Internalizing Environmental Externalities: The Role of Geographic Common Ownership *

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Abstract

This paper proposes and tests the hypothesis that common ownership of nearby firms, which I call *geographic common ownership*, incentivizes firms to internalize environmental externalities. Using US EPA Toxic Release Inventory data from 1987 to 2019, I find that facilities sharing significant common institutional ownership with nearby firms tend to release fewer toxic chemicals, compared to other facilities of the same parent firm. An analysis using mergers of financial institutions as a quasi-natural experiment suggests that the effect of geographic common ownership on toxic pollution is causal. Consistent with the idea that common owners internalize pollution externalities across their portfolio firms, mutual funds with larger ownership stakes in the area of a facility are more likely to vote in favor of shareholder-sponsored environmental proposals at the facility's parent firm. Collectively, my findings highlight the potential role of common ownership in overcoming market failures pertaining to environmental externalities.

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"Environmental costs could reduce cash flows for companies held in portfolios and lower future dividends. Some environmental costs externalized by companies in large, widely diversified portfolios will be incurred by other companies in the same portfolio."

——*Principles for Responsible Investment (2010)*

1 Introduction

Over the past three decades, US public firms have become increasingly interconnected through common stock ownership (He and Huang, 2017; Backus et al., 2021). This phenomenon has spurred a burgeoning literature that explores the impact of common ownership on corporate decisions and broader economic outcomes.[1] Some studies suggest that common ownership can reduce firms' incentives to compete in product markets, potentially leading to increases in product prices and reductions in consumer surplus (Azar et al., 2018, 2022; O'Brien and Salop, 2000; Xie and Gerakos, 2020). Others posit that common ownership fosters information sharing and coordination among commonly-owned firms, improving innovation efficiency, shareholder monitoring, and corporate disclosure (He et al., 2019; Li et al., 2023; López and Vives, 2019; Park et al., 2019). Yet, existing research has predominantly focused on common ownership among industry peers. This paper proposes and tests another channel through which common ownership affects corporate behavior: whether common ownership of geographically proximate firms, which I call *geographic common ownership*, influences corporate environmental policy.

The emission of toxic chemicals from industrial enterprises in particular has emerged as an important environmental concern, imposing substantial costs on our society. Since the public release of the US Toxic Release Inventory (TRI) data in 1987, a large literature has shown that such toxic emissions are not only damaging to the environment but also negatively influencing nearby firms' financial performance through channels such as reduced

[1] See, e.g., He and Huang (2017), Azar et al. (2018), Antón et al. (2023b), Li et al. (2023), López and Vives (2019), Park et al. (2019), Dai and Qiu (2021), and Cheng et al. (2022).

revenue, diminished labor productivity, and increased compliance costs.[2] Despite these well-documented effects, firms often face limited incentive to internalize these environmental externalities in their production processes, leading to a textbook example of a market failure.

This paper investigates whether common ownership can incentivize firms to internalize their environmental externalities. Industrial facilities engaged in manufacturing, processing, or use of toxic substances have been increasingly connected to nearby firms via common institutional ownership. As Figure 1 shows, the proportion of facilities whose parent firm is owned by an institutional blockholder that also owns a block stake in a public firm headquartered nearby, defined as those within a 50-mile radius of the facility's location, surged from 20% in 1990 to more than 80% in 2019.[3] Given this growing trend of ownership connections in the geographic dimension, this paper examines the potential impact of geographic common ownership on toxic chemical pollution.

[Figure 1 Here]

The idea is the following. If managers in industrial firms are responsive to their shareholders' interest, they should take into account the environmental externalities their facilities impose on the nearby firms held by the same shareholders. As a result, they may want to reduce toxic pollution from the facilities located in close proximity to other cross-held firms. By doing so, common owners can benefit from the reduced exposure to negative environmental impacts caused by these facilities.

This hypothesis relies on two plausible assumptions. First, diversified shareholders, i.e., common owners, are assumed to have an objective to maximize total portfolio value, rather than individual firm value (Hansen and Lott, 1996; Rotemberg, 1984; Backus et al., 2021). Because of this objective, common owners care about the between-firm externalities in their

[2] See, e.g., impacts of toxic pollution on public health (Chay and Greenstone, 2003; Currie and Schmieder, 2009), labor productivity (Xue et al., 2021; Chang et al., 2016; Fu et al., 2021; Zivin and Neidell, 2012), top management turnover (Levine et al., 2018), employment, capital stocks, and product outputs (Greenstone, 2002), and property value (Currie et al., 2015; Chay and Greenstone, 2005).

[3] Similarly, approximately 25% of public firms listed on the AMEX, NYSE, and NASDAQ shared a common institutional blockholder with at least one public firm located within 50 miles of their headquarters in 1990. This proportion had significantly risen to 70% by 2019 as shown in Panel B of Figure 1.

portfolio. Second, the costs of toxic pollution dissipate spatially from pollution sites. That is, a facility's detrimental environmental practices are likely to impose higher external costs on nearby firms than those located farther away. To illustrate this point with a real-world example, let's consider IBM, which owns a semiconductor manufacturing facility in New York. The toxic chemicals emitted by this facility are more likely to affect Pfizer, a pharmaceutical and biotechnology company headquartered in New York, than Travere Therapeutics, a bio-pharmaceutical company located in California. While BlackRock owned a block stake in all three firms in 2014, IBM's managers should have a stronger incentive to internalize the pollution externalities of its facility vis-a-vis Pfizer due to their geographic proximity. Therefore, this hypothesis emphasizes the importance of distinguishing geographic common ownership from industrial common ownership conventionally studied in the literature, when examining the effects of common ownership on corporate environmental policies.

Establishing a causal relation between geographic common ownership and toxic chemical pollution is empirically challenging. Omitted variables, such as investor and firm characteristics, may simultaneously drive both geographic common ownership and toxic pollution. For instance, large asset managers like BlackRock, Vanguard, and State Street hold nontrivial ownership stakes in many US public firms. As such, facilities held by these asset managers are more likely to have the same institutional owners as geographically proximate firms. At the same time, these asset managers may exhibit pro-environmental preferences in response to the surging investor demand for environmental and social considerations. Consequently, they may direct the facilities operated by their portfolio firms to lower toxic chemical pollution, thereby creating an omitted variable problem.

Using US EPA Toxic Release Inventory data from 1987 to 2019, I address the above endogeneity issues by exploiting within-firm variation in the amount of toxic chemicals released by facilities and their ownership connections with nearby firms. In the baseline regression with firm-by-year and facility state-by-year fixed effects, I find that a facility that is located within a 50-mile radius of the headquarters of another firm with the same institutional blockholder releases 23% fewer toxic chemicals compared to other facilities of the same parent. This within-firm analysis identifies the effect of geographic common ownership on toxic pollution by controlling for any time-varying unobserved heterogeneity at the parent firm (including shareholders' general pro-environmental preferences as discussed above) and the facility's home state. This anti-pollution effect persists in a battery of robustness checks, including the use of alternative measures of common ownership, geographic proximity, and pollution. In heterogeneity tests, I find the effect is more pronounced for facilities owned by the "Big 3" institutional investors (BlackRock, Vanguard, and State Street), but it remains statistically significant for facilities owned by "non-Big-3" investors. Additionally, I observe a stronger effect for facilities owned by institutional shareholders who allocate more investments to firms with high Environmental, Social, and Governance (ESG) ratings, as those are arguably more concerned about environmental externalities.

A potential issue with this analysis is that the choice of where to open a facility, which serves as a determinant of my measure of geographic common ownership, might be endogenous. As such, the within-firm analysis above may overlook omitted variables at the facility level that determine both their exact location and the level of toxic pollution. To overcome such concerns, I exploit mergers of financial institutions as exogenous shocks to common ownership, while keeping individual facility locations fixed. Unlike previous studies that examine common ownership among industry peers (He and Huang, 2017), this paper assigns treatment and control groups at the facility level based on the likelihood that the facility experiences an exogenous increase in geographic common ownership after a merger. Using a stacked difference-in-differences approach (Goodman-Bacon, 2021; Baker et al., 2022), I find that treated facilities, those expected to experience an increase in geographic common ownership after a merger, release around 21% fewer toxic chemicals compared to control facilities. This analysis reveals that facilities reduce toxic pollution by scaling down production rather than transferring pollutants to other facilities within the parent firm or implementing abatement technology that reduce pollution. I also find evidence suggesting that the effect of geographic common ownership on toxic pollution explained by mergers is only present when a facility is in a close proximity to cross-held firms, highlighting the crucial role of geographic proximity in internalizing environmental externalities.

While the aforementioned findings suggest that geographic common ownership reduces toxic chemical pollution, it remains unclear whether shareholders with geographic common ownership indeed prefer a corporate policy of internalizing negative environmental externalities. Using mutual fund proxy voting data, I investigate the tendency of geographic common owners to promote pro-environmental corporate polices. I find that mutual funds that hold significant investment stakes in firms located near a polluting facility are more likely to vote in favor of shareholders-sponsored environmental proposals of the facility's parent firm. Specifically, in a fund-voting level regression incorporating both proposal and fund-by-quarter fixed effects, a one-standard-deviation increase in the portfolio weights of these nearby public firms is associated with a 10% higher propensity to vote for pro-environmental proposals. This finding is consistent with the hypothesis that shareholders whose portfolio is concentrated in a geographic area have an incentive to internalize the environmental externalities of their portfolio firms.

The contribution of this paper is twofold. First, the paper contributes to the burgeoning literature on common ownership. Institutional investors, who are major participants in the US equity market, often hold non-trivial ownership stakes in multiple firms, making them diversified common owners. The rise of index investing and consolidation of asset managers accelerated the increase in common institutional ownership in recent decades (He and Huang, 2017; Azar et al., 2018; Backus et al., 2021). Several studies have documented the impacts of common ownership among industry competitors on firm- or industry-level outcomes, such as, product market competition (Azar et al., 2018; Antón et al., 2023b), firm performance and coordination (He and Huang, 2017), innovation efficiency (Li et al., 2023; López and Vives, 2019), advertising strategy (Lu et al., 2022), corporate disclosure (Park et al., 2019), corporate social responsibility (Dai and Qiu, 2021; Cheng et al., 2022), and shareholder monitoring (He et al., 2019). While common ownership of industry peers has garnered substantial attention from academics and policymakers, there has been limited research on common ownership beyond industry rivals.[4] This paper fills this gap by examining geographic common ownership, which captures ownership connections among geographically proximate entities. The findings in this study reveal that geographic common ownership can exert a positive effect on mitigating negative corporate environmental impacts. Importantly, this paper sheds light on a strand of the literature examining the effect of common ownership on corporate social responsibility (CSR). Existing studies, focusing on common ownership of industry peers, present seemingly contradicting evidence regarding the relationship between common ownership and corporate CSR scores (Dai and Qiu, 2021; Cheng et al., 2022). However, the findings in this paper suggest that geographic proximity, as opposed to operating in the same industry, is the key driver that internalizes corporate environmental externalities.

Second, this paper also adds to the existing literature on corporate toxic emissions. Since 1987, US facilities meeting certain criteria and emission thresholds are obligated to disclose information on toxic chemical releases to the public. A large number of studies have explored the determinants and consequences of toxic chemical pollution. For example, Akey and Appel (2021) document that greater liability protection for parent firms is associated with a significant increase in the amount of toxic chemicals released from their affiliated facilities. Shive and Forster (2019) find that private firms are less likely to pollute and incur EPA penalties than public firms. Khanna et al. (1998) show that the repeated public disclosure of information on toxic emissions data lead to negative market reactions, which in turn has a negative real impact on subsequent toxic chemical releases. Xu and Kim (2022) argue that financial constraints faced by parent firms contribute to a higher levels of toxic pollution. By exploiting within-firm variation in toxic releases, recent studies also find that local institutional ownership and CEO's hometown favoritism influence a facility's toxic chemical pollution (Kim et al., 2019; Li et al., 2021). Dasgupta et al. (2023) emphasize the role of a facility's geographic proximity to its industry peers who are subjected to EPA inspections in determining its own toxic emissions. This paper complements the literature by examining how a firm's ownership structure affects its emissions. Specifically, I find that

[4]One exception is Freeman (2021) who finds overlapping ownership between customers and suppliers enhance the duration of supply chain relationship.

common ownership with nearby firms can negatively influence both the quantity and toxicity of chemicals a facility releases. To some extent, this study is related to Kim et al. (2019) who find that higher local institutional ownership is associated with lower levels of toxic emissions due to the local preferences of institutional investors. Different from their study, the findings in this paper are not dependent on investors' preferences nor their geographical proximity to the facility. My paper instead suggests that an increase in ownership connections between the facility and nearby firms, under few plausible assumptions, can result in a lower level of corporate pollution.

This paper has potential policy implications. Policymakers are increasingly concerned about the potential anti-competitive effect of common ownership among industry peers (Azar et al., 2018, 2022). Several measures have been proposed by academics to limit common ownership through curbing the influence of large institutional investors.[5] However, such proposals might come at the expense of forgoing diversification benefits offered by these investors. This paper examines the potential impact of common ownership on corporate environmental policies, offering a new channel that should be taken into account when assessing the welfare consequences of common ownership.

2 Analytical Framework

According to the Friedman doctrine (1970), the only social responsibility of firms is to maximize shareholder wealth. If shareholders are separate owners who invest in one firm, maximizing shareholder wealth in individual firms is equivalent to maximizing their own

[5]These proposals are to regulate the ability of institutional investors to hold significant multiple stakes in certain industries and/or to restrict the voting rights of these common owners. For example, Eric Posner and two other academics have proposed a policy that "institutional owners of stock in oligopolistic industries would benefit from a safe harbour from government enforcement of the Clayton Act if they either limit their shareholdings in that industry to a small stake (no more than 1% of the total size of the industry) or hold the shares of only a single firm per industry", according to the KPMG Common Ownership and Competition Report.

profit.[6] Firms should therefore refrain from spending on unprofitable pro-environmental activities. Put differently, firms should not consider other stakeholders' interest beyond the profit implications. For example, corporate managers acting in shareholders' interest should not invest in pollution control for reducing pollution generated by the firm, beyond the potential benefit of avoiding potential environmental lawsuits or maintaining productivity of its own employees. As a result, a social welfare loss occurs when such environmental costs are externalized to other individuals and businesses in the community.

In the context of toxic chemical releases, previous studies have documented substantial negative environmental externalities of toxic chemical pollution to surrounding corporations. First, the presence of toxic substances can have adverse economic impacts on the profitability of neighboring firms that are sensitive to environmental conditions, e.g., those in agriculture, fishing, mining, insurance, beverage industries. Second, toxic pollution may discourage workers from residing and working in contaminated areas (Levine et al., 2018; Xue et al., 2021), which can lead to a decreased labor supply in the local market. Consequently, workers may demand higher compensation for living in a polluted environment, thereby increasing the labor cost for businesses in the vicinity. Third, the negative health effects of toxic chemicals can directly reduce labor productivity, further impacting the efficiency and output of affected nearby firms (Currie et al., 2015; Zivin and Neidell, 2012; Dockery et al., 1993). Lastly, local environmental pollution can also affect asset prices (Choi et al., 2022). Investors who anticipate regulatory risks associated with pollution to materialize in future may require compensation for bearing such risks, decreasing the value of firms located in polluted areas (Greenstone, 2002).

Several mechanisms have been proposed to mitigate such negative environmental externalities. Coase (1960) offers a private-sector solution, suggesting that in a complete competitive market with no transaction costs, bargaining will lead to a Pareto efficient outcome regardless of the initial allocation of property rights. In practice, some believe that certain

[6] An influential paper by Hart and Zingales (2017) argues that firms should maximize shareholders' utility rather than financial returns, when shareholders have prosocial preferences and externalties are not perfectly separable from the firms' production decisions. This paper is agnostic about shareholders' preferences and shows that externalities could be internalized even if firms' objective is to maximize shareholders' profits.

government interventions, such as price policies or quantity regulations, should be implemented to curb corporate pollution (Pigou, 1920; Baumol, 1972; Koehler and Spengler, 2007; Khanna et al., 1998). Besides, recent studies argue that prosocial preferences of shareholders and consumers could also influence firms to reduce pollution (Hart and Zingales, 2017; Akey and Appel, 2020; Grappi et al., 2017).

This paper introduces a novel mechanism that negative environmental externalities can be internalized by firms through common ownership. In the US equity market, common ownership has become a prominent ownership structure with the expansion of institutional investors in the past few decades (He and Huang, 2017; Lewellen and Lowry, 2021; Backus et al., 2021). Most institutional shareholders are diversified investors, with an objective of maximizing the total value of their portfolios. Per Rotemberg (1984) and Hansen and Lott (1996), when shareholders hold diversified portfolios, the firm's objective function tend to deviate from maximizing its own profit to maximizing a combination of its own profit and the profit of other firms jointly held by the same set of shareholders.

