The Journal of FINANCE
The Journal of THE AMERICAN FINANCE ASSOCIATION

THE JOURNAL OF FINANCE • VOL. LXXX, NO. 2 • APRIL 2025

Sustainability or Greenwashing: Evidence from the Asset Market for Industrial Pollution

RAN DUCHIN, JANET GAO, and QIPING XU*

ABSTRACT

We study the asset market for pollutive plants. Firms divest pollutive plants in response to environmental pressures. Buyers are firms facing weaker environmental pressures that have supply chain relationships or joint ventures with the sellers. While pollution levels do not decline following divestitures, sellers highlight their sustainable policies in subsequent conference calls, earn higher returns as they sell more pollutive plants, and benefit from higher Environmental, Social, and Governance (ESG) ratings and lower compliance costs. Overall, the asset market allows firms to redraw their boundaries in a manner perceived as environmentally friendly without real consequences for pollution but with substantial gains from trade.

*Ran Duchin is at Carroll School of Management, Boston College. Janet Gao is at McDonough School of Business, Georgetown University. Qiping Xu is at Gies College of Business, University of Illinois Urbana–Champaign. We are indebted to Editor Antoinette Schoar and two anonymous referees. For helpful comments, we thank Todd Gormley; Jonathan Karpoff; Paul Malatesta; John Matsusaka; Matthew Ringgenberg; Sophie Shive; Denis Sosyura; Michael Weisbach; conference participants at the 2022 University of Washington Summer Conference, the 2022 Wabash River Finance Conference, the 2022 Financial Research Association (FRA) conference, the 5th Shanghai Financial Forefront Symposium, the 2022 Clemson ESG and Policy Research Conference, the 2023 Western Finance Association (WFA) conference, the 2023 Financial Intermediation Research Society (FIRS) conference, the 14th Florida State University Truist Beach Conference, the 16th Annual Drexel Corporate Governance Conference (2023), the 2023 Bretton Woods Conference, the 2023 ASU Sonoran Winter Finance Conference, the Fourth BI Conference on Corporate Governance (2023), the 2023 International Industry-Academia-Research-Application Cooperation Conference at UIBE, the 2023 HKU Tel Aviv Finance Forum, the "Meet the Editors" Conference at Dalhousie University (2023), the 2024 Climate Finance and ESG Conference at Baruch College; and seminar participants at the University of Rochester, the University of Southern California, the University of Florida, Peking University, Rutgers University, the University of Massachusetts Amherst, the University of Hong Kong, the University of Connecticut, the Hong Kong Polytechnic University, Durham University, George Mason University, Nankai University, and the University of Western Ontario. Xu gratefully acknowledges the financial support from the Office of Risk Management & Insurance Research at the University of Illinois Urbana-Champaign. We have read *The Journal of Finance* disclosure policy and have no conflicts of interest to disclose.

Correspondence: Qiping Xu, Gies College of Business, University of Illinois at Urbana-Champaign, Champaign, IL 61820; e-mail: qipingxu@illinois.edu

DOI: 10.1111/jofi.13412

A GROWING TREND IN CORPORATE finance, as a result of pressure from activists, regulators, and governments, is the divestment of polluting assets. As Panel A of Figure 1 shows, the average value of divestitures of polluting assets has increased considerably since 2015. While this trend reflects mounting concerns about climate change, it raises the question of how effective such divestment is. On the one hand, Environmental, Social, and Governance (ESG)

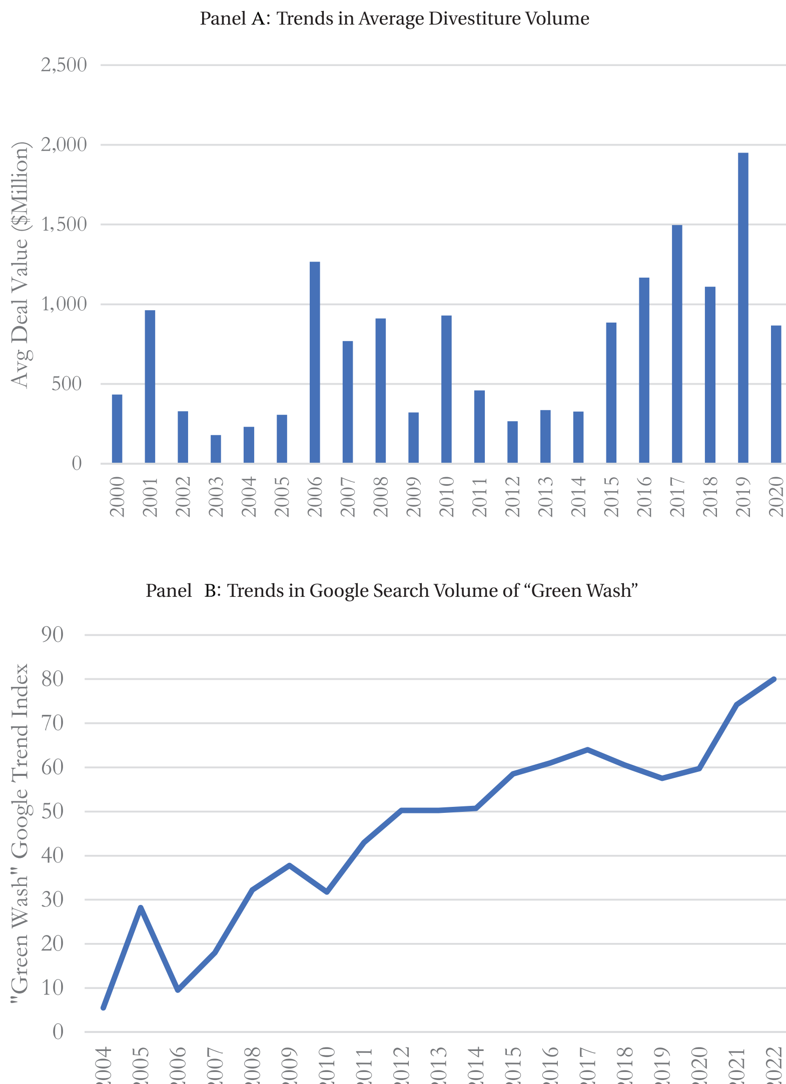

Figure 1. Time trends in divestitures and attention to greenwashing. Panel A reports annual average deal values (in $millions) of divestitures of pollutive plants from 2000 to 2020. Pollutive plants are plants in the Toxic Release Inventory Program of the U.S. Environmental Protection Agency. Panel B reports annual average Google search volumes of the phrase "green wash" from 2004 to 2022. (Color figure can be viewed at wileyonlinelibrary.com)

supporters can point to campaigns that have successfully encouraged many firms to sell off dirty assets. On the other hand, selling off assets or shares in and of itself does nothing to save the planet because another entity acquires them.[1] Moreover, the effect of divestment on the environment may even be negative because it can remove the option to engage with firms to reduce pollution.[2] The latter view suggests that the divestment of polluting assets can simply be a "greenwashing" strategy through which firms falsely give the impression that they are more environmentally sound. Indeed, as Panel B of Figure 1 shows, attention to greenwashing has risen more than eightfold since 2004 according to Google Trends.

In this paper, we aim to shed new light on this question by studying the reallocation of industrial pollution in response to environmental pressures through acquisitions and sales of pollutive assets in the real asset market. Specifically, we investigate how firms respond to environmental pressures, which firms buy and sell pollutive assets, how pollution levels change around the transfer of ownership, and what gains firms realize from trading these assets.

We study these questions in a conceptual framework that considers heterogeneous firms holding pollutive assets and facing varying levels of environmental pressures. Environmental pressures arise from prosocial preferences of various stakeholders, including investors, employees, customers, suppliers, policymakers, regulators, and activists (e.g., Hart and Zingales (2017), Broccardo, Hart, and Zingales (2022), and Oehmke and Opp (2022)). Firms can respond to environmental pressures by (i) selling their pollutive plants, (ii) reducing the amount of pollution produced by their plants, (iii) closing down their pollutive plants, or (iv) doing nothing. Their choice of response will depend on the intensity of the environmental pressures they face and on the relative costs and benefits of operating pollutive assets versus the alternatives for a given level of environmental pressures.

