closer (farther) from the SRMF.

The SRMF, upon receiving a signal, at cost κ can monitor whether the plant has invested in abatement. Monitoring reveals the truth with certainty, and we assume that the SRMF has enough influence to impose investment in abatement if the plant has not done so.

The SRMF is motivated to incur the monitoring cost κ because EPA actions against a portfolio firm imposes costs on the SRMF. This cost is higher if the plant inspected by the EPA has not invested in abatement (in which case, as noted above, we assume that the penalty to the plant is also higher). Let P denote this additional cost.

Denoting the inspection probability by the EPA as π_R, the SRMF's expected gain, net of the monitoring cost, if it observes signal $s_i = 1$ and monitors, is:

$$\begin{aligned}\Gamma(s_i = 1) &= \pi_R P * Prob.\left[\tilde{f} = f_2 | s_i = 1\right] - \kappa \\ &= \pi_R P \frac{(1-\phi)(1/2)}{\phi(1/2) + (1-\phi)(1/2)} - \kappa \\ &= (1-\phi)\pi_R P - \kappa\end{aligned}$$

while that on observing signal $s_i = 0$ is:

$$\begin{aligned}\Gamma(s_i = 0) &= \pi_R P \frac{\phi(1/2)}{\phi(1/2) + (1-\phi)(1/2)} - \kappa \\ &= \phi \pi_R P - \kappa\end{aligned}$$

Clearly, $\Gamma(s_i = 0) - \Gamma(s_i = 1) > (2\phi - 1)\pi_R P > 0$ $since$ $\phi > 1/2$.

Let us denote the informativeness of a nearby SRMF's signal by ϕ^N, while that of a distant SRMF by ϕ^D. By assumption, $\phi^N > \phi^D$.

We assume that prior to the EPA enforcement action, for a nearly SRMF, $\phi^N \pi_R^i P - \kappa < 0$. Therefore, monitoring does not occur, irrespective of the signal the SRMF receives. It follows that the distant SRMF also does not monitor plant i.

Now suppose a nearby EPA enforcement occurs. As noted, we regard this as an increase in π_R^1 for plant 1, with the new value $\pi_E^i > \pi_R^i$.

(i) It is immediate from equation (1) that this change will immediately cause the local plant to "transfer" emissions (i.e., production) to the distant plant. Specifically, $\frac{de_1}{d\pi_R^1} = \frac{dq_1}{d\pi_R^1} = -\frac{p}{4c}$. (2) Moreover, the more "flexible" the firm is (lower c), the more the transfer.

(ii) We will assume that ϕ^N is sufficiently high that the increase in regulatory risk will induce the local SRMF to incur the monitoring cost κ if and only if $s_i = 0$ is observed. For this, we need $\phi^N \pi_R^1 P - \kappa > 0 > (1 - \phi^N)\pi_E^1 P - \kappa$. The average emission level for plant 1 is reduced further. The expected emission reduction by plant 1 is $(1/2)\phi \Delta e$.

(iii) For ϕ^D sufficiently low, there will be no investment in abatement for plants that do not have a local SRMF but have only a distant SRMF. This requires $\phi^D \pi_E^1 P - \kappa < 0$ (in fact, since ϕ^D and ϕ^N both exceed $1/2$, $\phi^D \pi_E^1 P - \kappa < 0$ implies $0 > (1 - \phi^N)\pi_E^1 P - \kappa$ which has been previously assumed to ensure that monitoring only occurs if $s_i = 0$).

(iv) Finally, we can get additional implications regarding the behavior of distant SRMFs if we relax the assumption that the draws of $\tilde{f}$ for the two plants owned by the same firm are iid. For example, assume that the $\tilde{f}$ for the two plants are correlated, and $\phi^D = 1/2$. It can be shown that in this case, the signal from plant 2 has no information value for the abatement decision in either plant, so the previous analysis for plant 1 based on i.i.d draws of $\tilde{f}$ which only considered signals from plant 1 still goes through. However, suppose $Prob.[\widetilde{f^2} = f_2|\widetilde{f^1} = f_2] = \rho \; and \; [\widetilde{f^2} = f_1|\widetilde{f^1} = f_1] = \rho,$ where $\widetilde{f^\iota}$ denotes the cost realization draw in plant i, and $1 \geq \rho \geq 1/2$. Then we have $Prob.[\widetilde{f^2} = f_2|s_1 = 0] = \rho\phi + (1-\rho)(1-\phi)$ and $Prob.[\widetilde{f^2} = f_2|s_1 = 1] = (1-\rho)\phi + \rho(1-\phi)$. Note that even for ρ close to the value of 1, the likelihood that the distant plant has not invested in abatement conditional on the signal from the local plant being $s_1 = 0$ is less than ϕ. Thus, no monitoring of the distant plant occurs based on the signal generated by the local plant. However, once monitoring of the local plant occurs, conditional on the local plant not having invested in abatement, the probability that the distant plant has also not done so is ρ. If ρ is high, this can lead to subsequent monitoring, and delayed investment in abatement by the distant plant.