Rotemberg (1984) and Backus et al. (2021) provide detailed explanations on how common ownership shapes a firm's objective function. Suppose shareholders hold diversified portfolios. Their investment profits are the weighted sum of the portfolio firms' profit as follows:

$$v_s = \sum_{\forall g} \beta_{gs} \pi_g, \tag{1}$$

where v_s is shareholder s' portfolio profits, β_{gs} is cash flow right on firm g by shareholder s, and π_g is firm g's profit. As shareholders' portfolios differ, managers in firm i need to solve the multiple shareholder problem by applying a Pareto weight to each shareholder's portfolio profit. The weight is assumed to be control right (γ_{is}), which represents the influence that the shareholder can exert on the firm or how responsive corporate managers should be to the shareholder. Thus, firm i's objective function (Q_i) can be rewritten as follows:[7]

$$
\begin{aligned}
Q_i &= \sum_{\forall s} \gamma_{is} v_s \\
&= \sum_{\forall s} \gamma_{is} \sum_{\forall g} \beta_{gs} \pi_g \\
&= \sum_{\forall s} \gamma_{is} \beta_{is} \pi_i + \sum_{\forall s} \gamma_{is} \sum_{\forall g \neq i} \beta_{gs} \pi_g \\
&\propto \pi_i + \sum_{\forall g \neq i} \underbrace{(\frac{\sum_{\forall s} \gamma_{is} \beta_{gs}}{\sum_{\forall s} \gamma_{is} \beta_{is}})}_{\kappa_{ig}} \pi_g
\end{aligned}
\tag{2}
$$

The term, $\frac{\sum_{\forall s} \gamma_{is} \beta_{gs}}{\sum_{\forall s} \gamma_{is} \beta_{is}}$, is the so-called profit weight (κ), which captures the importance of firm g's profit into firm i's profit function. This implies that, under the common ownership structure, corporate managers considering shareholders portfolio value tend to internalize their decision externalities to the firms held by the same shareholders into their own objective function. The extent of such incentive is proxied by κ.

The presence of κ in the objective function of commonly-owned firms has important consequences to corporate decisions. A notable example is that the common ownership structure can lead to an anti-competitive effect in product markets as discussed extensively in the literature. In this strand of literature, common ownership, typically proxied by κ, is measured among industry rivals. The general hypothesis is that cross-held firms tend to compete less against each others for the interests of their common shareholders.

Similarly, I posit that the common ownership incentivizes firms to internalize their negative environmental externalities to cross-held local firms. Such internalization creates an anti-pollution effect. Different from prior studies, the construction of κ is based on geographic proximity between a polluter (i.e., facility) and its cross-held firms, as opposed to industrial relationship. In other words, firm g in Equation 2 only represents the firm that is located in the vicinity of firm i's facility (e.g., a 50-mile radius). This choice is motivated by

[7]In the last step, the equation is normalized by $\sum_{\forall s} \gamma_{is} \beta_{is}$ on both sides.

the fact that environmental activities, such as toxic emissions, have salient spatial feature: environmental externalities dissipate spatially with the distance from the toxic pollution sites. Hence, I argue that geographic proximity, rather than industry relationship, plays a crucial role in determining the internalization of environmental externalities.

In Appendix B, following Antón et al. (2023a), I develop a profit-maximization model demonstrating the relationship between common ownership, geographic proximity, and corporate pollution. In the model, firms' pollution is a function of pollution abatement efforts and production outputs. In the presence of geographic common ownership, the model equilibrium reveals that firms' optimal spending on pollution abatement is positively associated with the extent of common ownership with local firms but negatively with the geographic proximity between the polluters and nearby firms. Furthermore, the equilibrium production output is negatively related to geographic common ownership. This negative relationship is further attenuated by the increase in the geographical distance between the local firms. Put together, geographic common ownership mitigates corporate pollution through both the abatement and output channels.

3 Data and Measurement

3.1 Sampling

To construct the sample, I start from a universe of US public firms with common stocks listed on the NYSE, NASDAQ, and AMEX. To be included in the sample, firms are required to operate at least one facility that reports the release of toxic chemical(s) in a year to the US EPA. Besides, firms must have non-missing annual sales, positive book value of total assets, and available year-end stock price from the Center for Research in Security Prices (CRSP) and Compustat databases. The sample period starts from 1987, the first year when the toxic chemical pollution data become publicly available, and ends in 2019.

3.1.1 Toxic Release Data

I obtain the toxic emissions of facilities from the EPA's TRI database. The TRI program provides granular data on the quantity of toxic chemicals released into the air, water, and land at the facility-chemical-year level. Under the current EPA reporting standard, US facility must report annually the quantity of each toxic chemical, if it hires ten or more full time employees, operates in certain NAICS industry, and manufacture, process, or otherwise use toxic chemicals in excess of certain thresholds.[8] Firms in the TRI data are matched with Compustat firms based on standardized parent name.[9] In the main analysis, I filter out observations with zero toxic emission at the facility-chemical-year level and aggregate the emission across all chemicals within a facility in a given year.[10] Except for the toxic release data, the EPA also creates a Risk-Screening Environmental Indicators (RSEI) model that incorporates information on the amount of toxic chemicals released or transferred from facilities, together with factors that capture each chemical's relative toxicity to environment and human health.

3.1.2 Mutual Fund Voting Data

I obtain the US mutual fund voting records from the ISS Voting Analytics database. The voting sample period spans from 2004 to 2019. Since July 2003, the US Securities and Exchange Commission (SEC) mandated the reporting of all votes cast by US-registered management companies on corporate ballots for both the US and non-US firms they hold via Form N-PX. The data include proposals on all agenda items sponsored by either corporate managers or shareholders. This paper focuses on shareholder-sponsored environmental proposals, which covers subjects related to toxic chemicals, pollution, carbon emissions, and

[8]The current TRI toxic chemical list contains 787 individually listed chemicals and 33 chemical categories. See the latest reporting criteria on the EPA TRI website. Most chemicals on the TRI list trigger reporting if a facility manufactures or processes the chemical in excess of 25,000 pounds or otherwise uses the chemical in excess of 10,000 pounds during the reporting year. Some chemicals of special concern have lower reporting thresholds (e.g., 100 or 10 lbs, 0.1 gram for dioxins).

[9]I am grateful to Adrian Lam for providing a comprehensive linking table between the two databases.

[10]The main results remain robust using the facility-chemical-year level sample.

other environmental activities. Appendix E provides a complete list of such proposals. For each proposal, I observe the voting decision made by individual mutual fund (i.e., "For", "Against", "Withhold", "Abstain" and "Do Not Vote"). I match mutual funds between the ISS Voting Analytics and the CRSP Mutual Funds database, following a linking note from Peter Iliev's website.[11] For each matched fund voter, I obtain its quarterly shareholding from the CRSP Mutual Funds Portfolio Holdings database. Mutual funds' business addresses are sourced from CRSP Fund Summary data following Alok et al. (2020).

3.1.3 Firm Ownership and Other Data

Quarterly institutional ownership is obtained from the Thomson Reuters Institutional Holdings (S34) database which covers common stock holding of institutional investors with $100 million or more assets under management from the SEC Form 13F. I keep the institutional ownership in the last quarter each year. Besides, for each big-3 asset manager, I consolidate the shares the manager holds, through affiliated investment companies, for each stock in a given year end. Institutional investor's business address is sourced directly from the Form 13F through EDGAR.[12] Firms' historical headquarters are obtained from the Form 10-K or from Compustat when Form 10-K is not available. Firm-level environment and employee benefit ratings are sourced from MSCI ESG (formerly referred as KLD) database.[13] The Fama-French 48 industry classification is obtained from Kenneth French's website. A list of financial institution mergers is obtained from Lewellen and Lowry (2021) and He and Huang (2017).

[11] Appendix D details the procedures to match ISS with CRSP mutual fund databases.

[12] I construct a linking table that maps Thomson Reuters' investor id (mgrno) to the SEC filer id (cik). The mapping is based on the similarity of investor name and portfolio holdings.

[13] MSCI ESG database provides firm-level ESG rating score in seven dimensions: community, diversity, employee relations, environment, product, human rights, and corporate governance. To construct firm-level MSCI environment and employee relations ratings, I subtract the number of weaknesses from the number of strengths for both dimensions.

3.2 Measurement of Variable

3.2.1 Geographic Common Ownership

Literature on common ownership has developed several measures capturing the overlapping ownership of industry rials. Following prior studies, I construct two proxies for geographic common ownership. The first proxy is *GeoCO Dummy*, an indicator set to one if a facility's parent firm is owned by an institutional blockholder (with stock ownership of 5% or more) who also owns a block stake on any firms that headquarter within 50 miles of the facility, and zero otherwise. This measure shares a similar feature with He and Huang (2017)'s measure of cross-ownership among industrial rivals except that *GeoCO Dummy* is constructed based on geographic proximity between facilities and firms. Second, as discussed in Section 2, profit weights (κ) measure the importance of the profit of commonly-owned firms relative to a firm's own profit in its objective function. The profit weight measure has been used to capture the extent of common ownership among industry peers (Azar et al., 2018; Backus et al., 2021). In a similar fashion, the second measure of the geographic common ownership is constructed as follows:

$$GeoCO_{if} = \sum_{\forall i \neq g} w_g (\underbrace{\frac{\sum_{\forall s} \gamma_{is}\beta_{gs}}{\sum_{\forall s} \gamma_{is}\beta_{is}}}_{\kappa_{ig}}), \tag{3}$$

where f and i indicate a facility and its parent firm; g represents firms that headquarter within 50 miles of facility f; w is the fraction of a firm's market capitalization over the total market capitalization of all the firms located within 50 miles of facility f; γ and β denotes control and cash flow rights, respectively; s indicates institutional shareholder. Following the literature, I assume $\gamma = \beta$ given that majority of US public firms adopt the one-share-one-vote rule. β is computed by dividing the number of shares that investor s holds over the total number of shares outstanding of the firm. Note that $\frac{\sum_{\forall s} \gamma_{is}\beta_{gs}}{\sum_{\forall s} \gamma_{is}\beta_{is}}$ is κ_{ig}, measuring the common ownership between facility f's parent firm i and its local cross-held firm g. $GeoCO_{if}$ is therefore the weighted average of geographic common ownership between facility f and all cross-held firms in the vicinity. For the TRI firms with multiple facilities in a year, there is a variation in geographic common ownership across facilities held by the same parent firm, if these facilities locate in different areas with different sets of cross-held local firms. This variation is crucial in the following empirical analysis, providing an opportunity to examine the effect of geographic common ownership on toxic pollution within a given parent firm.[14]

3.2.2 Toxic Chemical Pollution

I measure a facility's environmental impact using the natural logarithm of its total quantity of toxic chemicals released to air, water, and land in pounds ($LogPollution$). In a robustness check, I employ on-site toxic releases as an alternative pollution variable which is measured by the natural logarithm of the total quantity of toxic chemicals released around the facility's location ($LogOnsitePollution$). Regarding pollution abatement and control, I construct $SourceReduction$, which measures the number of source reduction activities implemented to prevent or reduce the amount of toxic chemicals. Besides, given that toxic chemicals have various levels of toxicity to environment and human, I measure the pollution toxicity by the natural logarithm of the sum of toxic chemical onsite releases multiplied by the toxicity weight ($LogRSEI$).[15]

3.2.3 Control Variables

I compute the following firm characteristics in a given fiscal year: $LogAsset$ is the natural log of the book value of total assets; $LogSale$ is the natural log of annual sales; $Leverage$ is the long-term leverage divided by the book value of assets; $ProfitMargin$ is the net

[14]In robustness check, I show the main results are robust to an alternative measure of geographic common ownership based on Lewellen and Lowry (2021). Their measure is similar to the profit weight without the scaler, $\sum_{\forall s} \gamma_{is}\beta_{is}$. Analogous to Lewellen and Lowry (2021), the alternative measure of geographic common ownership is constructed as $GeoCindex_{if} = \sum_{\forall g} w_g(\sum_{\forall s} \gamma_{is}\beta_{gs})$, where all subscript notations follow those in $GeoCO$. Different from $GeoCO$, $GeoCindex$ does not scale the cross-ownership by firm i's ownership concentration. To some extent, this measure addresses the concerns that the incomplete ownership data may underestimate $\sum_{\forall s} \gamma_{is}\beta_{is}$ and thus inflate $GeoCO$. According to Amel-Zadeh et al. (2022), the non-institutional investors, e.g., family and corporate insiders, have less diversified ownership and thus the likelihood of underestimating the cross ownership, $\sum_{\forall s} \gamma_{is}\beta_{gs}$ is small.

[15]I weight the pollution for each chemical using the greater of the cancer and the non-cancer toxicity weights obtained from the TRI RSEI data. The weight for each chemical is publicly available on the EPA website.

operating incomes over total sales; ROA is the operating incomes over the book value of total assets; *R&D* is the research and development expenditures divided by total assets with *R&D* set to zero if missing; $TangibleAsset$ is the proportion of the book value of tangible assets over total assets; $CAPEX$ is capital expenditures over total assets; $Cash$ is the cash and cash equivalents over total assets; $Tobin's\ q$ is the market value of both equity and debt claims over replacement cost proxied by total book assets; IO is the total institutional ownership measured based on Form 13F filings; and $MarketShare$ is the fraction of a firm' sales over the total sales in the Fama-French 48 industry that the firm primarily belongs to. In addition, I construct three facility-level variables: $NumChemical$ measures the number of unique chemicals manufactured, processed, or otherwise used by the facility in a year; $NearParentHQ$ is a dummy variable set to one if the facility is located within 50 miles of its parent firm's headquarter; and $LocalOwnership$ measures the total ownership held by institutional investors whose business address is located within 50 miles of the facility.

3.3 Summary Statistics

Table 1 presents the summary statistics for the key variables used in the empirical analysis. Panel A reports the statistics at the firm-facility-year level. The average *GeoCO Dummy* is 0.53, suggesting approximately half of the facilities located within a 50-mile radius of the headquarters of cross-block-held firms. The mean value for *GeoCO* and $GeoCindex$ are 0.32 and 0.01, respectively. The average total quantity of toxic chemicals is 1.22 million pounds, while the average onsite release is 0.16 million pounds. Both pollution variables exhibit a high degree of positive skewness. The average number of source reduction activities are less than one. On average, facilities manufacture, process, or use 4.5 types of toxic chemicals. The average ownership held by institutional investors who locate within a 50-mile radius of the facility's location is approximately 0.32%. In Panel B, the summary statistics are reported at the firm-year level. The sample firms are on average larger, more profitable, and have more institutional ownership than average US public firms with common stocks listed on the three primary exchange markets.

[Table 1 Here]

4 Within-Firm Analysis

In this section, I test the main hypothesis that a firm's facility that is located near the headquarter of other firms with which they share a common institutional shareholder tend to release fewer toxic chemicals, compared to other facilities of the same focal firm. The within-firm regression at the firm-facility-year level is specified as follows:

$$LogPollution_{ifst} = \alpha_{it} + \gamma_{st} + \beta_1 GeoCO(Dummy)_{ifst-1} + \sum_{k=2}^{4} \beta_k FacilityControls_{ifst-1} + \epsilon_{ifst}, \tag{4}$$

where i, f, s, and t denotes firm, facility, facility's state, and year, respectively. The dependent variable, *LogPollution*, is the natural logarithm of the total quantity of toxic chemicals in pounds produced by facility f in year t. The key dependent variable is either (1) *GeoCO Dummy*, a dummy variable set to one if a facility's parent firm is owned by an institutional blockholder who also owns a block stake (ownership of 5% or more) on a public firm headquartered within a 50-mile radius of the facility in year $t-1$, or (2) *GeoCO*, which represents the continuous measure of geographic common ownership of facility f in year $t-1$, as defined by Equation 3 in Section 3.2. The regression includes three facility-level control variables: (1) $NumChemical$, which measures the number of toxic chemical types manufactured, processed, or otherwise used by the facility; (2) $NearParentHQ$, a dummy variable set to one if the facility is located within a 50-mile radius of the headquarter of its parent firm; (3) and $LocalOwnership$, which is the total ownership held by institutional investors whose business address is within 50 miles of the facility (Kim et al., 2019).

Importantly, the regression incorporates firm-by-year and facility's state-by-year fixed effects, which control for time-varying unobserved heterogeneity at the parent firm level (e.g., shareholders' general environmental preferences as well as firms' characteristics such as profitability and financial constraints) and the facility's state level (e.g., environmental regulation and economic condition in the facility's state). As illustrated in Figure 2, the identification in this analysis comes from exploiting the within-firm variation in toxic pollution across facilities with different levels of geographic common ownership based on their geographic proximity to cross-held firms. Standard errors are clustered at the parent firm and the facility's state levels. Figure 4 visualizes the geographic distribution of facilities in year 2000. Facilities are dispersed across the US, and I do not observe significant separate clustering between the facilities that are located in close proximity to cross-block-held firms (*GeoCO Dummy* = 1) and those that are not (*GeoCO Dummy* = 0).