To evaluate these possibilities, we construct measures of the environmental pressures that firms face from investors, ESG rating agencies, policymakers, and the public at large. These measures include a firm's coverage by ESG rating agencies, pension fund holdings, the political climate where the company is headquartered, the frequency of environmental risk incidents, and a composite index that is the average of the preceding measures. Using these variables, we estimate choice models that evaluate firms' responses to environmental pressures. We find that divestment is a prominent response to environmental pressures. In particular, a one-standard-deviation increase in the composite environmental pressure index leads to a 54% increase in divestment likelihood (relative to the sample average), compared to a considerably smaller increase in the likelihood of plant closure or abatement efforts of 9% to 31%. As such,

[1] See, for example, "Why the Sustainable Investment Craze is Flawed?" by James Mackintosh, *The Wall Street Journal*, January 23, 2022.

[2] See, for example, "See 'Net zero' oil firms are selling their dirty assets: What are the ESG implications?" by Emile Hallez, *ESG Clarity*, May 13, 2022.

we focus the remainder of the analyses on the implications of environmental pressures for divestment and the boundaries of the firm.

Consistent with a Coasean framework (Coase (1937)), we argue that variation in environmental costs will induce some firms to sell pollutive assets and other firms to buy pollutive assets. As a result, firm boundaries around pollutive assets will vary across companies. Firms that face stronger environmental pressure will find it optimal to divest pollutive assets, whereas firms that face weaker environmental pressure will find it optimal to buy (or own) pollutive assets. In a real-asset-market model à la Jovanovic and Braguinsky (2004), this implies that the market would clear by transferring pollutive assets from high-pressure firms to low-pressure firms.

We compile a data set of 888 divestitures of pollutive industrial plants from 2000 to 2020 and investigate both their determinants and implications for buyers and sellers. We hand-collect and merge data from several databases, including divestiture data from the Securities Data Company (SDC) database, toxic release data from the Environmental Protection Agency's (EPA) Toxic Release Inventory (TRI) database, ESG ratings from Kinder, Lydenberg, and Domini (KLD), Refinitive, and MSCI, conference call data from Thomson Reuters' Street Events (SE) Database, ESG-related incident data from Factset's RepRisk ESG Business Intelligence database, county-level vote share data from the MIT Election Data and Science Lab, supply chain and joint venture data from the Compustat Segment, Factset, and SDC databases, and data on firms' organizational and ownership structures from Compustat, Orbis, and 13-F filings.

We begin our empirical analyses by studying the decision to sell and buy pollutive assets. We obtain two key findings. First, firms are more likely to divest pollutive assets when they face stronger environmental pressures, and these effects are considerably more pronounced when pollution levels are higher. A one-standard-deviation increase in the composite environmental pressure index leads to a 32% increase in the likelihood of divesting polluting plants relative to the sample average. Furthermore, an interquartile increase in a plant's total toxic release leads to a 2.3 percentage points increase in the likelihood of divestment in response to environmental pressures. A similar interquartile increase in a plant's pollution intensity, defined as the ratio of toxic release to total employment, leads to a 1.3 percentage points increase in the likelihood of divestment. The magnitudes of these effects are nontrivial compared to the sample-wide average divestiture likelihood of 1.9 percetnage points. These effects hold for each of the individual constituents of the index and do not exhibit noticeable pretrends before the occurrence of environmental risk incidents.

Second, compared to the sellers, buyers of pollutive assets face significantly weaker environmental pressures. Buyers are 5.5 percentage points more likely to be privately held, 4.7 percentage points less likely to be covered by ESG rating agencies, 5.4 percentage points more likely to be headquartered in a Republican county, and 5.2 percentage points more likely to have not experienced negative environmental risk incidents prior to the deal. These effects are economically large, representing increases of 8% to 34% relative to the sample mean, and are nonexistent for divestitures of nonpollutive assets.[3]

Taken together, these results give rise to a separating real-asset-market equilibrium whereby public firms that face mounting environmental pressures sell their most pollutive assets to firms that face weaker pressures. As such, our findings identify divestitures as a mechanism that reallocates pollutive assets to cater to investors' prosocial preferences (e.g., Heinkel, Kraus, and Zechner (2001), Pástor, Stambaugh, and Taylor (2021), Piccolo, Schneemeier, and Bisceglia (2022), among others). This result contributes to related literature on the divestment of brown firms in capital markets by financial institutions and investment funds (Broccardo, Hart, and Zingales (2022), Edmans, Levit, and Schneemeier (2022), Green and Vallee (2022)).

We next examine changes in pollution around divestitures. In plant-chemical difference-in-difference (DID) Poisson regressions, we find no difference between the change in pollution at divested plants and the change in pollution at plants that were not divested. The estimates are statistically indistinguishable from zero and remain largely unchanged after the inclusion of chemical-plant, chemical-year, state-year, and industry-year fixed effects. These findings continue to hold after weighing toxic release levels by the toxicity of each chemical, in collapsed plant-year panel regressions, and in stacked regressions that consider potential biases due to heterogeneous dynamic treatment effects (e.g., Gormley and Matsa (2011), Baker, Larcker, and Wang (2022)). In similar plant-chemical DID specifications, we find no difference between pollution abatement efforts at sold versus unsold plants either.

Since divestitures are clearly nonrandom, it is possible that sellers choose to keep plants whose pollution they can treat and divest assets whose pollution they cannot treat. Buyers may also adjust production and pollution levels at their other plants upon acquiring new pollutive plants. To evaluate these possibilities, we trace the combined pollution levels of sellers' and buyers' plants around divestitures. We find that following divestitures, there is no reduction in the pollution levels of sellers' and buyers' combined plants. It is also possible that firms reallocate capital, possibly to greener establishments, by divesting pollutive assets that become obsolete. We find no empirical support for obsolescence or capital reallocation: productivity growth rates and survival rates are similar across sold and unsold plants, and divestitures are not accompanied by the introduction of new plants. To further mitigate concerns about selection and omitted variables, we focus on divestitures that follow quasi-exogenous environmental risk incidents. We find no changes in pollution following those divestitures and no pretrends in pollution before they occur.

Taken together, the findings above suggest that the allocation of assets resulting from divestitures does not lead to reductions in pollution and

[3] We find no evidence that sellers gain from selling their environmental liabilities to distressed firms that enjoy bankruptcy protection from environmental litigation. On average, the default probabilities of buyers are lower than those of sellers.

is unrelated to technological obsolescence or investment in new, possibly greener, plants.

A possible interpretation of these findings is that firms respond to environmental pressures through a greenwashing divestment strategy whereby companies divest pollutive plants to mitigate stakeholder pressures without having any real effects on pollution levels. We provide several results that support this interpretation. First, we investigate the role of information costs as an indirect proxy for the potential for deception or misalignment between corporate managers and outside stakeholders. This line of research is rooted in an extensive literature on corporate governance that considers the role of information asymmetry in agency conflicts and interest misalignment (e.g., Demsetz and Lehn (1985), Almazan and Suarez (2003), Duchin, Matsusaka, and Ozbas (2010)). We find that firms with complex organizational structures and more dispersed ownership are more likely to respond to environmental pressures by divesting pollutive assets. This suggests that divestment is more likely when stakeholders face higher information costs of monitoring firms' environmental performance, consistent with greenwashing.

Second, we find that the divested assets are sold to firms that have preexisting business ties or develop new business ties with the sellers following the sale. Specifically, the buyers of divested plants tend to be firms with preexisting or newly developed supply chain relationships or joint ventures with the sellers. Such connections likely reduce counterparty risk and information asymmetry, allowing sellers to maintain their access to the sold assets at lower cost. We also find that the likelihood of transferring pollutive assets to connected firms increases when the connected firms face weaker environmental pressures. These findings lend further support to a greenwashing strategy, as they suggest that the divestment of pollutive plants reflects a cosmetic redrawing of firm boundaries, whereby sellers respond to environmental pressures through divestitures along their supply chains that maintain their access to the sold plants.

Third, we use a Bidirectional Encoder Representations from Transformers (BERT) language model to analyze the text of firms' conference calls with investors. We find that following divestitures of pollutive plants, sellers are considerably more likely to mention and emphasize improvements in their environmental policies. Consistent with greenwashing, this evidence suggests that sellers advertise their commitment to sustainability and the environment following divestitures, despite the muted effect of diverstitures on pollution levels and the tendency to sell those assets to connected firms.

In the final set of analyses, we investigate the gains from trading pollutive assets. These analyses provide several results. First, following pollutive asset divestitures, sellers' ESG ratings increase by roughly 103% relative to the sample average, with a particularly strong improvement for environmental ratings (160% relative to the sample average). Second, following divestitures, the likelihood of an EPA enforcement action drops by about 5 to 7 percentage points, which compares to a sample mean of 7 percentage points. Moreover, the costs of regulatory enforcement, including fines and cleanup costs, also decline considerably.