Appendix B
Table B1: Variable Definitions

Variable	Definition	Source
Toxic	A plant's total on-site harmful chemical releases, which are standardized using the industry mean and standard deviation in each year.	NETS, EPA Toxics Release Inventory (TRI) Program
Post ClosePeerEA	A plant is defined as a treated plant if the EPA takes an enforcement action against any of its nearby (i.e., within 100 miles) peer plants during the year. *Post ClosePeerEA* is a dummy variable that is equal to 1 for treated plant-year observations in the three years after the EPA takes an enforcement action against a peer plant located in close proximity, and 0 for other plants located outside 100 miles radius, for plants of firms that are not direct rivals of the violating peer (outside TNIC3 but in the same TNIC2 product market), and for the pre-enforcement years of the treated plant.	NETS, TRI, Hoberg-Phillips Data Library
Size	Natural logarithm of market capitalization. Market capitalization is calculated as stock price (*PRCC_F*) multiplied by the number of shares outstanding (*CSHO*).	Compustat
Book-to-Market	Book value of equity (*CEQ*) divided by market capitalization.	Compustat
Return on Asset	Operating income before depreciation (*OIBDP*) divided by book value of total assets (*AT*).	Compustat
Ln(Sale)	Natural logarithm of aggregate firm-level sales (*SALE*).	Compustat
Leverage	The sum of long-term debt (*DLTT*) and debt in current liabilities (*DLC*) divided by market value of assets, where market value of assets is computed as total assets (*AT*) minus book value of equity (*CEQ*) and plus market capitalization.	Compustat
Corr_Toxic	The correlation of harmful chemical releases in a given year between plant $p1$ and plant $p2$ is measured as $Corr\_Toxic_{p1,p2} = \frac{Q_{p1}Q'_{p2}}{(Q_{p1}Q'_{p1})^{1/2} \times (Q_{p2}Q'_{p2})^{1/2}}$, where $Q_k = (P_{k1}, \dots, P_{k14})$; $k \in (p1, p2)$ is a vector of health hazards associated with harmful chemicals used by plant *p1* (or plant *p2*), with each element of the vector being the total quantity (in pounds) of harmful chemicals. We match the harmful chemicals into 14 types of health hazards as defined by EPA's Integrated Risk Information System (IRIS) ranging from hazards to human nervous system or the respiratory system. The toxic release quantity is standardized by industry in each year.	NETS, TRI

Appendix B
Table B2: Pairwise Correlations of Chemical Releases among Plants of Peer Firms
This table reports the results from the following plant-pair level regressions that examine the similarity of harmful chemical releases between two plants:

$$Corr\ Toxic_{p1,p2,t} = \beta_0 + \beta_2\ TNIC3_{1,2,t} + \delta + \tau + e_{i,t} \qquad (1)$$

where $Corr\ Toxic_{p1,p2,t}$ is the similarity of harmful chemical releases measured in year t between plant $p1$ and plant $p2$ that belong to firm 1 and firm 2, respectively. The calculation of $Corr\ Toxic_{p1,p2,t}$ is detailed in Appendix B1. Briefly, $Corr\ Toxic_{p1,p2,t}$ is the correlation between two vectors of harmful chemicals of the two plants, where each element of the vector is the amount (in pounds) of a chemical. $TNIC3_{1,2,t}$ is a dummy variable that is equal to 1 if firm 1 and firm 2 are in the same TNIC3 product market and zero otherwise. The control group contains plant pairs whose parent firms are in the same TNIC2, but not the same TNIC3, product market (i.e. firm pairs that are not in the same TNIC2 product market are removed). δ represents firm 1's industry × firm 2's industry fixed effects and τ indicates year fixed effects. As toxic releases could be cross-sectionally and serially correlated, we compute standard errors double-clustered at the pair and year levels. Firms in the same product market could also have similar production technology, which uses similar inputs and releases similar harmful chemicals. To examine the similarity of peer firms' technologies, we follow Jaffe (1986) and calculate a measure of technological proximity, $Tech\ Proximity_{1,2}$, between two peer firms using the classes of their patent applications. In Column 2, we replace the dependent variable with *Tech_Proximity*. Standard errors are double clustered at the pair and year level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. The variables are defined in Appendix Table B1.