Table 2 reports the results of estimating Equation 4 using the panel sample from 1987 to 2019 at the firm-facility-year level. In Column (1), using *GeoCO Dummy* as the independent variable, I find that facilities located within a 50-mile radius of the headquarters of other firms with which they share the common blockholder produce significantly fewer toxic chemicals, compared to other facilities of the same parent firm. The economic magnitude is sizable at -23.7%, which is equivalent to 14,585 pounds fewer toxic emissions conditional on the median annual emissions of 61,540 pounds per facility over the sample period. The results in Column (2) remain quantitatively and qualitatively similar after including the facility-level control variables. In Columns (3) and (4), I replace *GeoCO Dummy* with *GeoCO*, the continuous measure of geographic common ownership. I find that the lagged geographic common ownership of a facility is significantly and negatively associated with its toxic pollution in the subsequent year. In terms of economic magnitude, a one-standard-deviation increase in *GeoCO* (0.267) is associated with a 17.9% (0.673×0.267) decrease in toxic chemical pollution.[16]

[Table 2 Here]

I have conducted several robustness checks for the within-firm results. First, I use an alternative measure of geographic common ownership, *GeoCindex*, which is identical to *GeoCO* except that the profit weight component (κ) only captures the overlapping ownership

[16] As reported in Appendix F, the results remain quantitatively and qualitatively similar using parent firm-by-year and facility's county-by-year fixed effects.

($\sum_{\forall s} \gamma_{is}\beta_{gs}$) between the facility's parent firm and other firms headquartered nearby, without considering the scaler of ownership concentration in focal firm ($\sum_{\forall s} \gamma_{is}\beta_{is}$). Appendix G reports the results. I continue to observe that toxic chemical pollution is negatively related to the ownership connections between the facility and its local firms at the 1% level of significance. In terms of economic magnitude, a one-standard-deviation increase in *GeoCindex* (0.005) is associated with 16.7% lower toxic emissions, corroborating the findings in Table 2.

Second, I test the sensitivity of the within-firm results by altering the geographic radius used to define geographically close peers. Panel A of Appendix H shows that facilities located within 25 miles of cross-block-held firms release 20.5% fewer toxic chemicals, compared to other facilities of the same parent. However, Panel B reports that this effect becomes weaker (or even statistically insignificant for *GeoCO*) when I use 100-mile radius to define local firms, implying that the effect decays with geographic proximity between facilities and cross-held firms.

Third, I estimate Equation 4 at the facility-chemical-year level. To account for chemicals' heterogeneity, the regression additionally includes $chemical \times year$ fixed effects. As reported in Appendix I, I find the results are robust to using this more granular chemical-level sample.

Fourth, I use the onsite releases of toxic chemicals as an alternative dependent variable, which captures the emissions around the location of the facility. This test addresses the potential concern that toxic pollution may be transferred to a distinct offsite location without impacting the local environment around the facility. In Panel A of Appendix J, I show that the geographic common ownership is significantly and negatively related to onsite toxic emissions. The economic magnitude is even larger than the total toxic pollution in Table 2, which further supports the idea that the reduction of toxic pollution is driven by internalization of externalities to local environment shared with the cross-held local firms.

Fifth, to capture the toxicity of the released chemicals, I compute a measure of toxicity-adjusted pollution (*LogRSEI*). In Appendix K, I find that a facility's geographic common ownership is significantly negatively associated with the toxicity of chemicals released from the facility onsite. Lastly, in Appendix L, I estimate the regression in Equation 4 decade by decade from 1987 to 2019. I find that the estimated coefficients are significantly negative in all the sub-periods.

5 Difference-in-Differences Analysis

5.1 Financial Institution Mergers and Toxic Pollution

Although the within-firm analysis suppresses the potential influences of time-varying firm- and state-level heterogeneity on a facility's toxic emissions, omitted variables at the facility level may still be correlated with both toxic emissions and geographic common ownership. Besides, reverse causality is another endogeneity issue that geographic common ownership may be inversely determined by the levels of toxic chemical pollution of the facility. To overcome these issues, I employ financial institutions mergers as an exogenous shock to facilities' geographic common ownership and study how the facility responses to the shock by altering its toxic chemical pollution. Figure 3 illustrates this identification strategy.

Financial institutions mergers have been exploited to study the effect of common ownership of industry firms on industrial competition and coordination (Lewellen and Lowry, 2021; He and Huang, 2017). The identification relies on the stylized fact that the financial institutions often merge for reasons unrelated to the fundamentals of the portfolio firms and the facilities operated by these firms. The advantage of this identification is that mergers occur several times across the sample period and affect different sets of firms and facilities in each time. To construct the event sample, I first obtain a full list of 64 financial institutions mergers provided by Lewellen and Lowry (2021). To mitigate the concern that some merger events may coincide with the 2008 Global Financial Crisis, I then remove 6 mergers announced during the 2008-2009 period.[17] Lastly, I retain the mergers that include at least one treated facility (described below). This filtering process results in 24 mergers in the final

[17] These events include mergers between Lehman Brothers and David J Greene, RiverSource and J&W Seligman, Bank of America and Merrill Lynch, Barclays and Lehman-Invest Bkg Bus, Wells Fargo and Wachovia, and Blackrock and Barclays Global Fund Advisors.

event sample. Event firms are referred to the firms that are block-held by one of the merging institutions.

Different from prior studies, the treatment and control samples in this paper are constructed at the facility level. Specifically, treated facilities are defined as facilities (1) whose parent firm is block-held by one of the merging institutions in the quarter prior to the merger announcement and (2) that locate in a less-than-50-mile distance with the headquarter of any firms block-held by the other merging institution. With this definition, treated facilities are likely to experience an increase in geographic common ownership after the merger. Control facilities are facilities (1) that are operated by the firms block-held by one of the merging institutions in the quarter prior to the merger announcement and (2) that are not classified as treated facilities. I refer to "treated firms" ("control firms") as the event firms that (do not) operate any treated facilities in the quarter prior to the merger announcement. However, it is important to note that not all the facilities owned by the treated firms are treated facilities. For treated firms that are treated multiple times by different mergers, I retain the observations associated with the first treatment. In addition, I drop the observations of the control (treated) firm in a merger event if that firm becomes a treated (control) firm in the following merger that occurs within six years of the former merger. These filters are to avoid overlapping event windows that may bias the estimate due to the potential treatment effect heterogeneity (Goodman-Bacon, 2021; Baker et al., 2022). Eventually, I obtain 423 treated facilities and 1,070 control facilities. At the parent firm level, there are 245 event firms consisting of 129 treatment and 116 event firms.

Using the merger events, I estimate the following stacked difference-in-differences (DiD) regression at the firm-facility-year level:

$$\begin{aligned} LogPollution_{mifst} = \alpha_{mf} + \gamma_{mt} + \beta_1 Treat \times Post + \sum_{j=2}^{11} \beta_j FirmControls_{mit-1} \\ + \sum_{k=12}^{14} \beta_k FacilityControls_{mifst-1} + \epsilon_{mifst}, \end{aligned} \tag{5}$$

where m denotes merger events and all other subscriptions follow Equation 4. The dependent variable is $LogPollution$, the natural log of toxic chemical pollution emitted by facility f in merger event m. The key independent variable is the interaction between $Treat$ and $Post$. $Treat$ is a dummy set to one for treated facility as defined above. $Post$ is an indicator variable set to one for the three fiscal years after the merger completion year, and zero for the merger completion year as well as three fiscal years before that year. The regression includes the merger-by-facility and merger-by-year two-way fixed effects. I cluster standard errors at the merger level.

Table 3 reports the estimation results. In Column (1), I find that the estimated coefficient of $Treat \times Post$ is significantly negative with a point estimate of -0.234 at the 1% level of significance, suggesting that the treated facilities reduce toxic chemical pollution by on average 23.4% relative to the control facilities, after the financial institutions mergers. The results remain similar after controlling for the lagged firm-level control variables in Column (2) and additionally the lagged facility-level control variables in Column (3). These controls are defined in Section 3.2.

I perform the following robustness checks for the DiD analysis. First, Appendix I shows that the findings remain intact when estimating the DiD regressions at the firm-facility-chemical-year level, with the additional merger-by-chemical or the merger-by-facility-by-chemical fixed effects. Second, to support the channel that toxic emissions create negative externalities to geographically close firms, I also examine the on-site releases as an alternative outcome variable in the DiD analysis. As reported in Appendix J, I find that the treated facilities reduce their on-site releases by roughly 14% around the financial institutions mergers, compared to the control facilities. Third, to measure pollution toxicity, I replace $LogPollution$ with $LogRSEI$ as the alternative outcome variable. Panel B in Appendix K.1 reports that the toxicity of on-site chemicals released from the treated facilities reduce by 31.4% relative to that from control facilities around the mergers. Lastly, Appendix N provides evidence that the results are robust for the Poisson estimation (Cohn et al., 2022).

[Table 3 Here]

Next, I conduct several supplementary tests. Firstly, I provide support for the common trend assumption of the identification by testing the dynamics of toxic emissions around the financial institutions mergers. Specifically, I estimate the following dynamic DiD regression:

$$\begin{aligned} LogPollution_{mifst} = \alpha_{mf} + \gamma_{mt} + \sum_{s=-3}^{3} \beta_s Treat \times I_{Year\,s} + \sum_{j=4}^{13} \beta_j FirmControls_{mit-1} \\ + \sum_{k=14}^{16} \beta_k FacilityControls_{mifst-1} + \epsilon_{mifst}, \end{aligned} \tag{6}$$

where $Treat \times Post$ is replaced with the interactions between $Treat$ and a series of year indicators starting from three years before and three years after the merger completion date, omitting the completion year as the benchmark. Panel A of Table 4 reports the estimated results of the dynamic DiD regressions. I find that the coefficients of $Treat \times Year_s$ are not significantly different from zero, implying that the total toxic chemical pollution between treatment and control facilities before the mergers is statistically indifferent, which supports the identifying assumption of a parallel trend. Importantly, the coefficients of the interactions become significantly negative after the mergers. In terms of economic magnitude, treated facilities reduce toxic emissions by 10.9% in the first year after the mergers, 26.7% in the second, and 22.9% in the third year, compared to the control facilities. The results are robust for including firm- and facility-level control variables. Panel A in Figure 5 plots the estimated coefficients, while Panel B plots the average log of total toxic pollution around the mergers. I continue to find that the toxic pollution of treated facilities shares a similar pre-treatment trend with the control but begin to decrease immediately after the mergers.

[Table 4 Here]

Secondly, an important premise of identification is that geographic common ownership should increase for the treated facilities after the mergers relative to the control facilities. In Panel B of Table 4, I verify this premise by replacing the dependent variable of $LogPollution$ with the measure of geographic common ownership, $GeoCO$, in Equation 5. I find that treated facilities on average experience a 0.011 significant increase in geographic common ownership around the mergers compared to control facilities. This increase is equivalent to 17.2% relative to the unconditional mean of geographic common ownership of 0.064 before the event. Figure 6 plots the dynamic coefficients estimated in a dynamic DiD regression with $GeoCO$ being the dependent variable and the time trend of average $GeoCO$ around the mergers for both treatment and control facilities.

In the last set of tests, I employ two alternative control samples matched with the treatment firms or facilities. First, I match treatment firms with other manufacturing firms that report toxic emissions but are not block-held by the merging institutions. Specifically, for each treated facility, I define the alternative control facilities as those owned by out-of-event firms that (1) belong to the same Fama-French 48 industry with the parent firm of the treated facility (i.e., treatment firm) and (2) are closest in market capitalization to the firm. Column (2) in Panel C of Table 4 reports the results. I find that coefficient of $Treat \times Post$ remains significantly negative at -35.5%. Second, for each treated facility, I match it with an out-of-event facility that is defined as the facility that (1) is owned by an out-of-event firms, (2) belongs to the same NAICS industry with the treated facility, and (3) locates most closely with the treated facility. As reported in Column (3) of Panel C, the treatment effect continues to be significantly negative using this matched control sample.

5.2 Pollution Reallocation or Production Cut

Facilities may reduce toxic emissions by reallocation of pollutants, reduction of production, or implementation of pollution abatement technology. First, I test whether the parent firm transfers pollutants released from the treated facilities to other facilities of the same firm. To this end, I define the same-parent control facilities as those that belong to the same parent firm with the treated facilities, and different-parent control facilities as those that are operated by event firms but do not share the same parent firm with the treated facilities. If within-firm reallocation drives the results documented in Section 5, the magnitude of the coefficient of $Treat \times Post$ in the regression with same-parent (different-parent) facilities being control facilities should be greater (smaller) than that reported in Table 3. As reported in Column (1) of Panel A in Table 5, the estimated coefficient of $Treat \times Post$ in the regression with the same-parent control facilities is -20.6%, which is close to the main DiD results presented in Table 3. On the other hand, I find a stronger effect (-32.5%) using the facilities that do not share a different parent of treated facilities. These findings together do not support the argument that toxic emissions are transferred from treated facilities to other facilities within a parent.

[Table 5 Here]

A more direct verification of within-firm reallocation is to conduct a firm-year level DiD analysis by aggregating the toxic pollution to the firm level across facilities operated by the parent firm. To capture the degree of the treatment effect at the firm level, I construct a continuous treatment variable, $ContinuousTreat$, which is the proportion of toxic chemical pollution attributed to the treated facilities in the year prior to the mergers. Column (1) in Panel B of Table 5 shows that firms that operate at least one treated facilities reduce on average 47.4% toxic emissions after the mergers, relative to the event firms comprised of all control facilities. These evidence again suggests that within-firm reallocation is unlikely to drive the results in Section 5.[18]

Second, I test whether the reduction in toxic emissions is driven by cutting production. I use a firm's market share as a proxy for production level. Market share is measured as the proportion of a firm's sales revenue to the total sales of public firms that belong to the same Fama-French 48 industry. In Column (2) of Panel B, Table 5, I find that the treatment firm that comprises of all treated facilities on average experiences a 0.45% reduction in market share after the mergers, relative to the control firm. The reduction of market share is sizable at 59.21% relative to the median market share of 0.76% in the firm-year level sample. This finding suggests that treatment firms reduce toxic emissions by scaling down their production.

[18]Except for within-firm reallocation of pollution, toxic chemicals could also be transferred to other firms (e.g., suppliers and customers) outside the parent firm. The TRI data do not allow me to reliably identify such transfers. However, an untabulated table shows that there is no significant change in the total value of book assets between treatment and control firms around the mergers, implying that there is no overt cross-firm transfer of toxic pollution.

Lastly, I study whether treatment firms compromise profitability and growth opportunities when cutting toxic emissions. The results in Columns (3) and (4) show that there is no significant difference in ROA and Tobin's q between treatment and control firms after the mergers, although the estimated coefficients of $Treat \times Post$ are negative. In Appendix P, I find there is no significant difference in the pollution controls between the treatment and control facilities around the mergers, suggesting that the reduction of pollution in treated facilities is not driven by more pollution control activities.

5.3 Geographic or Industrial Common Ownership

In this paper, geographic common ownership captures the extent of which corporations/facilities located within a geographic area are connected through common shareholdings. To distinguish the effect of geographic common ownership from that of industrial or horizontal common ownership, I test whether common ownership between facilities and cross-held industrial rivals could lead to a similar effect of reducing toxic pollution.

To test the effect of industrial common ownership, I redefine treatment and control facilities in the DiD setting based on the likelihood that their parent firms experience an increase in industrial common ownership after the financial institution mergers. Specifically, I use either Fama-French 48 industry or Hoberg-Phillips text-based network industrial classification (TNIC) to measure industrial relationship among event firms (Hoberg and Phillips, 2016). Therefore, treated facilities are those facilities whose parent firm is held by one side of the merging institution and shares the same primary the Fama-French 48 industry (or TNIC) with at least one portfolio firm held by the other side of the merging institution in the quarter before the merger announcement. Control facilities are the rest of facilities owned by other event firms. Appendix O reports the results. I find that, compared to the control facilities, treated facilities do not significantly reduce toxic chemical pollution after the mergers. Interestingly, although insignificant, both coefficients of $Treat \times Post$ are negative. A possible explanation is that the increase in horizontal common ownership leads to lower production output due to the anti-competitive effect, which in turn marginally reduces pollution.