Importantly, we show that the findings on buyer-seller environmental pressure differences and business ties, environmental disclosures in conference calls, and changes in ESG ratings or EPA enforcement actions are present only following the divestment of pollutive assets—the findings are nonexistent following the divestment of nonpollutive assets. As such, the results that we document are not a general feature of asset sales, mitigating concerns about omitted correlated variables that capture divestiture motives unrelated to environmental pressures and pollution.

Do shareholders recognize the above benefits from offloading pollutive assets? To address this question, we estimate sellers' cumulative abnormal returns (CARs) around the announcement of pollutive asset divestitures. We find that the average CAR is significantly higher when the divested plant is more pollutive. Our estimates suggest that an interquartile increase in pollution is associated with a 3 to 4 percentage point increase in the average CAR. We also find that the average CAR is significantly higher for divestitures accompanied by positive environmental disclosures, suggesting that firms' strategic disclosures influence investors' reactions.

We also provide market-based evidence that the buyers of pollutive assets gain from these trades by paying discounted prices. Specifically, we find that the gains of the buyers relative to the sellers increase with pollution levels of the transferred assets. We estimate that in the divestitures of the most pollutive plants (top quartile of the sample), buyers earn roughly $400 million higher value gains relative to the sellers. This finding is consistent with buyers' comparative advantage in owning and operating pollutive assets insulated from environmental pressures.

The central contribution of this paper is to provide new evidence on the reallocation of industrial pollution through the divestment of pollutive assets. Our findings suggest that the real asset market allows companies to respond to environmental pressures by selling off their pollutive assets, thereby improving their environmental ratings and regulatory compliance, without losing access to these assets. Overall pollution levels, however, do not decline following such divestitures. As such, our findings are more consistent with greenwashing, suggesting that ESG rating agencies, environmental regulators, and prosocial investors fail to recognize that divestitures of pollutive assets are ineffective conduits to reduce industrial pollution.

Overall, our findings extend prior research on (i) industrial pollution, (ii) ESG, and (iii) divestitures. The literature on industrial pollution policies studies their determinants, which range from legal liabilities (e.g., Alberini and Austin (2002), Stafford (2002), Shapira and Zingales (2017), Akey and Appel (2021), Bellon (2021)) to third-party auditors (Duflo et al. (2013)), reputational penalties (Karpoff, Lott, and Wehrly (2005)), supply chains (Schiller (2018)), financial attributes (Chang et al. (2021), Xu and Kim (2022)), imports and exports (Holladay (2016), Li and Zhou (2017)), competition (Simon and Prince (2016)), ownership structures (Shive and Forster (2020)), and political ideologies (Bisetti et al. (2022)), among others. We add to this literature by showing that industrial firms react to environmental pressures by divesting their pollutive assets in a concerted effort to improve their ESG ratings and lower their regulatory compliance costs, but without any real effects on toxic emissions.

We also add to the growing literature on ESG (see Hong, Karolyi, and Scheinkman (2020) and Gillan, Koch, and Starks (2021) for a review). One strand of this literature studies the benefits of ESG, showing, for example, that better ESG performance helps firms mitigate downside risks (e.g., Lins, Servaes, and Tamayo (2017), Albuquerque et al. (2020), Ding et al. (2021), Hoepner et al. (2024)). A second strand of this literature studies ESG monitoring and its effect on corporate ESG performance (e.g., Dimson, Karakaş, and Li (2015), Akey and Appel (2019), Dyck et al. (2019), Naaraayanan, Sachdeva, and Sharma (2021), Barko, Cremers, and Renneboog (2022), Heath et al. (2023)). A third strand of this literature focuses on impact investing, emphasizing the role of ESG performance in capital market allocation (e.g., Starks, Venkat, and Zhu (2017), Hartzmark and Sussman (2019), Krueger, Sautner, and Starks (2020), Zaccone and Pedrini (2020), Barber, Morse, and Yasuda (2021), Bolton and Kacperczyk (2021), Hong, Wang, and Yang (2021), Pástor, Stambaugh, and Taylor (2021)). We contribute to this literature by showing that firms respond to ESG-related pressures, and improve their ESG ratings, through cosmetic asset divestment along their value chains. As such, our evidence complements several recent studies revealing the drawbacks of outstanding ESG rating schemes. These studies show that ratings from different agencies do not agree with one another, and do not reflect firms' actual ESG policies (Chatterji et al. (2016), Gibson, Krueger, and Schmidt (2019), Dimson, Marsh, and Staunton (2020), Berg, Koelbel, and Rigobon (2022)).

Lastly, our paper contributes to the literature on divestitures. Several papers study the motives behind divestitures (e.g., operating, agency, leverage, liability, or tax considerations) and the resulting efficiency gains and resource allocation (e.g., Mulherin and Boone (2000), Maksimovic and Phillips (2001), Schlingemann, Stulz, and Walkling (2002), Bates (2005)). Other studies have focused on divestitures as a reorganization mechanism that corrects past mistakes such as bad acquisitions (e.g., Kaplan and Weisbach (1992), Capron, Mitchell, and Swaminathan (2001), Maksimovic, Phillips, and Prabhala (2011), Arcot, Gantchev, and Sevilir (2020), Mavis et al. (2020)). We add to this literature by documenting the role of the divestiture market in cosmetically reorganizing the firm in response to environmental pressures. Our empirical design differentiates between environmental motives and other considerations by comparing the divestment of pollutive and nonpollutive assets.

The remainder of the paper is organized as follows. Section I discusses the data and variables. Section II investigates the motivation behind the divestment of pollutive plants. Section III traces pollution and pollution abatement activities around divestitures. In Section IV, we analyze the strategic mechanisms through which firms benefit from the divestment of pollutive assets. Section V provides robustness checks. Finally, Section VI concludes.

I. Data and Variables

A. Environmental Pressures

We examine the environmental pressures that firms face from investors, ESG rating agencies, policymakers, and the public at large.

We first consider the public listing status of a firm. Publicly listed firms are subject to more scrutiny and disclosure requirements regarding their environmental impact compared to private firms. For example, in 2010, the Securities and Exchange Commission (SEC) provided guidance regarding public firms' disclosure related to climate change. In contrast, there are no disclosure guidelines/requirements for private firms. We define *Public* as an indicator equal to one if a firm is publicly traded, and zero otherwise. An important caveat is that, due to data limitations, we cannot match the full set of TRI plants to private companies. We can therefore use firms' public listing status in only a subset of the analyses.

Second, we consider whether a firm is covered by an ESG rating agency. Prior studies show that ESG ratings provide information about firms' sustainability practices, and generate value-relevant responses from investors (see Hartzmark and Sussman (2019), Krueger, Sautner, and Starks (2020), Zaccone and Pedrini (2020), among others). We obtain ESG ratings of U.S. public firms from the KLD database. We define the variable *Rated* as an indicator equal to one if a firm is covered by the KLD database in a given year, and zero otherwise.

We also track how a firm's ESG rating changes over time. KLD evaluates each firm along the following six categories: Community, Diversity, Employee relations, Environment, Human rights, and Product. For each category, it counts the number of strengths and weaknesses. Following Cronqvist and Yu (2017), we create an aggregate *CSR Score* measure by netting the total number of strengths and weaknesses across all categories. In other words, each strength adds one point while each weakness subtracts one point from the aggregate score. We also separately compute the environmental category's net strength and create the variable *Environmental Score* to track firms' environmental ratings. In robustness tests, we augment KLD ratings with ESG ratings from the Refinitive and MSCI databases.

Next, we consider the demand for environmental performance arising from firms' investor base. Prior studies highlight the importance of long-term investors such as pension funds in exerting "green preferences" on firms (Starks, Venkat, and Zhu (2017)). We define *Pension Holdings* as an indicator equal to one if the percentage of a company's shares owned by pension funds is above average, and zero otherwise, using institutional investor holdings from 13-F filings.

We also examine pressures stemming from local residents, as captured by local political ideologies. Prior research shows that political ideologies affect industrial firms' pollution activities (Fredriksson et al. (2005), Beland and Boucher (2015), Bisetti et al. (2022)), and that left-wing ideologies are generally associated with stronger pressure to reduce pollution. We conjecture that firms headquartered in Republican-leaning counties face weaker environmental pressures compared to those headquartered in Democratic-leaning counties. We use county-level vote share data compiled by MIT Election Data and Science Lab to determine whether a firm's headquarters is located in a Democratic-learning county. We then define *Democratic HQ* as an indicator equal to one if the county of a firm's headquarters has a greater share of votes in support of the Democratic candidate than the Republican candidate during the most recent presidential election.