Interpretation: In Column 1, the coefficient on $TNIC3_{1,2,t}$ is positive and statistically significant at the 1% level, suggesting that plants of TNIC3-peer firms have a higher *Corr Toxic* than other non-TNIC3 plants. The coefficient estimate on *TNIC3* in Column 1 indicates that the difference in the correlations of harmful chemical releases between TNIC3-pairs and TNIC2-pairs is 0.016, representing 16% of the sample average of *Corr_Toxic.* Consistently, the positive and significant coefficient in Column 2 indicates that peer firms' technologies are more similar to each other than non-peer firms. Together, these results assure that Hoberg and Phillips TNIC3 classification reasonably reflects the similarity of toxic releases among plants of peer firms.

	Corr_Toxic	*Tech_Proximity*
Variable	(1)	(2)
TNIC3	0.016***	0.137***
	(22.728)	(29.880)
Firm 1 Industry × Firm 2 Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Number of Obs	1,931,457	58,862
Adj. R-squared	0.033	0.220

Appendix B
Table B3: Enforcement Actions and Air Quality Index around Peer Plants

This table reports the results from the stacked difference-in-differences (DiD) regressions examining the effect of EPA enforcement actions on the air quality index measured around a plant. The EPA calculates daily air quality indexes based on five major air pollutants measured at thousands of monitoring stations: ozone, carbon monoxide, nitrogen dioxide, sulfur dioxide, and fine particulate matter smaller than 2.5 micrometers (PM2.5). The daily aggregate air quality index is the average of these five daily individual indexes. To derive the air quality index at a plant's location, we average the aggregate air quality index across all monitoring stations located within one (1) mile radius from the plant. The annual *AQI* measure for a given plant is then the average of its daily *AQI* over a year. Standard errors are double clustered at the plant and year level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. The variables are defined in Appendix Table B1.

Interpretation: In Columns 1 and 2, the coefficient on *Post ClosePeerEA* is negative and statistically significant at the 1% level, suggesting that air quality index around a plant improves in the three years after the EPA takes an enforcement action against a nearby peer plant. Given that AQI is objectively measured, these results suggest that our findings are unlikely to be driven by any self-reported bias arising from the TRI database.

	Dependent Variable: *AQI*	
Variable	(1)	(2)
Post ClosePeerEA	-0.028**	-0.029**
	(-2.249)	(-2.314)
Plant × Cohort FEs	Yes	Yes
Year × Cohort FEs	Yes	Yes
County × Cohort FEs	No	Yes
Number of Obs	1,338,490	1,338,490
Adj. R-squared	0.880	0.882

Appendix B

Table B4: Decaying Effects of Plant Responses and Proximity to Enforcement Actions

This table reports the results from the regressions examining whether there are decaying effects of the peer plant's response as the distance between a plant and its violating peer plant becomes larger. The regression specification is similar to that reported in Table 2. For a given plant, *Post* $PeerEA_{(100,\ 200)}$ (or *Post* $PeerEA_{(>200)}$) is a dummy variable equal to 1 for the three years after the EPA takes an enforcement action against its violating peer plant that is located between 100 miles and 200 miles (or greater than 200 miles) from the plant. Standard errors are double clustered at the plant and year level. *F*-statistics for the differences in the coefficients between *Post ClosePeerEA* and *Post* $PeerEA_{(>200)}$ are 15.10 (*p*-value<0.001) for Column 1 and 14.68 (*p*-value<0.001) for Column 2. *F*-statistics for the differences in the coefficients between *Post ClosePeerEA* and *Post* $PeerEA_{(100,\ 200)}$ are 0.45 (*p*-value = 0.509) for Column 1 and 0.31 (*p*-value = 0.581) for Column 2. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. The variables are defined in Appendix Table B1.