5.4 Cross-Sectional Analysis

I conduct several cross-sectional tests based on the DiD analysis, which could shed light on the mechanisms that drive the reduction of toxic emissions from treated facilities after the mergers. First, I examine whether the geographical distance between the treated facilities and their cross-held local firms moderates the incentive to internalize environmental externalities. My hypothesis implies that treated facilities tend to lower their toxic emissions as they locate closer to the nearby firms that are cross held by a common institutional investor after the mergers. Therefore, I decompose $Treat \times Post$ in Equation 7 into $Treat \times Post \times Low\ Distance$ and $Treat \times Post \times High\ Distance$, where $Low\ Distance$ ($High\ Distance$) is dummy variable set to one if the distance between the treated facility and its cross-held local firms is below (above) the sample median in the corresponding merger event. As reported in Column (1) of Table 6, I find that treated facilities located closer to cross-held local firms reduce toxic emissions by 32.8% after the mergers, while those located farther away from the cross-held local firms do not appear to lower toxic chemical pollution. This finding highlights the crucial role of geographic proximity in determining the internalization of environmental externalities under the common ownership structure.

[Table 6 Here]

Second, I examine whether the ESG practices of cross-held local firms propagate to treated facilities, leading to a reduction in toxic emissions after the merger. I posit that treated facilities are more likely to lower toxic pollution after they are connected through common ownership with local firms that are concerned about their environment impact and employee benefit. I aggregate the environment and employment MSCI-KLD scores across all cross-held local firms for each treated facility, weighted by the firms' market capitalization. I construct four dummy variables ($HighENVFirm$, $LowENVFirm$, $HighEMPFirm$, and $LowEMPFirm$) based on the sample median of these weighted scores in the corresponding merger event. In Columns (2) and (3), I find that the reduction of toxic emissions can only be observed when the treated facilities are surrounded by cross-held firms with higher-than-the-median environment and employee benefit scores. This evidence suggests that ESG practices could be propagated across firms through geographic common ownership.

6 Common Owner's Voting

Shareholder voting is one of the important governance mechanisms through which shareholders could exert influence on corporate policies (Aghion et al., 2013; Appel et al., 2016; Brav et al., 2008; McCahery et al., 2016). In recent years, there is a growing number of environmental proposals initiated by shareholders, primarily by asset management companies (He et al., 2023). Although these proposals are almost never passed, the granularity of mutual fund voting data offers a advantage to infer the shareholders' attitudes toward environmentally friendly policies in a revealed preference framework. I hypothesize that mutual funds holding substantial ownership stakes in the area of a facility are more likely to vote in favor of the environmental proposals at the facility's parent firm, as these funds have an incentive to internalize environmental externalities across their portfolio firms.

To identify environmental proposals, I first extract all shareholder proposals labeled by ISS as "SRI" proposals. After that, I search environment-related keywords such as "Environment", "Toxic", "Pollution", "Waste", "Health", and "GHG" in the proposal description. This sampling process yields 142 environmental proposals from 2004 to 2021. A full list of such proposals is provided in Appendix E. I further require that the proposing firms are TRI firms that operate any facilities that report toxic chemical releases to the EPA.[19] To obtain mutual fund portfolio holdings from CRSP, I match ISS mutual funds with CRSP mutual funds as detailed in Appendix D.

I estimate the following linear probability regression:

$$VoteFor_{kpit} = \theta_p + \phi_{kt} + \beta_X X_{kit-1} + \sum \beta_Z Z_{kit-1} + \epsilon_{kpit}, \tag{7}$$

[19]The results remain qualitatively and quantitatively similar when I use all proposing firms in the ISS data. In such case, I use the headquarter, instead of the location of facilities operated by the proposing firms, to study fund voters' geographic portfolio exposure.

where k, p, i, and t denotes mutual fund, proposal, firm, and year-quarter, respectively. $VoteFor$ is a dummy variable set to one if the mutual fund votes for the proposal, and zero otherwise. X_{kit-1} represent one of the following key independent variables measured in year $t-1$: (1) $Geo\,Portfolio\,Weight$ (%) is the total portfolio weights of all public firms headquartered within a 50-mile radius of the facility operated by the proposal firm; (2) $Geo\,Portfolio\,Weight\,Dummy$ is a dummy variable set to one if $Geo\,Portfolio\,Weight$ is equal to or greater than 5%; (3) $Num\,GeoCO\,Firm$ measures the number of public firms headquartered within a 50-mile radius of the facility of the proposing firm and that are held by the fund with an ownership stake of 1% or more; and (4) $Num\,GeoCO\,Firm\,Dummy$ is dummy variable set to one if $Num\,GeoCO\,Firm$ is greater than zero. Z_{kit-1} are fund-firm level control variables, including $Portfolio\,Weight$ which captures the weight of the proposing firm in the fund's portfolio, and $Same\,County$ which takes a value of one if the fund and the proposing firm's headquarter belongs to in the same county, and zero otherwise. The regression incorporates both the proposal and the fund-by-quarter fixed effects. The identification therefore comes from the difference in votes cross mutual funds for a given environmental proposal, after controlling for time-varying unobserved fund heterogeneity.

Table 7 reports the results. In Column (1), I find that mutual funds' propensity to support environmental proposals is significantly and positively related to their portfolio weight of the firms near the facility of the proposing firm. In terms of economic magnitude, a one-standard-deviation increase in $Geo\,Portfolio\,Weight$ (i.e., 21.17%) is associated with a 10.58% ($21.17 \times 0.5\%$) increase in the likelihood of voting for the environmental proposals. In Column (2), I provide similar evidence that mutual funds are on average 4.7% more likely to support the environmental proposals if they allocate more than 5% of fund assets into the firms located near the proposing firm's facility. In Columns (3) and (4), I use the number of high-stake firms as an alternative measure of investment stakes concentrated around the facility. I find that funds are by 4.1% more likely to vote for the environmental proposals if they invest in at least one nearby firm with stock ownership of 1% or more. In totality, these findings support the hypothesis that shareholders with geographic common ownership promote a corporate policy that internalizes environmental externalities.

[Table 7 Here]

7 Conclusion

This paper examines the impact of ownership structure on corporate environmental policies. Using US EPA Toxic Release Inventory data from 1987 to 2019, I find that common institutional ownership with geographically proximate firms affects firms' toxic chemical pollution. More specifically, in the within-firm analysis, I observe that facilities located within a 50-mile radius of the headquarters of other firms owned by the same institutional blockholder release fewer toxic chemicals, compared to other facilities of the same parent firm. To further support the causal inference, I exploit mergers of financial institutions as a quasi-natural experiment. In response to an exogenous increase in geographic common ownership, the treated facilities reduce toxic chemical pollution after the mergers, compared to the control facilities. The pollution is reduced primarily by scaling down production, rather than transferring pollutants to other facilities operated by the same parent firm.

My findings highlight the important role of geographic proximity in the relationship between common ownership and environmental practices. Prior research on common ownership focuses in particular on ownership connections among industry peers and examines its effect on firm behavior and industry outcomes. This paper extends the literature by documenting that common ownership of geographically proximate firms affects the firms' incentive to internalize environmental externalities. In contrast, there is no compelling evidence suggesting that common ownership of industry competitors leads to lower levels of toxic chemical pollution.

Lastly, this paper provides direct evidence that common institutional shareholders, through proxy voting, express their preference for environmental policies that internalize the externalities of their portfolio firms. This finding implies that, in certain scenarios, the interest of diversified shareholders in maximizing profits can contribute to environmentally friendly corporate practices. This effect could become more pronounced in the future, provided that common ownership becomes an increasingly prominent ownership structure in the US and other economies.

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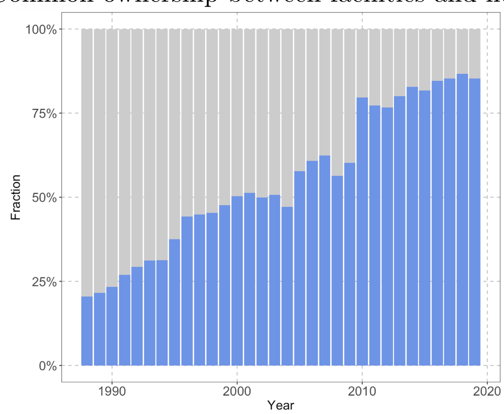
Tables and Figures

Figure 1: Rise of Geographic Common Ownership

The figures plot the time trend of geographic common ownership from 1990 to 2019. In Panel A, blue bar indicates the proportion of facilities (in the TRI data) whose parent is owned by an institutional blockholder who also owns a block stake in a public firm (with common stocks listed on the AMEX, NYSE, and NASDAQ) headquartered within a 50-mile radius of the facility's location. In Panel B, green bar indicates the proportion of public firms that share a common institutional blockholder with another public firm headquartered within a 50-mile radius of the focal firms' headquarters.

Panel A: Common ownership between facilities and nearby firms



Panel B: Common ownership between nearby firms

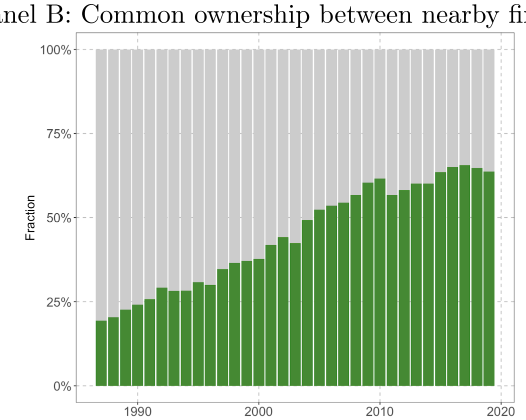


Figure 2: Illustrative Graph: Within-Firm Analysis

The diagram illustrates the relation between geographic common ownership and toxic chemical pollution. Firm A and B are owned by a large common institutional shareholder X. Firm A is the parent company of Facility E and F. Since Firm B is located within a 50-mile radius of Facility E, Facility E and Firm B are connected through common ownership. According to my hypothesis, Facility E has incentive to release fewer toxic chemicals because it internalizes the negative externalities of toxic chemical pollution to cross-held nearby Firm B. On the other hand, although Firm C is located within a 50-mile radius of Facility F, Firm C and Facility F do not share a common shareholder. Therefore, Facility F has less incentive to internalize environmental externalities to Firm C, leading to a higher level of toxic pollution than Facility E, ceteris paribus.

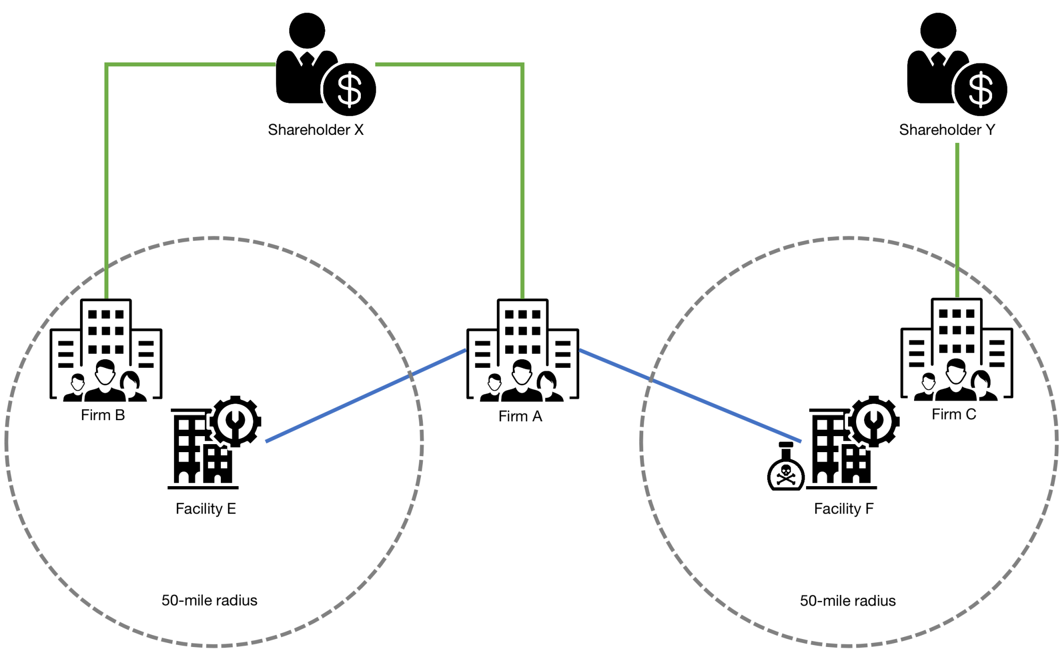


Figure 3: Illustrative Graph: Difference-in-Differences Analysis

The diagram illustrates how the exogenous shock of financial institution mergers to geographic common ownership affects toxic pollution. Before the merger, Firm L and Z are separately owned by an institutional blockholder V and W. Firm L is the parent company of Facility O and P. Firm Z is located within a 50-mile radius of Facility P. After the merger of shareholder V and W, Facility P and Firm Z become linked through geographic common ownership. As per my hypothesis, Facility P has incentive to release fewer toxic chemicals because it internalizes the negative externalities of toxic chemical pollution to cross-held nearby Firm Z. On the other hand, none of the event firms held by shareholder W locate near Facility O. As a result, Facility O does not alter its pollution incentives, leading to similar levels of toxic emissions before and after the merger, ceteris paribus.

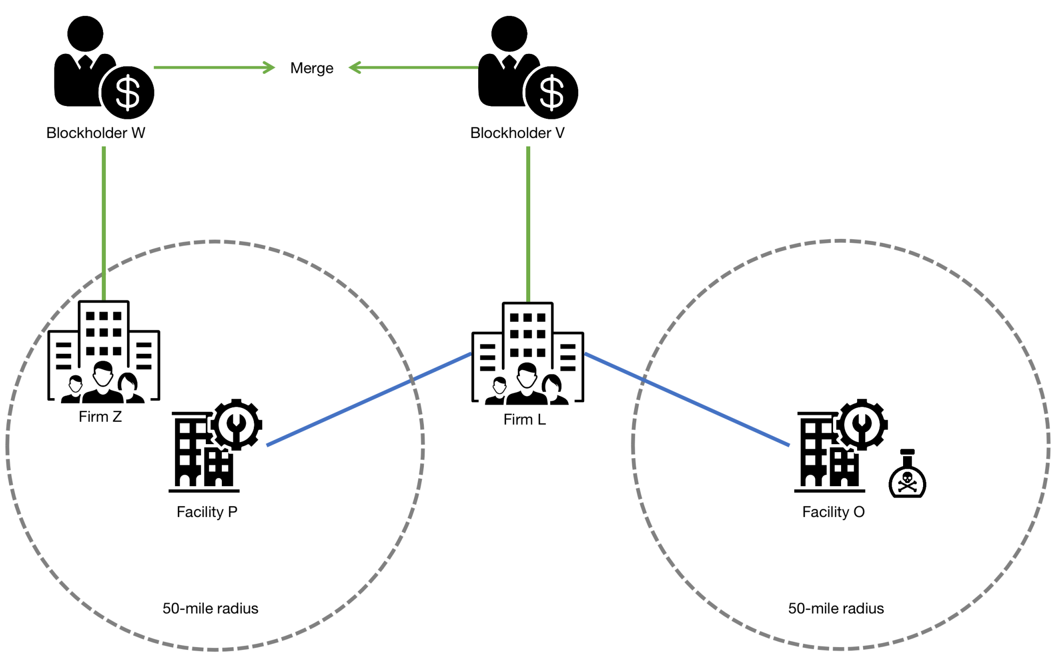


Figure 4: Facility Location

The graph plots the geographic distribution of facilities matched with Compustat public firms in year 2000. Green dots indicate the facilities with $GeoCODummy = 1$ while blue dots denote the facilities with $GeoCODummy = 0$. $GeoCODummy$ is a dummy variable set to one if there exists an institutional investor who block-holds the parent firm of the facility and a public firm headquartered within a 50-mile radius of the facility, and zero otherwise.