Lastly, we consider the occurrence of negative environmental incidents using data from the Reprisk database. Environmental events from Reprisk are commonly used in recent research to capture the extent of environmental pressures or shocks to firms' environmental reputation (Gantchev, Giannetti, and Li (2019), Akey et al. (2021), Derrien et al. (2021)). RepRisk provides data on business conduct risk by combining machine learning tools and human intelligence starting in 2007. It collects and screens data from over 100,000 public sources and various stakeholders to identify whether a firm has had an ESG risk incident. RepRisk classifies such events into 28 categories such as pollution, waste management, human rights, occupational health, child labor, and discrimination. It also assigns each event into one of three broad categories: "Environmental," "Social," or "Governance." Among these categories, we are interested in environmental events, and define *Env. Event* as an indicator for whether a firm incurs an environmental event in a given year. For comparison, we also construct separate indicators for the occurrence of negative social or governance events (i.e., *Social Event* and *Governance Event*, respectively).

We construct a composite index, *Pressure Index*, that encompasses the four dimensions of environmental pressures applicable to public firms (*Rated*, *Pension Holdings*, *Democratic HQ*, and *Env. Event*). This index equals the average across all indicators that are available for a firm-year. Given that *Env. Event* is available only starting 2007, *Pressure Index* equals the average value of the three other metrics prior to 2007.

B. Pollution and Abatement

We obtain chemical-level toxic emissions for each plant from the EPA's TRI program over the period 2000 to 2020. Toxic chemicals are defined as those that cause one or more of the following: (i) cancer or other chronic human health effects, (ii) significant adverse acute human health effects, and (iii) significant adverse environmental effects.[4] The resulting list contains over 600 individual chemicals and chemical categories as of 2020, the last year of our sample period. Reporting is mandatory if an establishment has at least 10 employees, operates in a specific list of North American Industry Classification System (NAICS) codes, and emits one or more specified chemicals above a certain quantity threshold.

[4] For more information regarding the TRI program, see https://www.epa.gov/toxics-release-inventory-tri-program.

The TRI program provides detailed information on the level of each type of chemical released by a plant during a given year. It also provides plants' addresses and NAICS industry classification codes. We construct measures of toxic release at the plant-chemical level. This granular measurement avoids lumping together chemicals with different toxicity levels. It also helps impose stringent fixed effects at the chemical level. We construct the variable *Total Pollution* as the total toxic emission of each chemical for each plant in a given year. We also calculate a chemical's *Pollution Intensity* by dividing the total toxic emission of each chemical by its production ratio.[5]

In addition to toxic release, the EPA records pollution abatement activities. Internet Appendix Section I.A provides an overview of the abatement process.[6] We capture abatement in two ways. The first measure considers source reduction activities, which reduce or eliminate pollutants by modifying production processes and promoting the use of nontoxic or less toxic substances. To construct this measure, we count the total number of source reduction activities (*#Source Reduction*) for each plant-chemical-year based on the EPA's Pollution Prevention (P2) database. The second measure considers postproduction waste management activities (Li, Xu, and Zhu (2021)), tracing the percentage of total generated toxic waste reduced through recycling (*%Recycling*), energy recovery (*%Recovery*), and treatment (*%Treatment*).

We use a string-matching algorithm to link TRI establishments operated by public parent companies to the Compustat database to extract accounting information. The TRI database records the ultimate parent company name for each establishment every year. The ultimate parent company name can change over time following ownership changes or parent company name changes. To map TRI plants to their owners at every point in time, we obtain historical names of publicly listed companies from the Center for Research in Security Prices (CRSP) and match those names to the names of plant owners.[7]

C. Divestitures

We collect data on divestitures completed between 2000 and 2020 from the SDC mergers and acquisitions (M&A) database. For each deal, SDC provides

[5] For chemicals directly used in the production process, the production ratio captures the ratio of $output_t$ relative to $output_{t-1}$. For chemicals used to support production, this measure indicates the change in usage. If a chemical is used in several activities, a weighted average is reported. We construct a proxy for total production by normalizing the production ratio to one in the first year when a chemical is reported and multiplying forward each year by the reported production ratio for each plant-chemical. Ratios not between $[0, 3]$ are excluded due to apparent errors in the data, and missing observations are replaced with the value of one (Akey and Appel (2021)).

[6] The Internet Appendix may be found in the online version of this article.

[7] We remove all punctuation marks, delete corporate designators such as "corporation," "company," "inc," and "llc," standardize the most common words to a consistent format, and generate a similarity score between the deduplicated TRI parent and Compustat/CRSP company names using a string-matching algorithm. For instance, "United States" is simplified to "US," "Manufacturing" to "MFG," and "Internationals" to "INTL." We then manually review the matches to verify they are correct.

the effective date, the names of the buyer and the seller, and the percentage of ownership transferred, among other details. In cases in which the buyer or the seller is recorded at the subsidiary firm level, SDC also reports the ultimate parent company's name and CUSIP identifier. We only retain deals classified as a "divestiture" or a "spin-off" by SDC. We also require the deal to represent a significant transfer of ownership, that is, the buyer must own more than 50% after the deal. We further remove deals involving financial firms, either as buyers or sellers. To do so, we read through the synopsis of each individual deal and exclude deals for which the buyer or the seller is a financial company, including private equity firms, banks, investment firms, and funds. We also exclude deals in which the buyer or the seller is majority-owned by a financial firm.

We identify divested TRI plants by matching plants' parent names to acquirer and target names in SDC. Internet Appendix Section I.B describes the matching procedure in detail. Our final sample contains 888 deals involving 1,105 unique plants. Internet Appendix Table IA.I describes the industry composition of divested plants. The vast majority of divested plants are located in a few manufacturing sectors known to be heavy polluters, such as chemical manufacturing and fabricated metal product manufacturing, among others.

In addition, we collect data on divestitures of nonpollutive assets over the period 2000 to 2020. Nonpollutive assets are those not linked to the TRI database. We follow the same approach and remove all transactions between financial buyers and sellers. Using these data, we compare the effects of divesting pollutive plants and nonpollutive assets.

D. Enforcement Actions and Compliance Costs

The EPA also records government agency investigations and enforcement activities in its comprehensive Enforcement and Compliance History Online (ECHO) database. ECHO provides key information regarding enforcement actions for investigations initiated by the EPA or state and local environmental agencies. It also reports the costs (in dollars) of federal and local penalties, compliance, recovery, and supplemental environmental projects. We aggregate these items to evaluate the total regulatory compliance costs for each case. Using these estimates, we analyze the changes in enforcement actions and compliance costs following the divestitures of pollutive plants.

E. Conference Call Transcripts

We obtain conference call transcripts from Thomson Reuters' SE database starting in 2001. Our analysis focuses on the management presentation portion of conference calls, rather than the Q&A portion, because we seek to capture voluntary disclosure by management and not information extracted by analysts. We then use a machine learning algorithm to identify the language related to environmental disclosure and the associated tone. This procedure includes several steps. First, we follow Bochkay, Choi, and Hales (2022) and start with a dictionary provided by the Sustainability Accounting Standards Board (SASB) that includes common words used by corporations when disclosing ESG performance. We refine the dictionary to focus on a set of words specifically related to environmental but not social or governance issues. We then parse conference call transcripts for all instances in which environmental keywords appear. For each appearance, we gather a text group containing $[-1, +1]$ sentences surrounding the key word.

After identifying these sentence groups, we manually read through 1,000 randomly selected examples to classify whether the text indicates a positive or negative environmental impact. For example, we consider the following statements to be positive: "We continued our strong safety and environmental performance," and "The application of our rigorous environmental management systems and practices resulted in improvements in spill performance and in emission reductions." Next, we deploy the BERT natural language processing model (Devlin et al. (2019)) using the manually classified sample described above as the training set.[8] We use the resulting classifications to define two indicator variables: *Positive Env. Disclosure* is an indicator that equals one if the firm discloses an improvement in its environmental performance, and *Negative Env. Disclosure* is an indicator defined analogously with respect to a decline in environmental performance.