Interpretation: We observe a decaying effect of peer enforcement action on a plant's toxic releases as its proximity to the violating peer plant is larger. Specifically, the coefficient on our main variable, *Post ClosePeerEA*, remains negative and statistically significant at the 1% level, whereas the coefficient on *Post* $PeerEA_{(100,\ 200)}$ is smaller and it becomes insignificant for *Post* $PeerEA_{(>200)}$. These results are consistent with the notion that enforcement threat is local and its effect on plant emissions decreases with proximity.

	Dependent Variable: *Toxic*	
Variable	(1)	(2)
Post ClosePeerEA	-0.027***	-0.026***
	(-4.258)	(-4.017)
Post $PeerEA_{(100,\ 200)}$	-0.019*	-0.019*
	(-1.877)	(-1.748)
Post $PeerEA_{(>200)}$	0.004	0.004
	(0.966)	(0.866)
Plant × Cohort FEs	Yes	Yes
Year × Cohort FEs	Yes	Yes
County × Cohort FEs	No	Yes
Number of Obs	158,211	158,211
Adj. R-squared	0.820	0.830

Appendix B

Table B5: Plants' Responses, the Magnitude of Enforcement Penalties, and Violation Types

Panel A reports the results from the regressions examining whether plant-level responses depend on the magnitude of the EPA enforcement penalties. For each enforcement action against a violating peer plant, total penalty is computed as the sum of state and local penalty, the total compliance costs (e.g., the dollar values of injunctive relief and the physical or nonphysical costs of returning the facility to compliance), and the cost that a defendant agrees to undertake in settlement of an enforcement action clean up the environment (if any). *HighCost* is a dummy variable that is equal to 1 if the total penalty is above the sample median and zero otherwise. Panel B reports the results from the regressions examining whether plant-level responses depend on the violation types of EPA enforcement actions. We classify the types of violations into two categories, where Category 1 strictly includes three types of major violations (i.e. violation of a law/Act or environmental requirement, illegal disposal of chemicals/discharge without a permit, and illegal use of a chemical) and Category 2 contains all other violations such as failure to submit waste disposal reports. *MajorViolation* is a dummy variable that is equal to 1 if the EPA enforcement action involves a Category 1 violation and zero otherwise. Standard errors are double clustered at the plant and year level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. The variables are defined in Appendix Table B1.

Interpretation: In Panel A, the coefficient on *Post ClosePeerEA* × *HighCost* is negative and statistically significant, suggesting that the effects of an enforcement action against a nearby peer plant on local plants' toxic releases are stronger when the total penalty imposed on the peer is high. In Panel B, the coefficient on *Post ClosePeerEA* × *MajorViolation* is negative and statistically significant, indicating that the effects are more pronounced when a peer plant violated a major environmental law. These results are consistent with salience hypothesis, which posits a positive association between plant response and the severity of nearby enforcement actions.

Panel A: The Magnitude of Enforcement Penalties and Plants' Responses

	Dependent Variable: *Toxic*	
Variable	(1)	(2)
Post ClosePeerEA × *HighCost*	-0.017***	-0.018***
	(-2.934)	(-3.424)
Post ClosePeerEA	-0.023***	-0.021***
	(-3.783)	(-3.634)
Plant × Cohort FEs	Yes	Yes
Year × Cohort FEs	Yes	Yes
County × Cohort FEs	No	Yes
Number of Obs	158,211	158,211
Adj. R-squared	0.829	0.840

Table B5: continued

Panel B: Violation Types and Plant Response

	Dependent Variable: *Toxic*	
Variable	(1)	(2)
Post ClosePeerEA × MajorViolation	-0.019**	-0.020**
	(-2.009)	(-2.044)
Post ClosePeerEA	-0.021***	-0.020***
	(-3.697)	(-3.609)
Plant × Cohort FEs	Yes	Yes
Year × Cohort FEs	Yes	Yes
County × Cohort FEs	No	Yes
Number of Obs	158,211	158,211
Adj. R-squared	0.838	0.848

Appendix B
Table B6: Historical Exposure to EPA Enforcement Actions

This table reports the results from the regression specification of Table 2 estimated using subsamples of plants' historical exposure to EPA enforcement actions. Each year, treated plants are divided into two groups where Group 1 contains treated plants that did not witness any enforcement action taken against the local peer plants over the past 5 years and Group 2 contains treated plants that witnessed at least one enforcement action taken against the local peer plants over the past 5 years. Control plants are the same for two groups and are defined as in Table 2. Standard errors are double clustered at the plant and year level. t-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. The variables are defined in Appendix Table B1.