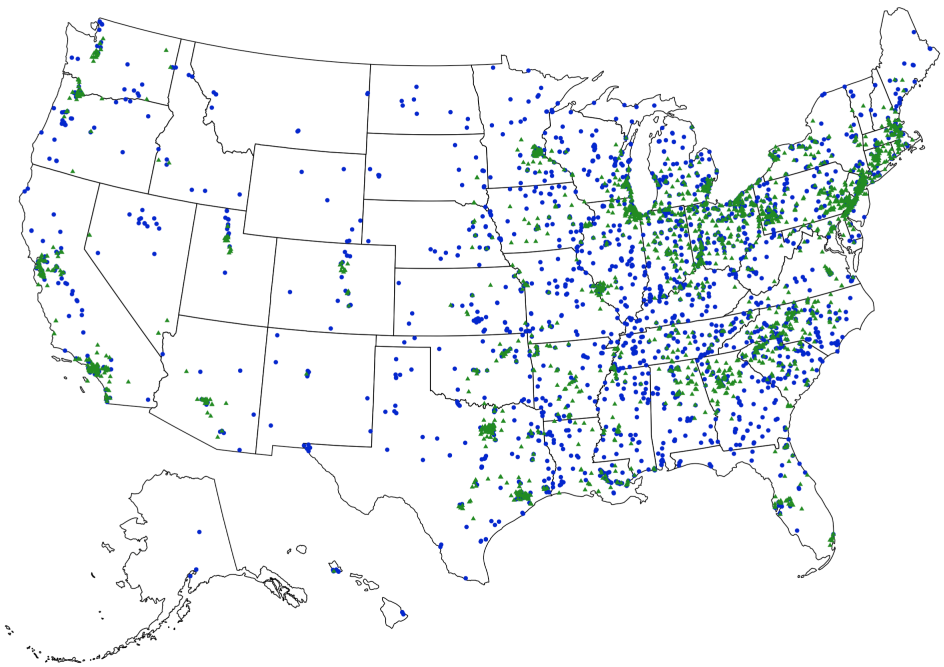
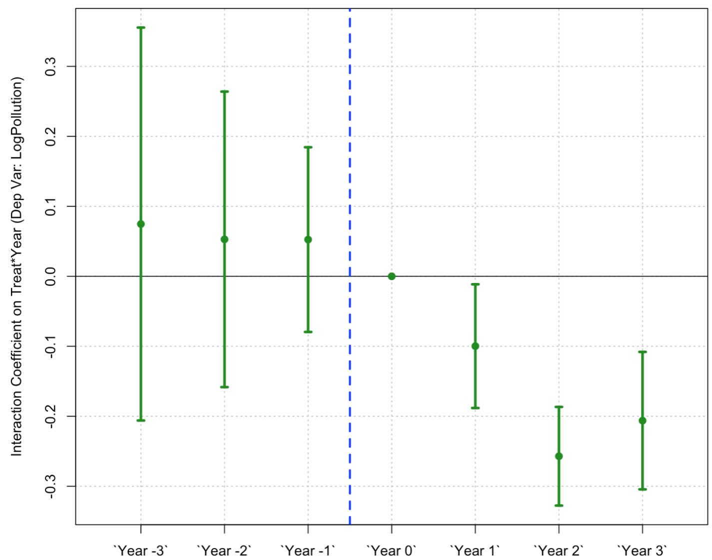


Figure 5: Changes in Toxic Chemical Pollution around Financial Institutions Mergers

The figures visualize the results in the difference-in-difference estimate in Panel A of Table 4. Figure A plots the estimation coefficients of $Treat \times Year_s$ with 95% confidence intervals in the dynamic DiD specification in Equation 7. The dependent variable is the natural log of toxic chemical pollution in pounds generated by the facility. Figure B plots the average log of toxic pollution from $Year_{-3}$ to $Year_3$ for both treatment and control facilities around financial institution mergers. Green line refers to the treated facilities while black line refers to the control facilities.

Panel A: Plot of estimated coefficients



Panel B: Plot of average $LogPollution$

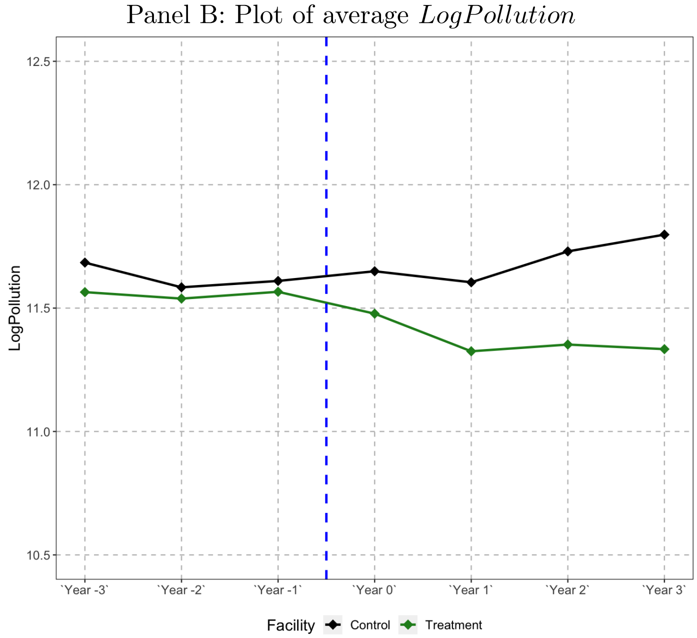
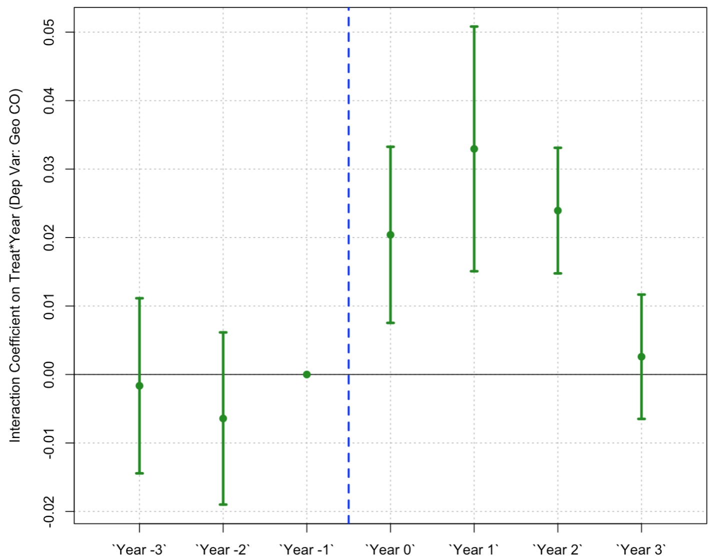


Figure 6: Changes in Geographic Common Ownership around Financial Institutions Mergers

The figures visualize the results in the difference-in-difference estimate in Panel B of Table 4. In Panel A, the figure plots the estimated coefficients of $Treat \times Year_s$ with 95% confidence intervals in the dynamic DiD regression where the dependent variable is the geographic common ownership measure, $GeoCO$. In Panel B, the figure plots changes in average $GeoCO$ from $Year_{-3}$ to $Year_3$ for both treatment and control facilities around financial institution mergers. Green line refers to the treated facilities while black line refers to the control facilities.

Panel A: Plot of estimated coefficients



Panel B: Plot of average $GeoCO$

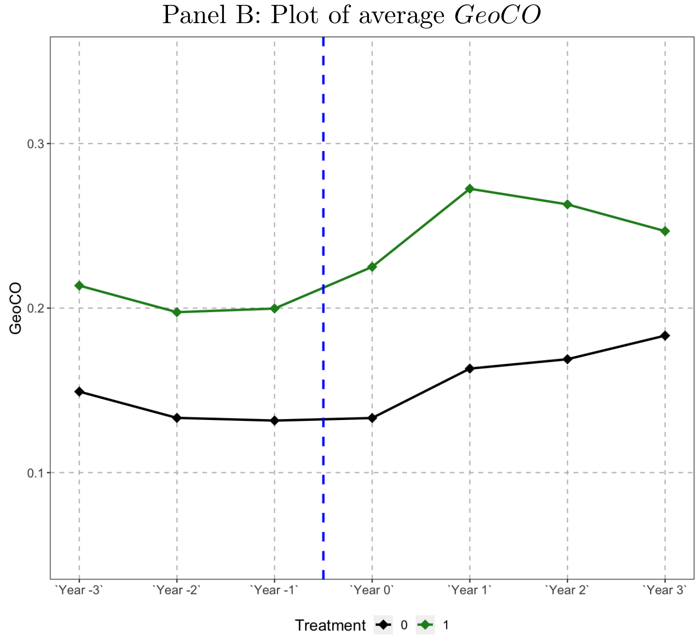


Table 1: Summary Statistics

The table reports the summary statistics of key variables. In Panel A, the unit of observations is a firm-facility-year. The sample includes 153,760 observations covering 16,889 unique facilities. In Panel B, the unit of observations is a firm-year covering 2,092 unique firms. All variables are winsorized at the 1% and 99% levels, and are defined in both Section 3.2 and Appendix A.

	N	Mean	SD	25th	Median	75th
			Panel A: Firm-facility-year			
GeoCO Dummy	153,760	0.53	0.50	0.00	1.00	1.00
GeoCO	153,760	0.32	0.27	0.12	0.26	0.46
GeoCindex	153,760	0.01	0.01	0.00	0.00	0.01
Pollution (lbs)	153,760	1,222,177.80	4,115,047.63	10,636.36	61,539.74	369,616.75
LogPollution	153,760	10.72	3.34	9.27	11.03	12.82
OnsitePollution (lbs)	153,760	161,908.19	557,804.73	30.00	3,800.00	45,783.00
LogOnsitePollution	153,760	8.14	4.06	5.64	9.00	11.03
SourceReduction	153,760	0.87	3.46	0.00	0.00	0.00
LogRSEI	151,623	19.04	5.67	14.89	18.60	23.20
NumChemical	153,760	4.50	4.96	1.00	3.00	5.00
NearParentHQ	153,760	0.15	0.36	0.00	0.00	0.00
LocalOwnership (%)	153,760	0.32	1.26	0.00	0.00	0.00
			Panel B: Firm-year			
LogAsset	23,123	6.97	1.95	5.55	6.93	8.31
LogSale	23,100	6.99	1.82	5.70	6.98	8.23
Leverage (%)	23,086	21.81	15.98	9.26	20.50	31.57
ProfitMargin(%)	23,100	3.41	10.84	1.25	4.39	7.86
ROA (%)	23,123	13.81	8.17	9.25	13.57	18.32
R&D (%)	23,123	2.33	3.52	0.00	0.93	3.00
TangibleAsset (%)	23,123	31.78	17.79	18.12	28.38	42.31
CAPEX(%)	23,123	5.32	3.93	2.57	4.32	6.96
Cash (%)	23,123	6.99	7.82	1.39	4.13	9.95
Tobin's q	23,122	1.59	0.83	1.06	1.34	1.82
IO (%)	23,057	57.59	26.61	38.00	61.06	79.00
MarketShare (%)	23,123	3.18	6.57	0.22	0.76	2.83

Table 2: Within-Firm Analysis

The table reports the results on the relation between geographic common ownership and toxic chemical pollution by estimating Equation 4 in the within-firm analysis. The unit of observation is a firm-facility-year. The dependent variable is the natural logarithm of total quantity of toxic chemical in pounds generated by a facility in year t. The key independent variable is geographic common ownership, proxied by the following two measures: (1) *GeoCO Dummy* is a dummy variable set to one if there exists an institutional investor who block-holds the facility's parent firm and a public firm headquartered within a 50-mile radius of the facility, and zero otherwise; and (2) *GeoCO* is a continuous measure that captures the weighted average profit weights between the facility and the public firms headquartered within a 50-mile radius of the facility as defined in Section 3.2. Control variables include the number of chemicals produced by the facility ($NumChemical$), an indicator set to one if the facility is located within a 50-mile radius of the headquarter of the parent firm ($NearParentHQ$), and the total ownership held by institutional investors whose business address is within a 50-mile radius of the facility's location ($LocalOwnership$). All independent variables are measured in year t-1. The regressions incorporate firm-by-year and facility state-by-year fixed effects. The standard errors are clustered by parent firm and facility's state. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Dep Var	$LogPollution_{ifst}$			
	(1)	(2)	(3)	(4)
$GeoCO\ Dummy_{ifst-1}$	-0.237***	-0.231***		
	(0.058)	(0.055)		
$GeoCO_{ifst-1}$			-0.673***	-0.649***
			(0.213)	(0.194)
$NumChemical_{ifst-1}$		0.232***		0.232***
		(0.052)		(0.052)
$NearParentHQ_{ifst-1}$		0.217*		0.213*
		(0.113)		(0.112)
$LocalOwnership_{ifst-1}$		-0.023*		-0.025*
		(0.013)		(0.013)
Parent-Year FE	Y	Y	Y	Y
Facility State-Year FE	Y	Y	Y	Y
Observations	153,760	153,760	153,760	153,760
Adjusted R^2	0.332	0.467	0.332	0.467

Table 3: Stacked Difference-in-Differences Analysis of Financial Institution Mergers

The table reports the results of the difference-in-differences analysis based on the quasi-natural experiment of financial institution mergers. All regressions are at the firm-facility-year level as specified in Equation 5. The dependent variable is the natural log of total toxic pollution in pounds by a facility in year t. The key independent variable is the interaction between $Treat$ and $Post$ defined in Section 5. The regressions in Column (1) are free of controls. The regressions include firm controls in Column (2) and additionally facility controls in Column (3), as specified in Equation 5. All control variables are measured in year t-1. The regressions incorporate merger-by-facility and merger-by-year fixed effects. The standard errors are clustered by merger event. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Dep Var	$LogPollution_{mifst}$		
	(1)	(2)	(3)
$Treat \times Post$	-0.234***	-0.241***	-0.219**
	(0.072)	(0.074)	(0.080)
$LogAsset_{mit-1}$		0.112	0.128
		(0.191)	(0.180)
$LogSale_{mit-1}$		-0.035	-0.093
		(0.204)	(0.201)
$Leverage_{mit-1}$		-0.008**	-0.008**
		(0.003)	(0.003)
$ProfitMargin_{mit-1}$		0.003	0.004
		(0.006)	(0.006)
ROA_{mit-1}		0.001	0.002
		(0.006)	(0.006)
$R\&D_{mit-1}$		0.003	0.002
		(0.030)	(0.026)
$TangibleAsset_{mit-1}$		0.008*	0.010**
		(0.004)	(0.003)
$CAPEX_{mit-1}$		0.001	-0.001
		(0.012)	(0.014)
$Cash_{mit-1}$		-0.017***	-0.016***
		(0.005)	(0.005)
$Tobin's\, q_{mit-1}$		0.080	0.048
		(0.051)	(0.050)
IO_{mit-1}		-0.115	-0.119
		(0.204)	(0.191)
$NumChemical_{mifst-1}$			0.086***
			(0.020)
$NearParentHQ_{mifst-1}$			-0.437
			(0.350)
$LocalOwnership_{mifst-1}$			-0.050***
			(0.005)
Merger-Facility FE	Y	Y	Y
Merger-Year FE	Y	Y	Y
Observations	8,679	8,679	8,679
Adjusted R^2	0.869	0.870	0.871

Table 4: Testing for Pretrend, Identification Premise, and Alternative Controls

The table reports the results of the robustness tests for the DiD analysis. All the regressions are at the firm-facility-year level. In Panel A, the dynamic DiD regressions are estimated as specified in Equation 7. In Column (1) of Panel B, the regression is estimated according to Equation 5 except that the dependent variable is geographic common ownership, *GeoCO*. Columns (2) and (3) of Panel B report the results of estimating Equation 5 with alternative out-of-event control groups. In Column (2), for each treated facility, the control facilities are defined as those owned by out-of-event firms that (1) belong to the same Fama-French 48 industry with the parent of the treated facility and (2) are closest in market capitalization to the parent. In Column (3), for each treated facility, the control facilities are the out-of-event facilities that (1) belong to the same NAICS industry with the treated facility and (2) locate most closely with the treated facility. All regressions include the firm and facility controls with merger-by-facility and merger-by year fixed effects. The standard errors are clustered by merger event. ***,**,* denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Coefficient dymanics

Dep Var	$LogPollution_{mifst}$		
	(1)	(2)	(3)
$Treat \times I_{Year\,-3}$	0.069	0.073	0.075
	(0.161)	(0.161)	(0.171)
$Treat \times I_{Year\,-2}$	0.045	0.048	0.053
	(0.118)	(0.119)	(0.128)
$Treat \times I_{Year\,-1}$	0.066	0.066	0.052
	(0.075)	(0.076)	(0.080)
$Treat \times I_{Year\,1}$	-0.109*	-0.114**	-0.100*
	(0.055)	(0.054)	(0.054)
$Treat \times I_{Year\,2}$	-0.267***	-0.270***	-0.257***
	(0.055)	(0.049)	(0.043)
$Treat \times I_{Year\,3}$	-0.229***	-0.237***	-0.206***
	(0.062)	(0.059)	(0.060)
Firm Controls		Y	Y
Facility Controls			Y
Merger-Facility FE	Y	Y	Y
Merger-Year FE	Y	Y	Y
Observations	8,679	8,679	8,679
Adjusted R^2	0.869	0.870	0.871

Panel B: Identification premise and out-of-event controls

Dep Var	$GeoCO_{mifst}$	$LogPollution_{mifst}$	
Control Group	Same as Table 3	match parent firm of treated facilities	match treated facilities
	(1)	(2)	(3)
$Treat \times Post$	0.011***	-0.355**	-0.271**
	(0.004)	(0.122)	(0.121)
Firm Controls	Y	Y	Y
Facility Controls	Y	Y	Y
Merger-Facility FE	Y	Y	Y
Merger-Year FE	Y	Y	Y
Observations	8,679	10,151	3,846
Adjusted R^2	0.732	0.864	0.860