F. Supply Chain and Joint Venture Relationships

We examine whether buyers and sellers of pollutive plants have preexisting business ties or develop new business ties following divestitures. We measure business ties based on supply chain relations and joint venture partnerships. We obtain data on supply chain relations from the Factset and Compustat Segment databases, and information on joint ventures from SDC (see also Allen and Phillips (2000) and Schilling (2009)). As discussed in Section IV.B, we compile a matched sample of acquirer-target pairs and define a pair to have business ties if the acquirer and the target share either a supply chain or a joint venture connection.

G. Announcement CARs

We compute CARs in the three-day window centered on the divestiture announcement date (i.e., $CAR[-1, +1]$). We define abnormal returns relative to the market model benchmark (*CAR, Market*) and relative to the

[8] Developed by Google, BERT has been pretrained on a huge amount of data. Compared to previous natural language processing models such as word2vec and GloVe, which treat a given word the same irrespective of the context in a sentence, BERT takes into account the context for each occurrence, allowing massive advancements in its ability to understand human language. In our validation sample, the accuracy rate for identifying a positive or a negative tone was approximately 80%.

Fama-French three-factor model benchmark (*CAR, FF*). Stock return data come from CRSP.

We also calculate the division of surplus between the buyer and the seller. This measure aims to evaluate the buyer's gain relative to the seller's. We compute this measure as the difference between the change in the buyer's market value of equity and the change in the seller's market value of equity in the three-day window around the deal's announcement. The change in market value is defined as the product of $CAR[-1, +1]$ around the deal's announcement date and the firm's total market capitalization, measured in the most recent calendar year-end prior to the announcement date.

H. Other Firm-Level Information

We compile measures of firms' organizational and ownership structures as a proxy for the information asymmetry between managers and outside stakeholders, including the number of business segments and operating industries (from Compustat Segment Files), the total number of subsidiaries and organizational layers based on firms' ownership structures (from Orbis), and the presence of blockholders (from 13-F data).

Lastly, we collect financial data from Compustat to create several control variables for public firms, including cash holdings, leverage, Tobin's Q, and asset tangibility. Detailed definitions of our variables are provided in the Appendix.

I. Summary Statistics

Table I presents summary statistics for all of the variables used in the paper. Panel A provides summary statistics for the firm-year sample. Among the set of publicly listed firms in our sample, less than 2% of firm-year observations correspond to the divestiture of a pollutive plant. Around 55% of firms are covered by ESG ratings, 66% are headquartered in a Democratic-leaning county, 46% have at least one pension fund as an institutional investor, and 19% have incurred a negative environmental risk incident. The average CSR score of the firms included in the KLD database is 0.28, and the average environmental score is 0.165. The likelihood of an EPA regulatory enforcement action is 7%, and the average annual enforcement costs across all sample firms is roughly $3 million. In conference call announcements, the likelihood of positive environmental disclosure is 12%.

Panel B provides statistics for the plant-chemical-year sample. The sample includes 1,056,361 plant-chemical-year observations. The average toxic release is roughly 16,893 pounds, and the median is 483 pounds, suggesting that the distribution is heavily skewed. For pollution abatement, the average number of source reduction activities is roughly two, and the percentage of total generated toxic chemicals reduced through recycling, recovery, and treatment is 24.4%, 8.4%, and 26%, respectively.

Table I

Summary Statistics

This table presents summary statistics for the variables used in the analyses. Panel A presents summary statistics for the annual panel of public firms. Panel B presents summary statistics for the annual panel of plants in the Toxic Release Inventory Program of the U.S. Environmental Protection Agency. The sample period is 2000 to 2020. All variable definitions appear in the Appendix.

Panel A: Firm-Level Sample

	N	Mean	Median	*SD*	P25	P75
Sell (Pollutive) (%)	19,459	1.90	0.00	13.64	0.00	0.00
Rated	19,459	0.55	1.00	0.50	0.00	1.00
Democratic HQ	17,936	0.66	1.00	0.47	0.00	1.00
Pension Holdings	19,459	0.46	0.00	0.50	0.00	1.00
Env. Event	11,680	0.19	0.00	0.39	0.00	0.00
Pressure Index	19,459	0.49	0.50	0.30	0.25	0.75
#Segments	15,303	3.48	3.00	2.18	1.00	5.00
#Industries	12,954	1.71	1.00	1.04	1.00	2.00
#Subsidiaries	10,646	68.40	27.00	149.70	9.00	72.00
#Layers	10,443	2.34	2.00	1.31	1.00	3.00
%Blockholders	19,459	0.20	0.19	0.16	0.06	0.30
CSR Score (KLD)	30,488	0.28	0.00	2.23	−1.00	1.00
Environment Score (KLD)	30,488	0.16	0.00	0.80	0.00	0.00
Enforcement Action	18,673	0.07	0.00	0.26	0.00	0.00
Enforcement Cost ($Mil)	18,673	2.93	0.00	94.56	0.00	0.00
Positive Env. Disclosure	38,061	0.12	0	0.32	0	0
Negative Env. Disclosure	38,061	0.06	0	0.24	0	0
Q	19,184	1.77	1.43	1.51	1.13	1.97
Leverage	19,402	0.26	0.25	0.19	0.13	0.37
Cash Holding	19,438	0.12	0.07	0.14	0.02	0.16
Tangibility	19,437	0.30	0.24	0.20	0.14	0.41

Panel B: Plant-Chemical-Level Sample

	N	Mean	Median	*SD*	P25	P75
Total Pollution	1,056,361	16,893	483.00	60,761	14.45	5,300
Pollution Intensity	1,056,361	25,227	454.30	102,924	15.57	5,702
#Source Reduction	1,242,312	1.97	0.00	4.76	0.00	1.00
%Recycling	1,056,361	24.40	0.00	40.64	0.00	46.38
%Recovery	1,056,361	8.37	0.00	24.08	0.00	0.00
%Treatment	1,056,361	26.06	0.00	39.51	0.00	58.82

II. Sellers and Buyers of Pollutive Assets

In this section, we investigate the motives behind the divestment of pollutive plants, and we characterize the buyers and sellers of pollutive plants. The empirical analyses focus on the role of environmental pressures in the divestiture market.

A. Firms' Responses to Environmental Pressures

We begin our empirical analyses by investigating how firms respond to environmental pressures from investors, regulators, and the public, and the importance of divestment compared to other possible responses. Specifically, we use a multilogit regression framework in which firms can respond to environmental pressures in several ways, including divesting pollutive plants, closing pollutive plants, increasing abatement efforts, or doing nothing. In the multilogit model, we estimate the likelihood of four mutually exclusive options: (i) divestment of pollutive plants, (ii) closure of pollutive plants without divestment or enhanced pollution abatement, (iii) enhanced pollution abatement without closure or divestment, and (iv) both plant closures and enhanced pollution abatement without divestment. The omitted benchmark is no action. The resulting estimates allow us to gauge the relative importance of divestment relative to other possible responses. As discussed in Section I.A, we consider the following measures of environmental pressures: *Rated*, *Pension Holdings*, *Democratic HQ*, *Env. Event*, and *Pressure Index*.

Table II reports the results from this analysis. The table is organized horizontally, such that rows correspond to separate multilogit models (each focuses on a different measure of environmental pressures), and columns correspond to possible responses (with "no response" being the omitted category). For ease of interpretation, we provide the marginal effects of each measure of environmental pressures. As such, the estimates capture the incremental effects of environmental pressures holding all other parameters at their sample averages. To illustrate the economic magnitudes of the estimates, we also report "Rel Magnitude," which equals the product of a unit (one-standard-deviation) increase in the environmental pressure indicators (composite pressure index) and the marginal effect estimate, scaled by the sample average of each outcome variable.

The main findings are twofold. First, the divestment of pollutive assets is a significant response to each type of environmental pressure. Across all measures of environmental pressures, the coefficient estimates are always highly statistically significant. Second, the economic importance of divestitures as a response to environmental pressures is higher than that of plant closures or abatement efforts, even if we weigh closures and abatement together against divestment alone (column (4)): the relative magnitude of divestitures (column (1)) exceeds that of plant closures (column (2)), abatement (column (3)), or closures and abatement combined (column (4)) across all measures of environmental pressures.