Interpretation: The coefficient on *Post ClosePeerEA* in Column 1 is negative and three times larger than that in Column 2. Z-statistic for the difference between the two coefficients is -1.720 (not tabulated), which is statistically significant at the 1% level. This result is consistent with the notion that a treated plant's response to a nearby peer enforcement action is stronger when its local peer plants did not experience any enforcement actions over the past 5 years (i.e. when the EPA was not active in the area over the past 5 years).

	Dependent Variable: *Toxic*	
	(1)	(2)
Variable	Group 1	Group 2
Post ClosePeerEA	-0.034***	-0.012*
	(-3.128)	(-1.825)
Plant × Cohort FEs	Yes	Yes
Year × Cohort FEs	Yes	Yes
County × Cohort FEs	Yes	Yes
Number of Obs	147,625	151,196
Adj. R-squared	0.836	0.857

Appendix B

Table B7: Local SRMFs Portfolio Holdings and Firms' Environmental Performance

This table reports the results from the regressions estimated at the firm-fund-year level that examine mutual funds' holdings of firms. The dependent variable, *Weight*, is a stock's weight in a fund's portfolio in the last quarter of a given year. *SRMF* is a dummy variable that is equal to 1 if a mutual fund is classified as socially responsible and 0 otherwise. *Close* is a dummy variable that is equal to 1 if a mutual fund, who holds a firm's stock, is located within 100 miles from one of the firm's plant and 0 otherwise. *Ln(ClosePlants)* is the natural logarithm of one plus the number of plants that are located within 100 miles from a mutual fund, who holds the parent firm's stock. All regressions control for fund, firm, and year fixed effects. Fund-level control variables are defined in Table 10. Standard errors are double clustered at the fund and year level. *t*-statistics are presented in parentheses. The variables are defined in Appendix Table B1.

Interpretation: Both the coefficients on *SRMF* and *Close* × *SRMF* are positive (negative) among High- (Low-) *EScore* firms. While the coefficient on *SRMF* is not surprising, the coefficient on *Close* × *SRMF* suggest that, even after accounting for the sustainability preferences of SRMFs, local SRMFs hold more (less) shares of High- (Low-) *EScore* firms located in close proximity. These strong local preferences are consistent with the notion that SRMFs have superior knowledge about local firms and can possibly monitor these local firms more easily than distant SRMFs.

	Dependent Variable: *Weight*			
	(1)	(2)	(3)	(4)
Variable	High *EScore*	Low *EScore*	High *EScore*	Low *EScore*
Close × *SRMF*	0.012***	-0.017***		
	(3.605)	(-4.255)		
Close	0.001	0.015***		
	(0.325)	(4.338)		
Ln(ClosePlants) × *SRMF*			0.008***	-0.007***
			(5.719)	(-4.381)
Ln(ClosePlants)			0.003*	0.003
			(1.671)	(1.545)
SRMF	0.016***	-0.025***	0.014***	-0.028***
	(5.387)	(-6.825)	(5.128)	(-8.587)
Ln(Fund Size)	-0.020***	-0.025***	-0.020***	-0.026***
	(-12.874)	(-11.594)	(-12.843)	(-11.609)
Exp Ratio	1.453*	2.751***	1.475*	2.744***
	(1.866)	(2.801)	(1.894)	(2.795)
Turn Ratio	-0.032***	-0.011***	-0.033***	-0.011***
	(-13.141)	(-4.147)	(-13.211)	(-4.138)
Fund Return	0.265***	-0.086*	0.265***	-0.086*
	(6.001)	(-1.684)	(5.986)	(-1.675)
Fund Flow	-0.070***	-0.067***	-0.070***	-0.067***
	(-3.337)	(-2.643)	(-3.333)	(-2.642)
Fund, Firm, Year FEs	Yes	Yes	Yes	Yes
Number of Obs	923,815	820,093	923,815	820,093
Adj. R-squared	0.542	0.546	0.542	0.546

Appendix B
Table B8: EPA Inspections and Local Socially Responsible Mutual Funds
This table reports the results from the regression specifications of Table 2 and Table 3 estimated using the number of inspections conducted by the EPA as the dependent variable. *Ln(Inspections)* is the natural logarithm of one plus the number of inspections of a plant in a given year. Standard errors are double clustered at the plant and year level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. The variables are defined in Appendix Table B1.