Table 5: Pollution Reallocation or Production Cut

The table reports the results of the analysis on reallocation or reduction of toxic pollution. In Panel A, the unit of observations is a firm-facility-year. The dependent variable is $LogPollution_{mifst}$, and the key independent variable is the interaction between $Treat$ and $Post$. In Column (1), the control facilities are defined as event facilities that share the same parent firm with the treated facilities. In Column (2), the control facilities are the event facilities that do not share the same parent firm with the treated facilities. The regressions incorporate merger-by-facility and merger-by-year fixed effects. In Panel B, the regression is at the firm-year level. The dependent variable is $LogPollution_{mist}$, which is the sum of toxic pollution of facilities operated by the parent firm, while the key independent variable is $ContinuousTreat \times Post$. $ContinuousTreat$ is a continuous variable that captures the proportion of toxic chemical pollution attributed to the treated facilities in the year prior to the merger. Thus, this variable is bound between zero and one, taking the value of zero if the event firm does not operate any treated facilities and one if all the facilities operated by the firm are treated facilities. From Column (1) to Column (4), the dependent variables is firm-level $LogPollution$, $MarketShare$, ROA, and $Tobin'sq$, respectively. The regressions include firm-level control variables, measured at year t-1. The regressions incorporate merger-by-firm and merger-by-year fixed effects. The standard errors are clustered by merger event. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Firm-facility-year level analysis

Dep Var	$LogPollution_{mifst}$	
Control group	Same parent of treated facility	Different parent of treated facility
	(1)	(2)
$Treat \times Post$	-0.206**	-0.325***
	(0.075)	(0.110)
Firm Controls	Y	Y
Facility Controls	Y	Y
Merger-Facility FE	Y	Y
Merger-Year FE	Y	Y
Observations	6,495	4,593
Adjusted R^2	0.861	0.882

Panel B: Firm-year level analysis

Dep Var	$LogPollution_{mist}$	$MarketShare_{mist}$	ROA_{mist}	$Tobin's\, q_{mist}$
	(1)	(2)	(3)	(4)
$ContinuousTreat \times Post$	-0.474**	-0.450***	-0.234	-0.083
	(0.221)	(0.139)	(0.487)	(0.068)
Firm Controls	Y	Y	Y	Y
Merger-Year FE	Y	Y	Y	Y
Merger-Firm FE	Y	Y	Y	Y
Observations	1,569	1,569	1,569	1,569
Adjusted R^2	0.931	0.902	0.740	0.803

Table 6: Heterogeneity Tests for the Difference-in-Differences Analysis

The table reports the results of the heterogeneity tests for the DiD analysis. All regressions are at the firm-facility-year level. The dependent variable is the natural log of total toxic chemical pollution, $LogPollution$. From Columns (1) to (3), treated facilities are decomposed into subgroups based on the distance between the treated facility and its cross-held local firms, and the environment and employee benefit scores of the cross-held local firms. In Column (1), $High\ Distance$ is a dummy variable set to one if the distance between the treated facility and its cross-held local firm is below the sample median in the corresponding merger, and zero otherwise. $Low\ Distance$ is the opposite of $High\ Distance$. Similarly, in Column (2), $Treat$ is decomposed into subgroups of $High\ ENV\ Firm$ and $Low\ ENV\ Firm$. $High\ ENV\ Firm$ ($Low\ ENV\ Firm$) is a dummy variable set to one if the average MSCI-KLD environmental scores of the cross-held firms headquartered within a 50-mile radius of the treated facility is above (below) the sample median, and zero otherwise. In Column (3), the decomposition is based on MSCI-KLD employee beneift score. $HighEMPFirm$ ($LowEMPFirm$) is set to one if the average MSCI-KLD employee benefit scores of the cross-held firms headquartered within a 50-mile radius of the treated facility is above (below) the sample median, and zero otherwise. All regressions include both firm- and facility-level control variables measured at year t-1. The regressions incorporate merger-by-facility and merger-by-year fixed effects. The standard errors are clustered by merger event. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Dep Var		$LogPollution_{mifst}$	
	(1)	(2)	(3)
$Treat \times Post \times Low\ Distance$	-0.328*		
	(0.189)		
$Treat \times Post \times High\ Distance$	0.037		
	(0.205)		
$Treat \times Post \times High\ ENV\ Firm$		-0.198**	
		(0.092)	
$Treat \times Post \times Low\ ENV\ Firm$		-0.102	
		(0.252)	
$Treat \times Post \times High\ EMP\ Firm$			-0.193**
			(0.092)
$Treat \times Post \times Low\ EMP\ Firm$			-0.108
			(0.316)
Firm Controls	Y	Y	Y
Facility Controls	Y	Y	Y
Merger-Facility FE	Y	Y	Y
Merger-Year FE	Y	Y	Y
Observations	7,351	7,174	7,174
Adjusted R^2	0.870	0.873	0.873

Table 7: Geographic Common Ownership and Mutual Fund Voting

The table reports the results of the voting activities of geographic common owners for shareholder-sponsored environmental proposals. The regression is at the fund-proposal level. The dependent variable is a dummy variable, $VoteFor$, set to one if the fund votes for the proposal, or zero otherwise. In Column (1), the key independent variable is the geographic portfolio exposure, $Geo\ Portfolio\ Weight$, which measures the aggregate portfolio weights of all public firms that are headquartered within a 50-mile radius of the locations of facilities of the proposing firm. In Column (2), the key independent variable is a dummy variable, $Geo\ Portfolio\ Weight\ Dummy$, set to one if $Geo\ Portfolio\ Weight$ is greater than 5%. In Column (3), the key independent variable is $Num\ GeoCO\ Firm$, the number of public firms that are headquartered within a 50-mile radius of the locations of facilities of the proposing firm and that are held by the fund with ownership stakes greater than 1%. In Column (4), the key independent variable is a dummy variable, $Num\ GeoCO\ Firm\ Dummy$, set to one if $Num\ GeoCO\ Firm$ is greater than zero. The regressions also include fund-firm level control variables: (1) $Portfolio\ Weight$ which captures the weight of the proposing firm in the fund's portfolio, and (2) $Same\ County$ which takes a value of one if the fund's business address and the proposing firm's headquarter belongs to the same county, and zero otherwise. The regressions incorporate proposal and fund-by-quarter fixed effects. Standard errors are clustered by fund. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable	$VoteFor_t$			
	(1)	(2)	(3)	(4)
$Geo\ Portfolio\ Weight_{t-1}$	0.005***			
	(0.001)			
$Geo\ Portfolio\ Weight\ Dummy_{t-1}$		0.047***		
		(0.015)		
$Num\ GeoCO\ Firm_{t-1}$			0.0005***	
			(0.0002)	
$Num\ GeoCO\ Firm\ Dummy_{t-1}$				0.041***
				(0.016)
$Portfolio\ Weight_{t-1}$	0.004***	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
$Same\ County_{t-1}$	0.080***	0.080***	0.080***	0.080***
	(0.027)	(0.027)	(0.027)	(0.027)
Proposal FE	Y	Y	Y	Y
Fund-Quarter FE	Y	Y	Y	Y
Observations	17,150	17,150	17,150	17,150
Adjusted R^2	0.730	0.730	0.730	0.730

Internet Appendix

A Variable Definition

1. **GeoCO Dummy:** an indicator set to one if a facility's parent firm is owned by an institutional blockholder (with ownership of 5% or more) who also owns a block stake on a public firm headquartered within 50 miles of the facility, and zero otherwise (Sourced: Form 13F, Thomson Reuters, and TRI).

2. **GeoCO:** the weighted average of geographic common ownership (captured by pairwise profit weights) between a facility and the cross-held firms headquartered within a 50-mile radius of the facility's location (Sourced: Form 13F, Thomson Reuters, and TRI).

3. **GeoCindex:** the weighted average of geographic common ownership (captured by pairwise profit weights without the scaler of ownership concentration) between a facility and the cross-held firms headquartered within a 50-mile radius of the facility's location (Sourced: Form 13F, Thomson Reuters, and TRI).

4. **Pollution:** the total quantity of toxic chemicals produced by a facility (Sourced: TRI).

5. **LogPollution:** the natural logarithm of the total quantity of toxic chemicals produced by a facility (Sourced: TRI).

6. **OnsitePollution (lbs):** the total quantity of toxic chemicals released on a facility's location (Sourced: TRI).

7. **LogOnsitePollution:** the natural logarithm of the total quantity of toxic chemicals released on a facility's location (Sourced: TRI).

8. **SourceReduction:** the number of source reduction activities implemented to prevent or reduce the amount of toxic chemicals (Sourced: TRI).

9. **LogRSEI:** the natural logarithm of the sum of the product of the onsite emission and the toxicity of toxic chemicals (Sourced: TRI).

10. **NumChemical:** the number of unique chemicals manufactured, processed, or otherwise used by a facility (Sourced: TRI).

11. **NearParentHQ:** an indicator set to one if the facility is located within 50 miles of its parent firm's headquarter (Sourced: Form 10K and TRI).

12. **LocalOwnership (%):** the total ownership held by institutional investors whose business address is located within 50 miles of the facility (Sourced: Form 13F and TRI).

13. **LogAsset:** the natural logarithm of the book value of total assets (Sourced: Compustat).

14. **LogSale:** the natural logarithm of annual sales (Sourced: Compustat).

15. **Leverage (%):** the long-term leverage divided by the book value of assets (Sourced: Compustat).

16. **ProfitMargin (%):** the net operating incomes over total sales.

17. **ROA (%):** the operating incomes over the book value of total assets

18. **R&D (%):** the research and development expenditures divided by total assets with *R&D* set to zero if missing (Sourced: Compustat).

19. **TangibleAsset (%):** the proportion of the book value of tangible assets over total assets (Sourced: Compustat).

20. **CAPEX (%):** capital expenditures over total assets (Sourced: Compustat).

21. **Cash (%):** the cash and cash equivalents over total assets (Sourced: Compustat).

22. **Tobin's q:** the market value of both equity and debt claims over replacement cost proxied by total book assets (Sourced: Compustat and CRSP).

23. **IO (%):** the total year-end institutional ownership (Sourced: 13F and Thomson Reuters)

24. **MarketShare (%):** the fraction of a firm' sales over the total sales in the Fama-French 48 industry which the firm belongs to (Sourced: Compustat and Kenneth French's website)

B The Model

B.1 Model Setup

I develop a parsimonious microeconomic model in which firms, under common ownership structure, maximize the combination of own profit and the profit of cross-held local firms, by choosing the optimal amount of pollution abatement to invest and the quantity of goods to produce.

Assume shareholders hold diversified portfolios and their objective is to maximize the total portfolio value measured by the weighted sum of portfolio firms' profit as follows:

$$v_s = \sum_{\forall g} \beta_{gs} \pi_g, \tag{8}$$

where s and g denotes shareholders and portfolio firms. v is the total portfolio value of shareholder. β is the ownership stake or cash flow right of the shareholder. π is the profit of the firm.

Assume there is no agency problem between shareholders and managers, firm managers' objective is to maximize average shareholders' wealth (Hansen and Lott, 1996; Rotemberg, 1984; Backus et al., 2021). Since the portfolios of individual shareholders differ, firm managers solve the multiple shareholder problem by applying a Pareto weight on each shareholder's portfolio value. This weight is proxied by control right γ, which captures the influence that a shareholder can exert on the firm. Thus, the firm's objective is $Q_i = \sum_{\forall s} \gamma_{is} v_s$. Substituted by Equation 8 and normalized by $\sum_{\forall s \gamma_{is} \beta_{is}}$ on both sides, the firm's objective can be rewritten as:

$$Q_i \propto \pi_i + \sum_{g \neq i} \underbrace{\left(\frac{\sum_{\forall g \gamma_{is} \beta_{gs}}}{\sum_{\forall s \gamma_{is} \beta_{is}}} \right)}_{\kappa_{ig}} \pi_g \tag{9}$$

Let κ_{ig} denotes $\frac{\sum_{\forall g \gamma_{is} \beta_{gs}}}{\sum_{\forall s \gamma_{is} \beta_{is}}}$, which is the profit weight that firm i put on firm g that is held by common shareholders (Backus et al., 2021).

There are N firms located in a geographic area indexed by $i \in \{1, 2, 3, ..., N\}$. These firms compete in the same industry and produce one homogeneous commodity, facing a symmetric inverse demand function as follows:

$$p_i(q) = A - q_i - \rho \sum_{g \neq i}^{N} q_g, \tag{10}$$

where p and q denotes product price and production level, respectively. Without loss of generality, let $\rho = 1$.

Firms generate P level of total toxic pollution, which is a function of the firms' production output (q), deterministic emission ratio (e), and the amount of pollution abatement or control (α), i.e.,

$$P_i = eq_i - \alpha_i. \tag{11}$$

Cost of implementing pollution abatement is quadratic in effort as given by $\frac{\alpha^2}{2}$, which captures the decreasing returns to scale.

Suppose that labor is the only production input. The production quantity (q) is labor productivity (u) multiplied by the number of labor working hours (l), i.e.,

$$q_i = u_i \times l_i. \tag{12}$$

Without loss of generality, labor cost per hour is assumed to be an identity function:

$$c(l_i) = l_i. \tag{13}$$

According to Pang (2018), labor productivity is inversely related to total toxic emissions of all the firms with a scaling factor of distance:

$$u_i = \frac{1}{\sigma + \theta[\sum_{\forall g \neq i}^{N}(\frac{P_g}{d_{ig}}) + P_i]}, \tag{14}$$

where σ is the inverse of labor productivity in the absence of toxic emissions, θ measures the damage to the workforce caused by toxic emissions, and d (> 1) is the geographic distance between two firms. The scaling factor d captures the concept that the impact of negative environmental externalities dissipates with the distance from pollution sites. That is, negative environmental externalities impose greater costs on firms in the vicinity compared to those located farther away.

B.2 Profit maximization

Under the common ownership structure, firm i's objective is to maximize the following profit function by choosing α_i and q_i:

$$\max_{\alpha_i, q_i} Q_i = p_i q_i - c(l_i) - \frac{\alpha^2}{2} + \sum_{\forall g \neq i}^{N} \kappa_{ig} \pi_g. \tag{15}$$

Substituting Equation 10 to 14 into Equation 15, the objective function of firm i can be rewritten as:

$$\max_{\alpha_i, q_i} Q_i = \big(A - q_i - \sum_{g \neq i}^{N} q_g\big) q_i - \big[\sigma + \theta(e q_i - \alpha_i) + \theta \sum_{\forall g \neq i}^{N} \frac{e q_g - \alpha_g}{d_{ig}}\big] q_i - \frac{\alpha_i^2}{2} + \sum_{\forall g \neq i}^{N} \kappa_{ig} \pi_g. \tag{16}$$

The first order conditions of Equation 16 with respect to α_i and q_i provide the equations below:

$$\alpha_i = \big(\sum_{\forall g \neq i}^{N} \frac{\kappa_{ig}}{d_{ig}} q_g + q_i\big)\theta \tag{17}$$

$$q_i = \frac{1}{2(\theta e + 1)} \big[A - \sum_{\forall g \neq i}^{N} q_g - \sigma - \theta \alpha_i - \sum_{\forall g \neq i}^{N} \kappa_{ig} \big(\frac{\theta e}{d_{ig}} + 1\big) q_g - \theta \sum_{\forall g \neq i}^{N} \frac{e q_g - \alpha_g}{d_{ig}}\big] \tag{18}$$

B.3 Model Equilibrium

Denote $\boldsymbol{\alpha^*}$ and $\mathbf{q}^*$ as the vector of the firms' equilibrium pollution abatement and production output, respectively:

$$\boldsymbol{\alpha}^* = \begin{bmatrix} \boldsymbol{\alpha_1^*} \\ \boldsymbol{\alpha_2^*} \\ \vdots \\ \boldsymbol{\alpha_N^*} \end{bmatrix}, \quad \mathbf{q}^* = \begin{bmatrix} \mathbf{q_1^*} \\ \mathbf{q_2^*} \\ \vdots \\ \mathbf{q_N^*} \end{bmatrix} \tag{19}$$

The first order conditions in Equations 17 and 18 can be rewritten as:

$$\boldsymbol{\alpha} = \theta(\boldsymbol{\kappa} \oslash \mathbf{d})\mathbf{q} \tag{20}$$

$$\big[\theta e(\boldsymbol{\kappa} \oslash \mathbf{d} + J_{N,N} \oslash \mathbf{d}) + J_{N,N} + \boldsymbol{\kappa}\big]\mathbf{q} = (A - \sigma) \cdot J_{N,1} - \theta\boldsymbol{\alpha}, \tag{21}$$

where $\boldsymbol{\alpha}$ is the vector of pollution abatement, $\mathbf{q}$ is the vector of production output, $\oslash$ is element-by-element Hadamard division, $J_{N,1}$ is $N \times 1$ vector of ones, $J_{N,N}$ is $N \times N$ matrix of ones, $\boldsymbol{\kappa}$ is the matrix of profit weights of firm pairs, and $\mathbf{d}$ is the matrix of distances between firm pairs. Specifically, $\boldsymbol{\kappa}$ and $\mathbf{d}$ are defined as follows:

$$\boldsymbol{\kappa} = \begin{pmatrix} 1 & \kappa_{12} & \dots & \kappa_{1n} \\ \kappa_{21} & 1 & \dots & \kappa_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \kappa_{n1} & \kappa_{n2} & \dots & 1 \end{pmatrix}, \quad \mathbf{d} = \begin{pmatrix} 1 & d_{12} & \dots & d_{1n} \\ d_{21} & 1 & \dots & d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{n1} & d_{n2} & \dots & 1 \end{pmatrix} \tag{22}$$

Substituting Equation 21 into Equation 20, the equilibrium pollution abatement, $\boldsymbol{\alpha^*}$, becomes:

$$\boldsymbol{\alpha^*} = \theta\big[(\theta e\boldsymbol{\kappa} \oslash \mathbf{d} + \theta e J_{N,N} \oslash \mathbf{d} + J_{N,N} + \boldsymbol{\kappa})(\boldsymbol{\kappa} \oslash \mathbf{d})^{-1} + \theta^2\big]^{-1}(A - \sigma) \cdot J_{N,1} \tag{23}$$

Proposition 1. Firms' equilibrium pollution abatement ($\boldsymbol{\alpha^*}$) increases in geographic common ownership (κ_{ig}) and decreases in the distance between firm i and cross-held local firm

g (d_{ig}).