The economic magnitudes are large. A one-standard-deviation increase in environmental pressures resulting from coverage by ESG rating agencies or pension fund holdings implies an 86% increase in the likelihood of choosing to divest pollutive plants (relative to the sample average) compared to other firms. Analogously, being headquartered in Democratic counties leads to a 25% increase in the likelihood of divesting pollutive plants compared to being headquartered in Republican counties. Negative environmental risk incidents

Table II

Firm Responses to Environmental Pressures

This table presents multilogit regression estimates examining how firms respond to environmental pressures. The possible responses include divestment of pollutive plants, closure of pollutive plants without divestment or enhanced pollution abatement, enhanced pollution abatement without closure or divestment, and both plant closures and enhanced pollution abatement without divestment. These responses are mutually exclusive. The omitted benchmark is no action. Enhanced pollution abatement is defined as the top quartile of changes in pollution management (the fraction of produced toxic chemicals being treated, recycled, or recovered) from the year before to the year after the occurrence of environmental pressures. We consider the following measures of environmental pressures: *Rated*—an indicator variable that equals one if the firm has an ESG rating and zero otherwise, *Pension Holdings*—an indicator variable that equals one if the percentage of a firm's shares held by pension funds is above the sample average, *Democratic County*—an indicator variable that equals one if the firm is headquartered in a county where the Democratic party won the majority vote in the most recent presidential election, *Env. Event*—an indicator variable that equals one if the firm experiences an environmental risk incident, and *Pressure Index*—a composite index that averages the preceding indicator variables. We present marginal estimates for each environmental pressure measure and calculate *Rel. Magnitude* as the marginal estimate relative to the sample average of each response. For *Pressure Index*, *Rel. Magnitude* is calculated as a one-standard-deviation increase in *Pressure Index* × the marginal estimates, relative to the sample average of each action. *Firm Char* includes *Q*, *Leverage*, *Cash Holdings*, and *Tangibility*. All variable definitions appear in the Appendix. Robust standard errors are included. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dep. Var.:	*Divestitures* (1)	*Closure Only* (2)	*Abatement Only* (3)	*Closure& Abatement* (4)		
Rated	0.017***	0.032***	0.022***	0.012***	Observations	12,764
	(0.002)	(0.006)	(0.006)	(0.003)	Pseudo-R^2	0.0171
Rel Magnitude	85.86%	22.41%	14.56%	30.15%		
Pension Holdings	0.017***	0.054***	0.015**	0.024***	Observations	12,764
	(0.002)	(0.006)	(0.006)	(0.003)	Pseudo-R^2	0.0208
Rel Magnitude	85.86%	37.82%	9.93%	60.30%		
Democratic HQ	0.005**	0.021***	0.009	0.004	Observations	12,127
	(0.003)	(0.007)	(0.007)	(0.003)	Pseudo-R^2	0.0127
Rel Magnitude	25.25%	14.71%	5.96%	10.05%		
Env. Event	0.028***	0.067***	0.007	0.022***	Observations	7,606
	(0.005)	(0.011)	(0.011)	(0.006)	Pseudo-R^2	0.0221
Rel Magnitude	141.41%	46.92%	4.63%	55.28%		
Pressure Index	0.037***	0.114***	0.047***	0.043***	Observations	12,764
	(0.003)	(0.011)	(0.011)	(0.005)	Pseudo-R^2	0.0262
Rel Magnitude	54.19%	23.15%	9.02%	31.33%		
Firm Char	Yes	Yes	Yes	Yes		

imply a 141% increase in the likelihood of divestment compared to other firms. And, a one-standard-deviation increase in *Pressure Index* increases the likelihood of divestitures by 54% (relative to the sample average).

Together, these findings suggest that the divestment of pollutive plants is a crucial response to environmental pressures. The remainder of the analyses investigate the market for divestitures of pollutive plants.

B. Sellers of Pollutive Assets

Having shown that divesting pollution is an important response to environmental pressures compared to other possible responses, such as plant closures and pollution abatement, we turn our attention to the divestiture market. We begin the analyses by estimating regressions that explain the propensity to divest pollutive plants. These analyses provide cross-sectional comparisons between firms facing higher versus lower levels of environmental pressures. The sample includes all public firms that own at least one TRI plant during the sample period, where we exclude firms that do not have pollutive plants to sell. Specifically, we estimate the regression

$$Divest_{i,t} = \beta Pressure_{i,t} + \phi_{j,t} + \epsilon_{i,t}, \tag{1}$$

where i denotes a publicly listed firm, j denotes the industry that the firm belongs to, and t denotes the year. The dependent variable is the indicator variable $Divest_{i,t}$, which equals one if firm i sells at least one plant in year t. We multiply this indicator by 100 such that the coefficients correspond to the percentage likelihood of divestiture. The parameter $\phi_{j,t}$ indicates industry-year fixed effects. The variable of interest is $Pressure_{i,t}$, which takes one of the following variables: (i) dummy for an ESG rating (*Rated*), (ii) dummy for above-average pension fund holdings (*Pension Holdings*), (iii) dummy for being headquartered in a Democratic county (*Democratic HQ*), (iv) dummy for having incurred a Reprisk environmental risk incident (*Env. Event*), and (v) a composite pressure index that averages the aforementioned indicators (*Pressure Index*).

All of the regression specifications control for a wide range of firm characteristics and include industry-year fixed effects. As such, the coefficients on environmental pressures capture a firm's divestment in response to environmental pressures relative to its industry peers at the same point in time. Standard errors are clustered by firm.

The results are presented in Panel A of Table III. We find a positive and statistically significant coefficient for all measures of environmental pressures, suggesting that environmental pressures are associated with a higher propensity to divest pollutive plants.

The estimates are highly statistically significant and economically meaningful. In particular, they suggest that firms covered by ESG rating agencies are 1.2 percentage points more likely to divest a plant compared to uncovered firms (column (1)). Firms with high pension fund holdings are 0.7 percentage points more likely to divest than other firms (column (2)), and the magnitude is similar for firms headquartered in Democratic-leaning counties (column (3)). The occurrence of environmental risk incidents increases the likelihood of

Table III

Environmental Pressures and the Divestment of Pollutive Plants

This table provides estimates from regressions that explore the link between environmental pressures and a firm's decision to divest pollutive plants. The dependent variable is *Sell (Pollutive)*, an indicator that equals 100 if the firm divests a pollutive plant in a given year. We consider the following measures of environmental pressures: *Rated*—an indicator variable that equals one if the firm has an ESG rating and zero otherwise, *Pension Holdings*—an indicator that equals one if the percentage of a firm's shares held by pension funds is above the sample average, *Env. Event*—an indicator for whether the firm experiences an environmental risk incident according to the Reprisk database, *Democratic County*—an indicator for whether the firm is headquartered in a county where the Democratic party won the majority vote in the most recent presidential election, and *Pressure Index*—a composite index that averages the preceding indicator variables. Panel B investigates the role of pollution levels and pollution intensities in the divestment of pollutive plants in response to environmental pressures. The unit of observation is a firm-year, and the sample includes all public firms owning plants in the Toxic Release Inventory Program of the U.S. Environmental Protection Agency. *Firm Char* include: *Q*, *Leverage*, *Cash Holdings*, and *Tangibility*. All variable definitions appear in the Appendix. Standard errors are clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Environmental Pressures and the Propensity to Divest

Pressure Measure Dep. Var.: *Sell (Pollutive)(%)*	*Rated* (1)	*Pension Holdings* (2)	*Democratic HQ* (3)	*Env. Event* (4)	*Pressure Index* (5)
Environmental Pressure	1.214***	0.720***	0.590**	1.897***	2.110***
	(0.303)	(0.269)	(0.278)	(0.506)	(0.593)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
Firm Char	Yes	Yes	Yes	Yes	Yes
Observations	18,826	18,826	17,369	11,295	18,826
R^2	0.059	0.059	0.056	0.072	0.060

Panel B: Environmental Pressures, Pollution, and the Propensity to Divest

Pollution Measure: Dep. Var.: *Sell (Pollutive)(%)*	*Quantity* (1)	*Quantity (Qtile)* (2)	*Intensity* (3)	*Intensity (Qtile)* (4)
Pressure Index × *Pollution*	0.693***	2.568***	0.514**	1.264**
	(0.157)	(0.615)	(0.234)	(0.604)
Pollution	−0.123*	−0.379	−0.116	−0.302
	(0.074)	(0.306)	(0.119)	(0.284)
Pressure Index	−2.384**	−2.341*	3.142***	1.852
	(1.129)	(1.198)	(0.902)	(1.415)
Industry-Year FE	Yes	Yes	Yes	Yes
Firm Char	Yes	Yes	Yes	Yes
Observations	12,084	12,084	11,742	11,742
R^2	0.078	0.079	0.074	0.075

divestiture by 2 percentage points (column (4)). Finally, based on column (5), a one-standard-deviation increase in the composite environmental pressure index is associated with a 0.6 percentage point increase in the likelihood of divestiture (= 0.3 × 2.109). These magnitudes are economically large (32%) compared to the sample average likelihood of divestment of 1.9 percentage points.