Interpretation: the coefficient on *Post ClosePeerEA* is positive and statistically significant. This result indicates that, following a nearby enforcement action against a peer plant, treated plants indeed experience an increase in the frequency of inspections by either the EPA or local authorities. However, the coefficient on *Post ClosePeerEA* × *CloseSRMF* is small and statistically insignificant, suggesting that there is no difference in inspection frequency between treated plants close to an SRMF and other treated plants. As such, the role of local SRMFs in monitoring local treated plants is unlikely to be driven by more frequent inspections of these plants.

	Dependent Variable: *Ln(Inspections)*			
Variable	(1)	(2)	(3)	(4)
Post ClosePeerEA× *CloseSRMF*			0.004	0.009
			(0.258)	(0.570)
Post ClosePeerEA	0.013**	0.015***	0.013**	0.014***
	(2.460)	(2.697)	(2.322)	(2.621)
Plant × Cohort FEs	Yes	Yes	Yes	Yes
Year × Cohort FEs	Yes	Yes	Yes	Yes
County × Cohort FEs	No	Yes	No	Yes
Number of Obs	68,509	68,509	68,509	68,509
Adj. R-squared	0.720	0.723	0.719	0.723

Appendix B
Table B9: Off-site Toxic Releases
This table reports the results from the regressions that examine off-site toxic releases at plants located in close proximity to an EPA enforcement action. Specifically, we re-estimate the plant-level regression in Table 2 by replacing the dependent variable with *Offsite_Toxic*. *Offsite_Toxic* is the total off-site harmful chemical releases of the plant standardized using the industry mean and standard deviation in each year. *Post ClosePeerEA* is a dummy variable that is equal to 1 for the three years after the EPA takes an enforcement action against one of the peer plants located in close proximity, and 0 otherwise. Standard errors are double clustered at the plant and year level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. The variables are defined in Appendix Table B1.

Interpretation: The coefficient on *Post ClosePeerEA* is statistically insignificant, suggesting that treated plants do not change their offsite toxic releases after observing an enforcement action against a nearby peer plant. This result is expected if treated plants are aware that a potential EPA scrutiny is likely to be comprehensive and plants cannot simply avoid it by changing the way they disclose toxic releases.

	Dependent Variable: *Offsite_Toxic*	
Variable	(1)	(2)
Post ClosePeerEA	-0.011	-0.014
	(-1.455)	(-1.156)
Plant × Cohort FEs	Yes	Yes
Year × Cohort FEs	Yes	Yes
County × Cohort FEs	No	Yes
Number of Obs	158,211	158,211
Adj. R-squared	0.689	0.672

Appendix B

Table B10: Firm-level Toxic Releases and the Role of Operational Inflexibility

This table repeats the regression of Table 12 Column 1 using subsamples that are split based on different operational flexibility measures. *Firm Toxic*, is the total standardized on-site harmful chemical releases of all plant owned by a firm. We identify a treated firm that owns at least one plant located within 100 miles of the violating peer plant. *Post Treatfirm* is a dummy variable that is equal to 1 for the three years after the EPA takes an enforcement action against the violating peer plant located within 100 miles of the treated firm's plants, and 0 otherwise. In Columns 1 and 2, the sample is split based on the sample median of firms' inventory levels. In Columns 3 and 4, the sample is split based on the sample median of operational inflexibility, which is a firm's historical range of operating costs scaled by the volatility of changes in sales over assets. In Columns 5 and 6, the sample is split based on the sample median of the number of plants per firm. Standard errors are double clustered at the plant and year level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. The variables are defined in Appendix Table B1.

Interpretation: The coefficient on *Post Treatfirm* is negative and significant in the sample of firms with high operational flexibility (Columns 2, 4, and 6), whereas it is insignificant in the sample of low-flexibility firms (Columns 1, 3, and 5). Consistent with the plant-level evidence, these results suggest that only firms with high operational flexibility can respond to a nearby peer enforcement action.

	Dependent Variable: *Firm Toxic*					
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Low Inventory	High Inventory	High Inflexibility	Low Inflexibility	Less Plants	More Plants
Post Treatfirm	-0.017	-0.058***	-0.014	-0.045***	-0.012	-0.066***
	(-0.871)	(-5.376)	(-0.514)	(-2.670)	(-0.385)	(-6.746)
Firm × Cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year × Cohort FEs	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs	14,539	14,769	14,746	14,242	13,624	16,790
Adj. R-squared	0.817	0.841	0.854	0.807	0.745	0.831