Substituting Equation 20 into Equation 21, the equilibrium production output ($\mathbf{q}^*$) becomes:

$$\mathbf{q}^* = [\theta e \boldsymbol{\kappa} \oslash \mathbf{d} + \theta e J_{N,N} \oslash \mathbf{d} + J_{N,N} + \theta^2 \boldsymbol{\kappa} \oslash \mathbf{d}]^{-1}(A - \sigma) \cdot J_{N,1} \tag{24}$$

Proposition 2. Firms' equilibrium production output ($\mathbf{q}^*$) decreases in geographic common ownership (κ_{ig}) but increases in the distance between firm i and cross-held local firm g. The distance between also weakens the negative relation between $\mathbf{q}^*$ and κ_{ig}.

From Equation 11, firms' pollution decreases in α and increases in q, representing the abatement and production channels, respectively. Therefore, according to **Propositions 1** and **2**, firms' equilibrium pollution decreases in geographic common ownership but increases in geographic proximity. Appendix C provides a numerical example to illustrate the effect of geographic common ownership on pollution choices.

C Numerical Example

Suppose there are two similar and geographically proximate firms, A and B, that produce same product in a duopoly industry. Their production strategy is simplified into two choices, polluting and clean production. The revenue, cost and profit for both strategies are given in the following table. Compared to the clean production, polluting production yields greater profit for the firm itself but exerts a external cost of \$25m to the other firm. An example of such external cost is a reduction in labor productivity caused by pollution externalities.

Production Strategy	Clean	Pollute
Revenue (\$m)	150	160
Cost (\$m)	75	Internal 80 + external 25
Profit without externality (\$m)	75	80

Consider how ownership structure influences firms' production strategy. In the first scenario, firm A and B are held by different set of shareholders, implying a zero value of geographic common ownership. Both firms adopt a production strategy that maximizes its own profit. The table below lists all four possible outcomes, where the profit of firm A is presented on the left and the profit of firm B on the right. The Nash equilibrium is (Pollute, Pollute), suggesting that both firms, knowing each other's production strategy, will choose to pollute in the equilibrium. However, (Clean, Clean) is the optimal outcome for both firms.

A Strategy \ B Strategy	Clean	Pollute
Clean	(75, 75)	(50, 80)
Pollute	(80, 50)	(55, 55)

The equilibrium changes as κ is factored into the firms' objective function under geographic common ownership. Suppose the objective function of both firms includes 100% of its own profit and 50% of the other firm's profit, i.e., when $\kappa = 0.5$. In equilibrium, both firms will adopt the clean production to maximize their objective function. This equilibrium is also optimal for the common owners. This numerical example shows how common ownership affects firms' pollution decisions.

A Strategy \ B Strategy	Clean	Pollute
Clean	(112.5, 112.5)	(90, 105)
Pollute	(105, 90)	(82.5, 82.5)

D Linking ISS with CRSP Mutual Funds

I perform the following procedure to link ISS mutual funds ($FundID$) with CRSP mutual funds ($CRSP\_PORTNO$). The same matching method is adopted by Sulaeman and Ye (2023). As described in Peter Iliev's note, each proxy voting record in the ISS data can be linked to the original SEC Form N-PX using the reference identifier ($NPXFileID$). From the SEC's N-PX file, I obtain a list of fund class tickers ($TICKER$) associated with the registered management investment company on the filing date. Because the CRSP Mutual Fund Summary data provide a direct linkage between the fund class tickers ($TICKER$) and the fund portfolio identifiers ($CRSP\_PORTNO$), I can map $FundID$ from ISS to $CRSP\_PORTNO$ from CRSP by $TICKER$ in each quarter.

In most cases (about 88% in my exercise), a $FundID$ in a quarter is matched with multiple $CRSP\_PORTNOs$, because a N-PX file typically refers to multiple funds under the same investment management company. For each $FundID$, I identify the most probable $CRSP\_PORTNO$ via matching the fund name between the two databases, using both Jaro-Winkler and Levenshtein Distance name-matching algorithms. I retain the pairs of $FundID$-$CRSP\_PORTNO$ with the minimum name distance according to the two algorithms and further require the distance to be less than 0.3 for Jaro-Winkler and 10 for Levenshtein Distance. In about 72% of the $FundID$-$CRSP\_PORTNO$ pairs, Jaro-Winkler or Levenshtein Distance reports a perfect match between the ISS and the CRSP fund names. For the remaining 28% of the cases where fund names are not exactly matched, I manually verify the accuracy of the mappings. As this name-matching methodology tightens the links between $FundID$ and $CRSP\_PORTNO$ within an investment management company in a quarter, it performs better than a general, unconditional matching using a universe of fund names from the two databases.

E List of Shareholders' Environmental Proposals

Table E.1: List of Shareholder-Sponsored Environmental Proposals

Proposal Description	No. Proposals
Adopt Quantitative GHG Goals for Products and Operations	44
Report on Sustainability, Including GHG Goals	17
Assess Environmental Impact of Non-Recyclable Packaging	16
Adopt Quantitative Company-wide GHG Goals	13
Report on environmental impact of fracturing	4
Report on Environmental Impact of Oil Sands Operations in Canada	4
Report on Reduction of Water Pollution	4
Adopt GHG Emissions Reduction Goals	3
Adopt policy to address coastal Louisiana environmental impacts	2
Disclose GHG Emissions Caused by Individual Products via Product Packaging	2
Report Accountability for Company's Environmental Impacts due to Operation	2
Report on Community Environmental Impact Disclosure Process	2
Report on Community Environmental Impacts of Operations	2
Report on Environmental Damage from Drilling in the National Petroleum Reserve	2
Report on environmental impact of fracturing operations	2
Report on Feasibility of Net-Zero GHG Emissions	2
Report on Fleet GHG Emissions in Relation to CAFE Standards	2
Report on GHG emission Reduction Scenarios	2
Report on the Feasibility of Achieving Net Zero GHG Emissions	2
Adopt and Report on Science-Based GHG Emissions Reduction Targets	1
Adopt Quantitative GHG Goals for GHG and Other Air Emissions	1
Adopt Quantitative GHG Goals for Maritime Shipping	1
Assess Environmental Impact of Polystyrene Foam Cups	1
Assess Environmental Impact of Using K-Cup Pods	1
Issue sustainability report, incl. GHG & water info	1
Report on Efforts to Reduce Plastic Pellet Pollution	1
Report on environmental impact of CAFOs	1
Report on Environmental Impact of Drilling in Sensitive Areas	1
Report on Environmental Impacts of Biomass and Assess Risks	1
Report on Feasibility of Adopting GHG Emissions Targets	1
Report on Feasibility of Adopting GHG Disclosure and Management	1
Report on Plastic Pollution	1
Report on Potential Env. Damage from Drilling in the Arctic National Wildlife Refuge	1
Report on Reducing Environmental and Health Harms to Communities of Color	1
Report on Reducing GHG Emissions	1
Total	142

F Alternative Fixed Effects

Table F.1: Within-Firm Analysis: County-by-Year Fixed Effects

The table repeat the within-firm analysis with a different set of fixed effects. The unit of observations is a firm-facility-year. The dependent variable is the natural logarithm of total quantity of toxic chemical in pounds generated by a facility in year t. The key independent variable is geographic common ownership, proxied by the following two measures: (1) *GeoCO Dummy* is a dummy variable set to one if there exists at least one institutional investor who block-holds the parent firm of the facility and a public firm headquartered within a 50-mile radius of the facility's location, and zero otherwise; and (2) *GeoCO* is a continuous measure that captures the weighted average profit weights between the facility and the public firms headquartered within a 50-mile radius of the facility's location as defined in Section 3.2. Control variables include the number of chemicals produced by the facility ($NumChemical$), an indicator set to one if the facility is located within a 50-mile radius of the headquarter of the parent firm ($NearParentHQ$), and the total ownership held by institutional investors whose business address is within a 50-mile radius of the facility's location ($LocalOwnership$). All independent variables are measured in year t-1. The regressions incorporate parent-by-year and facility county-by-year fixed effects. The standard errors are clustered by parent firm and facility's state. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Dep Var	$LogPollution_{ifst}$			
	(1)	(2)	(3)	(4)
$GeoCO\ Dummy_{ifst-1}$	-0.183***	-0.176***		
	(0.063)	(0.058)		
$GeoCO_{ifst-1}$			-0.814***	-0.648**
			(0.272)	(0.248)
$NumChemical_{ifst-1}$		0.220***		0.220***
		(0.051)		(0.051)
$NearParentHQ_{ifst-1}$		0.271**		0.268**
		(0.118)		(0.117)
$LocalOwnership_{ifst-1}$		-0.018		-0.019
		(0.014)		(0.014)
Parent-Year FE	Y	Y	Y	Y
Facility County-Year FE	Y	Y	Y	Y
Observations	153,760	153,760	153,760	153,760
Adjusted R^2	0.344	0.471	0.344	0.471

G Alternative Measure

Table G.1: Alternative Measure of Geographic Common Ownership

The table reports the results of the robustness test for the within-firm analysis on the relation between geographic common ownership and toxic chemical pollution by estimating Equation 4, using alternative measure of geographic common ownership. The unit of observation is a facility-year. The dependent variable is the natural log of total toxic pollution in pounds by a facility in year t. The key independent variable is geographic common ownership, proxied by $GeoCindex$ (Lewellen and Lowry, 2021). Control variables include the number of chemicals produced by the facility ($NumChemical$), an indicator set to one if the facility is located within a 50-mile radius of the headquarter of the parent firm ($NearParentHQ$), and the total ownership held by institutional investors whose business address is within a 50-mile radius of the facility's location ($LocalOwnership$). All independent variables are measured in year t-1. The regressions incorporate parent-by-year and facility state-by-year fixed effects. The standard errors are clustered by parent firm and facility's state. ***,**,* denote significance at the 1%, 5%, and 10% levels, respectively.

Dep Var	$LogPollution_{ifst}$	
	(1)	(2)
$GeoCindex_{ifst-1}$	-33.450***	-33.439***
	(9.146)	(8.314)
$NumChemical_{ifst-1}$		0.232***
		(0.052)
$NearParentHQ_{ifst-1}$		0.208*
		(0.112)
$LocalOwnership_{ifst-1}$		-0.024*
		(0.013)
Parent-Year FE	Y	Y
Facility State-Year FE	Y	Y
Observations	153,760	153,760
Adjusted R^2	0.332	0.467

H Alternative Geographic Radius

Table H.1: Alternative Geographic Radius

The table reports the results of repeating the within-firm analysis using alternative geographic radius. The unit of observation is a firm-facility-year. In both panels, the dependent variable is the natural logarithm of total quantity of toxic chemicals in pounds generated by a facility in year t. In Panel A (Panel B), the key independent variable is geographic common ownership, proxied by the following two measures: (1) *GeoCO Dummy* is a dummy variable set to one if there exists at least one institutional investor who block-holds the parent firm of the facility and a public firm headquartered within a 25-mile (100-mile) radius of the facility's location, and zero otherwise; and (2) *GeoCO* is a continuous measure that captures the weighted average profit weights between the facility and the public firms headquartered within a 25-mile (100-mile) radius of the facility's location as defined in Section 3.2. Control variables are the same as Table 2. The regressions incorporate parent-by-year and facility state-by-year fixed effects. The standard errors are clustered by parent firm and facility's state. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: 25-mile radius of facility location

Dep Var	$LogPollution_{ifst}$			
	(1)	(2)	(3)	(4)
$GeoCO\ Dummy_{ifst-1}$	-0.205***	-0.203***		
	(0.065)	(0.056)		
$GeoCO_{ifst-1}$			-0.477***	-0.533***
			(0.160)	(0.134)
Facility Controls		Y		Y
Parent-Year FE	Y	Y	Y	Y
Facility State-Year FE	Y	Y	Y	Y
Observations	153,760	153,760	153,760	153,760
Adjusted R^2	0.332	0.467	0.332	0.467

Panel B: 100-mile radius of facility location

Dep Var	$LogPollution_{ifst}$			
	(1)	(2)	(3)	(4)
$GeoCO\ Dummy_{ifst-1}$	-0.115**	-0.149***		
	(0.048)	(0.050)		
$GeoCO_{ifst-1}$			-0.487	-0.658
			(0.522)	(0.521)
Facility Controls		Y		Y
Parent-Year FE	Y	Y	Y	Y
Facility State-Year FE	Y	Y	Y	Y
Observations	153,760	153,760	153,760	153,760
Adjusted R^2	0.331	0.467	0.331	0.467

I Facility-Chemical-Year Level Analysis

Table I.1: Within-Firm Analysis at the Facility-Chemical-Year Level

The table repeats the within-firm analysis, using the facility-chemical-year level sample. The dependent variable is the natural log of the total quantity of a toxic chemical in pounds generated by a facility in year t. The key independent variable is the geographic common ownership, proxied by the following two measures: (1) *GeoCO Dummy* is a dummy variable set to one if there exists at least one institutional investor who block-holds the parent of the facility and a public company headquartered within a 50-mile radius of the facility, and zero otherwise; and (2) *GeoCO* is a continuous measure of geographic common ownership. The control variables include an indicator variable set to one if the facility is located within a 50-mile radius of the the parent company's headquarter ($NearParentHQ$) and the total ownership held by institutional investors whose business address is within a 50-mile radius of the facility's location ($LocalOwnership$). All independent variables are measured in year t-1. The regressions incorporate the parent-by-year, facility state-by-year, and chemical-by-year fixed effects in Columns (1) and (3), and parent-by-year and facility state-chemical-by-year fixed effects in Columns (2) and (4). The standard errors are clustered by parent firm and facility's state. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Dep Var	$LogPollution_{ifcst}$			
	(1)	(2)	(3)	(4)
$GeoCO\ Dummy_{ifcst-1}$	-0.096**	-0.108***		
	(0.036)	(0.034)		
$GeoCO_{ifcst-1}$			-0.434***	-0.457***
			(0.101)	(0.114)
$NearParentHQ_{ifcst-1}$	0.189**	0.170*	0.200**	0.179*
	(0.093)	(0.092)	(0.091)	(0.091)
$LocalOwnership_{ifcst-1}$	0.003	0.005	0.004	0.005
	(0.011)	(0.011)	(0.011)	(0.011)
Parent-Year FE	Y	Y	Y	Y
Facility State-Year FE	Y		Y	
Chemical-Year FE	Y		Y	
Facility State-Chemical-Year FE		Y		Y
Observations	709,279	709,279	709,279	709,279
Adjusted R^2	0.538	0.557	0.538	0.557

Table I.2: Stacked Difference-in-Differences Analysis at the Facility-Chemical-Year Level