A possible concern is that environmental pressures are correlated with other firm-level attributes, such as a firm's operational inefficiencies, which can lead to divestment through channels unrelated to the environment and pollution levels. We test for this possibility by investigating the role of pollution levels in divestment amid environmental pressures. Panel B of Table III presents regression estimates explaining the likelihood of divesting pollutive plants where the key independent variable is the interaction term *Pressure Index* $\times$ *Pollution*. We measure pollution using both total quantity and pollution intensity (quantity scaled by employment) of a firm, and consider both continuous measures of pollution and quartile rankings that address potential concerns related to skewness and facilitate interpretation of the coefficient estimates.

The results in Panel B indicate that pollution levels significantly increase the sensitivity of divestitures to environmental pressures. Heavy polluters are significantly more likely to divest pollutive plants in response to environmental pressures compared to light polluters. The estimates suggest that an interquartile change in a plant's total toxic release (from the least pollutive to the most pollutive quartile) increases the sensitivity of divestitures to environmental pressures by 7.7 ($= 2.569 \times 3$), which corresponds to a 2.3 percentage point higher likelihood of divestment in response to a one-standard-deviation increase (0.3) in the environmental pressure index. A similar interquartile increase in a plant's pollution intensity leads to a 1.3 percentage point increase in the likelihood of divestiture in response to a similar increase in environmental pressures.

The results thus far suggest that environmental pressures are associated with a higher propensity to divest pollutive plants, particularly when pollution levels are high. We note that many sources of environmental pressures are unlikely to be randomly assigned or exogenous. To mitigate this concern, we next conduct detailed analyses that focus on the occurrence of environmental risk incidents, exploiting within-firm, time-series variation in environmental pressures.

We argue that while firms' environmental practices contribute to the occurrence of Reprisk environmental incidents, such occurrence is unlikely to be fully expected by the firm, at least at an annual frequency. Our identifying assumption is that firms cannot fully control the timing of Reprisk environmental incidents, and hence firms do not change their operations dramatically in a narrow window preceding Reprisk incidents. As such, Reprisk events can serve as quasi-shocks to environmental pressures.[9]

In Table IV, we provide estimates from regressions explaining the likelihood of divesting pollutive plants (i.e., *Sell (Pollutive)*) in which the key independent variable is the occurrence of environmental risk incidents. These regressions include firm fixed effects to track the variation in the same firm's propensity to divest pollutive plants. Columns (1) and (2) of Table IV show that the

[9] Reprisk incidents can be viewed as similar to other events that raise attention to or awareness of firm behavior, such as the detection of fraud, scandals, or exposure to natural disasters.

Table IV

Environmental Risk Incidents and the Divestment of Pollutive Plants

This table provides estimates from regressions that examine the link between environmental risk incidents from the Reprisk database and firms' decision to divest pollutive plants. The dependent variable is *Sell (Pollutive)*, an indicator variable that equals one if the firm divests a pollutive plant in a given year, multiplied by 100. *Environmental Event* is an indicator variable that equals one if the firm experiences an environmental risk incident according to the Reprisk database. *Social Event* and *Governance Event* are defined analogously with respect to social and governance risk incidents from the Reprisk database, respectively. The unit of observation is a firm-year, and the sample includes all public firms owning plants in the Toxic Release Inventory Program of the U.S. Environmental Protection Agency. *Firm Char* include: *Q*, *Leverage*, *Cash Holdings*, and *Tangibility*. All variable definitions appear in the Appendix. Standard errors are clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dep. Var.: *Sell (Pollutive)(%)*	(1)	(2)	(3)	(4)
Environmental Event	1.068**	1.077**	1.133**	1.074*
	(0.535)	(0.542)	(0.544)	(0.615)
Social Event			−0.219	−0.490
			(0.430)	(0.449)
Governance Event			0.491	0.416
			(0.532)	(0.599)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	
Firm Char		Yes	Yes	Yes
Industry-Year FE				Yes
Observations	11,629	11,436	11,436	11,243
R^2	0.138	0.141	0.141	0.189

occurrence of a negative environmental risk incident increases the likelihood of a firm divesting its pollutive plants by 1.1 percentage points.

It is possible that any ESG risk incident, including those unrelated to the environment, hurt a company's overall reputation and performance, and thus lead to divestitures that are not necessarily related to environmental pressures or pollution. We evaluate this possibility by adding the occurrence of social and governance Reprisk incidents to the regression. These controls serve as a benchmark that captures the generic effects of reputation-damaging events. Columns (3) and (4) report the results. We do not find that social and governance events play a role in the divestment of pollutive assets. Environmental events continue to have a positive, significant effect on divestitures with virtually the same economic magnitude.

We next investigate the timing of divestitures surrounding the occurrence of environmental risk incidents and the possibility of preevent trends. To do so, we estimate a dynamic model that tracks how a negative environmental incident influences the likelihood of divestment each year before and after the incident. We regress the *Sell (Pollutive)* indicator on the interaction between *Env. Event* and individual dummy variables indicating years around a Reprisk environmental risk incident. In this specification, we control for both firm and year fixed effects.

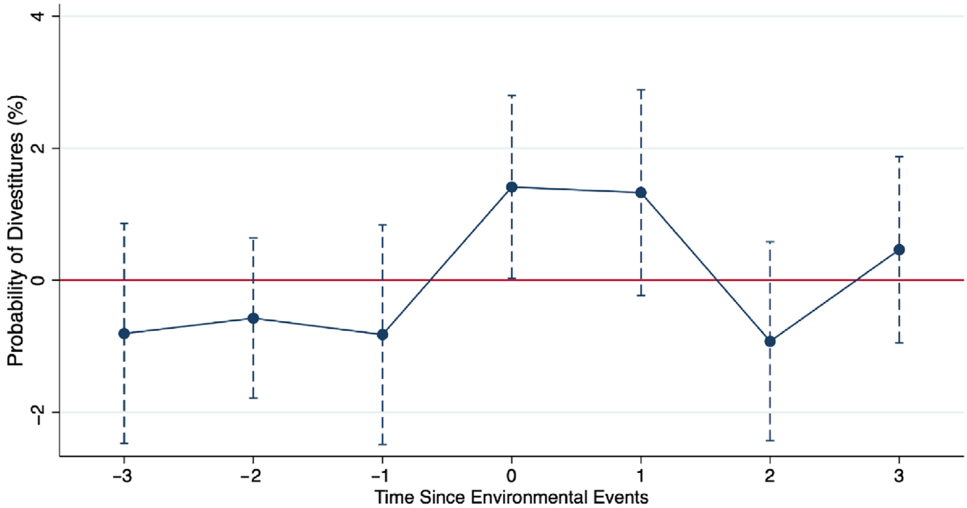

Figure 2. The likelihood of divestitures around environmental risk incidents. This figure presents estimates from a dynamic regression model that traces the likelihood of divesting pollutive plants in the three years before and after an environmental risk incident. The model regresses the *Sell (Pollutive)* indicator on a series of interaction terms between *Env. Event* and dummy variables indicating years around environmental risk incidents. *Sell (Pollutive)* equals one if the firm divests a pollutive plant in a given year. Pollutive plants are plants in the Toxic Release Inventory Program of the U.S. Environmental Protection Agency. *Env. Event* is an indicator that equals one if Reprisk reports an environmental risk incident for the firm in a given year. The regression includes firm and year fixed effects. The dashed vertical lines represent 90% confidence intervals based on standard errors clustered at the firm level. All variable definitions appear in the Appendix. (Color figure can be viewed at wileyonlinelibrary.com)

Figure 2 presents the results. We find no change in firms' divestment behavior prior to the occurrence of a Reprisk incident. In contrast, immediately following such an incident, the likelihood of divestment increases sharply by roughly 1.5 percentage points, an increase almost as large as the sample-average divestiture probability of 1.9 percentage points. Interestingly, the likelihood of divestment reverts to the preincident level around two years after its occurrence, suggesting that the effects are immediate. Overall, these findings indicate that the effect of environmental risk incidents on the divestment of pollutive plants is immediate, substantial, and not preceded by changes in divestment behavior, consistent with our identifying assumption.