The table repeats the results of the differences-in-differences analysis based on the quasi-natural experiment of financial institution mergers. In both regressions, the unit of observation is at the merger-facility-chemical-year level. The dependent variable is the natural log of total quantity of toxic chemicals in pounds generated by a facility in year t. The key independent variable is the interaction between $Treat$ and $Post$. The regressions include both firm and facility-level controls. All controls are measured in year t-1. The regressions incorporate merger-by-facility, merger-by-year, and merger-by-chemical fixed effects in the Column (1) and merger-by-facility-chemical and merger-by-year fixed effects in Column (2). The standard errors are clustered by merger event. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Dep Var	$LogPollution_{mifcst}$	
	(1)	(2)
$Treat \times Post$	-0.154***	-0.144***
	(0.039)	(0.049)
FirmControls	Y	Y
FacilityControls	Y	Y
Merger-Facility FE	Y	
Merger-Year FE	Y	Y
Merger-Chemical FE	Y	
Merger-Facility-Chemical FE		Y
Observations	61,210	61,210
Adjusted R^2	0.687	0.678

J On-Site Pollution Analysis

Table J.1: On-Site Toxic Pollution Regressions

The table reports the results of estimating the on-site release regressions for both the within-firm and the difference-in-differences analyses. In both panels, the dependent variable is the natural logarithm of the quantity of toxic chemicals released onsite in pounds by facility f in year $t-1$. In Panel A, the unit of observation is a facility-year. The key independent variables are three proxies for geographic common ownership as defined in Section 3.2. The regressions include facility-level controls along with the parent-by-year and facility state-by-year fixed effects. In Panel B, the unit of observation is at the merger-facility-year level. The key independent variable becomes the interaction between $Treat$ and $Post$ as defined in Section 5. The regression in Columns (1) is free of controls. The regression in Column (2) include firm controls, and additionally facility controls in Column (3). All control variables are measured in year $t-1$. The regressions incorporate merger-by-facility and merger-by-year fixed effects. The standard errors are clustered by parent and facility's state in Panel A and by merger event in Panel B. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Within-firm analysis

Dep Var	$LogOnsitePollution_{ifst}$		
	(1)	(2)	(3)
$GeoCO\ Dummy_{ifst-1}$	-0.394***		
	(0.070)		
$GeoCO_{ifst-1}$		-1.029***	
		(0.215)	
$GeoCindex_{ifst-1}$			-52.871***
			(10.607)
FacilityControls	Y	Y	Y
Parent-Year FE	Y	Y	Y
Facility State-Year FE	Y	Y	Y
Observations	135,909	135,909	135,909
Adjusted R^2	0.535	0.535	0.535

Panel B: DiD analysis

Dep Var	$LogOnsitePollution_{mifst}$		
	(1)	(2)	(3)
$Treat \times Post$	-0.129	-0.148*	-0.143*
	(0.088)	(0.087)	(0.086)
FirmControls		Y	Y
FacilityControls			Y
Merger-Facility FE	Y	Y	Y
Merger-Year FE	Y	Y	Y
Observations	7,916	7,916	7,916
Adjusted R^2	0.899	0.899	0.900

K Risk-Screening Environmental Indicators Analysis

Table K.1: Risk-Screening Environmental Indicators Regressions

The table reports the results of risk-screening environmental indicators analysis for both the within-firm and the difference-in-differences analyses. In both panels, the unit of observation is a facility-year. The dependent variable is the natural logarithm of the sum of toxic chemical onsite releases multiplied by the toxicity weight ($LogRSEI$). In Panel A, the key independent variables are the three proxies for geographic common ownership as defined in Section 3.2. The regressions include facility-level controls along with the parent-by-year and facility state-by-year fixed effects. In Panel B, the unit of observation is at the merger-facility-year level. The key independent variable is the interaction between $Treat$ and $Post$ as defined in Section 5. The regression in Columns (1) is free of controls. The regression in Column (2) include firm controls, and additionally facility controls in Column (3). All control variables are measured in year t-1. The regressions incorporate merger-by-facility and merger-by-year fixed effects. The standard errors are clustered by parent and facility's state in Panel A and by merger event in Panel B. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Within-firm analysis

Dep Var		$LogRSEI_{ifst}$	
	(1)	(2)	(3)
$GeoCO\ Dummy_{ifst-1}$	-0.296***		
	(0.091)		
$GeoCO_{ifst-1}$		-1.047***	
		(0.276)	
$GeoCindex_{ifst-1}$			-48.149***
			(14.128)
FacilityControls	Y	Y	Y
Parent-Year FE	Y	Y	Y
Facility State-Year FE	Y	Y	Y
Observations	134,373	134,373	134,373
Adjusted R^2	0.474	0.475	0.474

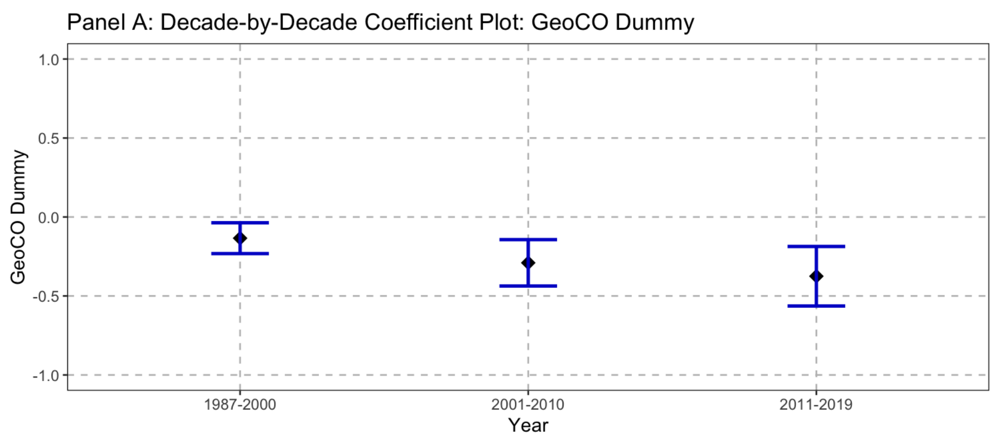
Panel B: DiD analysis

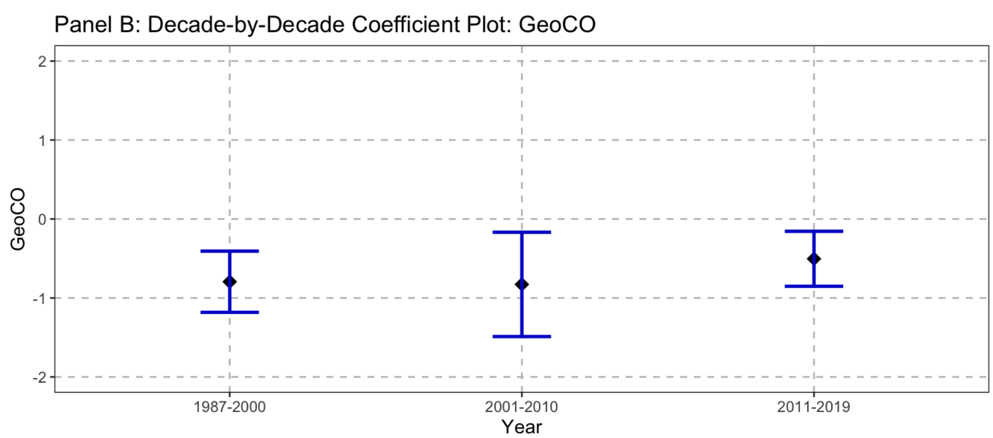
Dep Var		$LogRSEI_{mifst}$	
	(1)	(2)	(3)
$Treat \times Post$	-0.314**	-0.339**	-0.328**
	(0.128)	(0.132)	(0.130)
FirmControls		Y	Y
FacilityControls			Y
Merger-Facility FE	Y	Y	Y
Merger-Year FE	Y	Y	Y
Observations	7,800	7,800	7,800
Adjusted R^2	0.888	0.888	0.890

L Sub-period Analysis

Figure L.1: Decade-by-Decade Within-Firm Analysis

The graphs report the results of estimating the regressions in Equation 4 decade by decade. The 1987-2019 sample period is split into three sub-periods: (1) 1987-2000; (2) 2001-2010; and (3) 2011-2019. The key independent variable is $GeoCODummy$ in Panel A and $GeoCO$ in Panel B. Estimated coefficients with 90% confidence intervals are reported in both panels.





M Cross-Sectional Results of Within-Firm Analysis

Table M.1: Common Owners Heterogeneity

The table reports the results of the heterogeneity tests on common owners in the within-firm analysis. The unit of observations is a firm-facility-year. The dependent variable is the natural logarithm of total quantity of toxic chemical in pounds produced by a facility in year t. The key independent variables are *Big*3 & *GeoCO Dummy* and *NonBig*3 & *GeoCO Dummy* in Column (1). *Big*3 & *GeoCO Dummy* (*NonBig*3 & *GeoCO Dummy*) takes value of one if the parent of the facility is block held by a big 3 asset manager (non-big-3 asset managers) who also owns a block stake on any firms that headquarter within 50 miles of the facility. In Column (2), the key independent variables are the geographic common ownership of big 3 asset managers (*Big*3 & *GeoCO*) and of other asset managers (*NonBig*3 & *GeoCO*). In Column (3), the key independent variables are *Diversified* & *GeoCO Dummy* and *Undiversified* & *GeoCO Dummy*. *Diversified* & *GeoCO Dummy* (*Undiversified* & *GeoCO Dummy*) is a dummy variable set to one if the geographic blockholder holds a portfolio with more (less) than 200 stocks in a year. In Column (4), the key independent variables are the geographic common ownership of diversified investors (*Diversified* & *GeoCO*) and of undiversified investors (*Undiversified* & *GeoCO*). In Column (5), the key independent variables are *CSR* & *GeoCO Dummy* and *NonCSR* & *GeoCO Dummy*. *CSR* & *GeoCO Dummy* (*NonCSR* & *GeoCO Dummy*) is a dummy variable set to one if the geographic blockholder holds a portfolio with MSCI-KLD score higher (lower) than the sample median in a year. In Column (6), the key independent variables are the geographic common ownership of CSR investors (*CSR* & *GeoCO*) and of other institutional investors (*NonCSR* & *GeoCO*). The regressions include three facility-level control variables as in Table 2 and incorporate parent-by-year and facility's state-by-year fixed effects. The standard errors are clustered by parent firm and facility's state. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Dep Var	$LogPollution_{ifst}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Big3 & GeoCO Dummy	-0.367***					
	(0.090)					
NonBig3 & GeoCO Dummy	-0.187***					
	(0.060)					
Big3 & GeoCO		-0.764***				
		(0.229)				
NonBig3 & GeoCO		-0.634**				
		(0.238)				
Diversified & GeoCO Dummy			-0.236***			
			(0.055)			
Undiversified & GeoCO Dummy			-0.167			
			(0.102)			
Diversified & GeoCO				-0.650***		
				(0.195)		
Undiversified & GeoCO				-1.414		
				(1.648)		
CSR & GeoCO Dummy					-0.286***	
					(0.076)	
NonCSR & GeoCO Dummy					-0.105*	
					(0.059)	
CSR & GeoCO						-0.723***
						(0.240)
NonCSR & GeoCO						-0.420
						(0.330)
Facility Controls	Y	Y	Y	Y	Y	Y
Parent-Year FE	Y	Y	Y	Y	Y	Y
Facility State-Year FE	Y	Y	Y	Y	Y	Y
Observations	153,760	153,760	153,760	153,760	131,929	131,929
Adjusted R^2	0.467	0.467	0.467	0.467	0.472	0.473

Table M.2: Demographics Heterogeneity

The table reports the results of the cross-sectional tests for the within-firm analysis. The unit of observations is a firm-facility-year. The dependent variable is the natural logarithm of total quantity of toxic chemical in pounds produced by a facility in year t. The key independent variables are the interactions between geographic common ownership, proxied by either *GeoCO Dummy* or *GeoCO*, and $MoreMinorityState$. $MoreMinorityState$ is a dummy variable set to one if the proportion of minority (including Asian, Black, Hispanic, and Native American) of a state is higher than the US median in 2010. The regressions include three facility-level control variables as in Table 2 and incorporate parent-by-year and facility state-by-year fixed effects. The standard errors are clustered by parent firm and facility's state. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Dep Var	$LogPollution_{ifst}$	
	(1)	(2)
GeoCO Dummy	-0.308***	
	(0.063)	
GeoCO Dummy $\times$ $MoreMinorityState$	0.148**	
	(0.060)	
GeoCO		-0.651***
		(0.220)
GeoCO $\times$ $MoreMinorityState$		0.003
		(0.211)
Facility Controls	Y	Y
Parent-Year FE	Y	Y
Facility State-Year FE	Y	Y
Observations	153,760	153,760
Adjusted R^2	0.467	0.467

N Poisson Regressions

Table N.1: Stacked Difference-in-Differences Analysis Using Poisson Regressions

The table reports the results of estimating the Poisson regressions for the difference-in-differences analysis based on the quasi-natural experiment of financial institution mergers. Across all regressions, the unit of observation is at the merger-facility-year level. The dependent variable is the total toxic pollution in pounds by a facility in year t. The key independent variable is the interaction between $Treat$ and $Post$. The regression in Columns (1) is free of controls. The regression in Column (2) include firm controls, and additionally facility controls in Column (3). All control variables are measured in year t-1. The regressions incorporate merger-by-facility and merger-by-year fixed effects. The standard errors are clustered by merger event. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Dep Var	$Pollution_{mifst}$		
	(1)	(2)	(3)
$Treat \times Post$	-0.290***	-0.264***	-0.262***
	(0.096)	(0.084)	(0.080)
FirmControls		Y	Y
FacilityControls			Y
Merger-Facility FE	Y	Y	Y
Merger-Year FE	Y	Y	Y
Observations	8,679	8,679	8,679
Pseudo R^2	0.954	0.955	0.956

O Horizontal Common Ownership

Table O.1: Geographic versus Horizontal Common Ownership

The table reports the results of the difference-in-differences analysis using the same quasi-natural experiment of financial institution mergers as Table 3, except that the treatment and control facilities are defined based on industry relationships between their parents and other firms held by the merging institutions. Specifically, in Column (1), $Treat$ is set to one for the facility if its parent firm is held by one side of the merging institution and shares the same primary the Fama-French 48 industry with at least one portfolio firm held by the other side of the merging institution a quarter before the announcement of the merger. In Column (2), $Treat$ is set to one for the facility if its parent firm is held by one side of the merging institution and have a direct product market competition relationship with at least one firm held by the other side of the merging institution. In both regressions, the unit of observation is at the merger-facility-year level. The dependent variable is the natural log of total toxic pollution in pounds generated by a facility in year t. The key independent variable is the interaction between $Treat$ and $Post$. The regressions in Columns (1) and (2) include both firm and facility controls measured in year t-1. The regressions incorporate merger-by-facility and merger-by-year fixed effects. The standard errors are clustered by merger event. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Dep Var	$LogPollution_{mifst}$	
Treatment Definition	Fama-French 48 industry	TNIC competitors
	(1)	(2)
$Treat \times Post$	-0.147	-0.319
	(0.128)	(0.165)
Firm Controls	Y	Y
Facility Controls	Y	Y
Merger-Facility FE	Y	Y
Merger-Year FE	Y	Y
Observations	8,181	5,363
Adjusted R^2	0.878	0.886

P Source Reduction Activities

Table P.1: Source Reduction Activities

The table reports the results of source reduction activities for both the within-firm (Panel A) and the DiD (Panel B) analyses. In both panels, the dependent variable is $SourceReduction$ which is the number of source reduction activities reported by a facility in year t. In Panel A, the key dependent variables are proxies for geographic common ownership. The regressions include the same set of facility control variables and fixed effects as used in Table 2. In Panel B, the regressions incorporate merger-by-facility and merger-by-year fixed effects. All control variables are measured in year t-1. The standard errors are clustered by parent firm and facility's state in Panel A and merger event in Panel B. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Within-firm analysis

Dep Var	$SourceReduction_{ifst}$		
	(1)	(2)	(3)
$GeoCO\ Dummy_{ifst-1}$	0.029		
	(0.057)		
$GeoCO_{ifst-1}$		-0.002	
		(0.124)	
$GeoCindex_{ifst-1}$			-2.206
			(8.808)
FacilityControls	Y	Y	Y
Parent-Year FE	Y	Y	Y
Facility State-Year FE	Y	Y	Y
Observations	153,760	153,760	153,760
Adjusted R^2	0.213	0.213	0.213

Panel B: DiD analysis

Dep Var	$SourceReduction_{ifst}$		
	(1)	(2)	(3)
$Treat \times Post$	0.136	0.131	0.131
	(0.279)	(0.243)	(0.245)
FirmControls		Y	Y
FacilityControls			Y
Merger-Facility FE	Y	Y	Y
Merger-Year FE	Y	Y	Y
Observations	8,679	8,679	8,679
Adjusted R^2	0.614	0.618	0.618