C. Buyers of Pollutive Assets

The previous analyses focus on the sellers of pollutive assets, and show that firms respond to environmental pressures by divesting pollutive plants. Two natural questions that arise are who are the buyers of these assets, and whether they have a comparative advantage in operating and owning pollutive assets. To address these questions, we compare the characteristics of buyers

Table V

Environmental Pressures of Sellers and Buyers of Pollutive Plants

This table provides estimates from regressions that compare the environmental pressures that the buyers and the sellers of pollutive plants face. We consider the following measures of environmental pressures: *Public Firm*—an indicator variable that equals one if the firm is publicly listed, *Rated*—an indicator variable that equals one if the firm has an ESG rating and zero otherwise, *Pension Holdings*—an indicator variable that equals one if the percentage of a firm's shares held by pension funds is above the sample average, *Env. Event*—an indicator variable that equals one if the firm experiences an environmental risk incident according to the Reprisk database, *Democratic County*—an indicator variable that equals one if the firm is headquartered in a county where the Democratic party won the majority vote in the most recent presidential election, and *Pressure Index*—a composite index that averages the preceding indicator variables. The unit of observation is a deal-firm pair, and each deal corresponds to two observations: deal-seller and deal-buyer. All variable definitions appear in the Appendix. Robust standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dep. Var.:	*Public*	*Rated*	*Pension Holdings*	*Democratic HQ*	*Env. Event*	*Pressure Index*
	(1)	(2)	(3)	(4)	(5)	(6)
Buyer	−0.055**	−0.047**	−0.030	−0.054**	−0.052**	−0.059***
	(0.024)	(0.022)	(0.021)	(0.028)	(0.023)	(0.016)
Observations	1,776	1,776	1,776	1,155	968	1,776
R^2	0.003	0.003	0.001	0.003	0.005	0.008

and sellers. We conjecture that firms facing weaker environmental pressures may be better situated to acquire and operate pollutive assets.

In Table V, we compare buyers' and sellers' exposure to environmental pressures. In column (1), we focus on the public listing status of the transacting parties. In this analysis, we are not bound by the data limitations that restrict our attention exclusively to publicly listed firms as in the previous analyses. As such, we consider all buyers and sellers in divestitures of pollutive plants. The estimates in column (1) suggest that, relative to sellers, buyers of pollutive plants are 5.5 percentage points more likely to be private firms.

The rest of Table V shows that, compared to sellers, buyers of pollutive plants are 4.7 percentage points less likely to be covered by ESG rating agencies (column (2)), 3.0 percentage points less likely to have above-average pension fund ownership (although the difference is not statistically significant at conventional levels) (column (3)), 5.4 percentage points more likely to be headquartered in a Republican-leaning county (column (4)), and 5.2 percentage points less likely to experience a negative environmental incident before the deal (column (5)).[10]

The effects above are economically large, representing increases of 8% to 34% relative to average environmental pressures between buyers and sellers

[10] Note that the sample size differs across the columns/specifications due to data availability. In column (4), we exclude observations when buyers' or sellers' parent headquarter locations are outside the United States or unavailable in the SDC M&A database. In column (5), the sample does not include pre-2007 deals since Reprisk data are not available before 2007.

in our divestiture deal sample. When aggregating all environmental pressures into a composite pressure index, we find a similar effect: buyers' composite environmental pressure index is 5.9 percentage points lower than that of sellers (column (6)), corresponding to 16% of the divestiture deal sample average. Taken together, these estimates suggest that firms facing stronger environmental pressures tend to sell their pollutive assets to firms that face weaker environmental pressures.

III. Changes in Pollution around Divestitures

The findings in the previous section suggest that firms divest pollutive plants in response to environmental pressures, particularly when they are heavy polluters, and they are more likely to respond to such pressures by divesting plants than by closing plants down or treating pollution. Moreover, pollutive asset divestitures tend to transfer pollution from firms that face higher environmental pressures to firms that face weaker pressures.

A natural question that arises is whether pollutive plant divestitures affect pollution levels. If environmental pressures lead to the reallocation of assets to firms more capable of treating pollution, we should observe a decline in pollution levels at the sold plants. Alternatively, these asset transfers may reflect a greenwashing strategy whereby firms and their managers seek to mitigate stakeholder pressures without exerting real effects on pollution. To distinguish between these alternatives, we study how pollution levels change around divestitures at the sold plants and across the buyers and sellers combined.

We estimate the analyses in plant-chemical-year panels, which allow us to trace the amount and intensity of chemical-level emissions by each plant each year. These specifications mitigate concerns that different chemicals generate different environmental externalities.

We consider two test specifications. First, we estimate generalized DID regression specifications using two-way fixed effects

$$Pollution_{i,c,t} = \beta Divested_i \times Post_{i,t} + \alpha_{i,c} + \tau_{c,t} + \epsilon_{i,t}, \tag{2}$$

where i denotes the plant, c denotes the chemical type, and t denotes the year. The dependent variable, $Pollution_{i,c,t}$, takes a measure of total pollution, pollution intensity, or pollution abatement activities, such as source reduction and postproduction waste management such as recycling, recovery, or treatment. We use Poisson regressions for skewed dependent variables such as total pollution (Cohn, Liu, and Wardlaw (2022)). The key variable of interest is *Divested* × *Post*, which equals one following the divestment of a plant, and zero prior to divestment or for never-divested plants. Standard errors are clustered by plant.

The regressions include plant-chemical fixed effects ($\alpha_{i,c}$) and chemical-year fixed effects ($\tau_{c,t}$). In more stringent specifications, we control for state- and industry-year interactive fixed effects. These controls mitigate concerns about confounding explanations related to industry dynamics, local economic conditions, or state-level policies.

Second, we address concerns related to heterogeneous treatment timing effects in generalized DID regressions by estimating stacked event regressions.[11] To construct the stacked sample, we match each sold plant to never-sold plants in the same industry (three-digit NAICS codes, or NAICS3) and state. The combined set of treated plants sharing the same event year and their matched control units is labeled as a "cohort." We then stack all such cohorts together to form our testing sample. In the stacked regression specification, the control plants are sampled with replacement. We interact all of the fixed effects with cohort fixed effects, thereby saturating the regressions with cohort-plant-chemical, cohort-chemical-year, cohort-state-year, and cohort-industry-year interactive fixed effects. These fixed effects allow us to make within-cohort comparisons, contrasting each treated unit with its matched control group.

Panel A of Table VI presents the results. Columns (1) through (4) report results for total pollution levels and columns (5) through (8) report results for pollution intensity. For each outcome variable, we first use a generalized DID framework and then use stacked regressions. The estimates across all specifications suggest that, following divestitures, sold plants do not emit less toxic release compared to the control group. In particular, the coefficient estimates on the interaction *Divested* × *Post* are positive and statistically insignificant across all specifications.

In Panel B of Table VI, we trace the combined pollution levels of all plants owned by the seller and the buyer around divestitures, including divested and nondivested plants. Specifically, for all sellers' and buyers' existing plants, we define *Divested* as an indicator equal to one if their parent company has divested or acquired at least one plant in a given year, respectively. We then regress pollution on *Divested* × *Post*.

This specification investigates the possibility that firms choose to keep plants whose pollution they can treat and to divest assets whose pollution they cannot treat, but that the buyers can treat. The estimates in Panel B of Table VI indicate that the buyer and seller's combined pollution levels or pollution intensities do not decline following divestitures. This finding is inconsistent with sellers choosing to keep plants whose toxic release they can reduce, or with buyers reducing pollution at their other plants when acquiring new pollutive plants.

To further explore pollution levels around divestitures, we estimate dynamic regressions that decompose *Post* into separate year indicators around divestitures. Specifically, we estimate

$$Pollution_{i,c,t} = \sum_{k\geq -3} \beta_k Divested_i \times \mathbb{1}_{i,t=e_t+k} + \alpha_{i,c} + \tau_{c,t} + \epsilon_{i,t}, \tag{3}$$

[11] See De Chaisemartin and d'Haultfoeuille (2020), Borusyak, Jaravel, and Spiess (2024), Callaway and Sant'Anna (2021), Goodman-Bacon (2021), Imai and Kim (2021), Sun and Abraham (2021), Athey and Imbens (2022), and Baker, Larcker, and Wang (2022), among others.

Table VI

Changes in Pollution around Divestitures

This table presents estimates from difference-in-difference Poisson regressions explaining total pollution levels and pollution intensities at divested plants (Panel A) and all plants owned by buyers and sellers of pollutive plants (Panel B). The unit of observation is a plant-chemical-year. The sample includes all plants in the Toxic Release Inventory Program of the U.S. Environmental Protection Agency. *Total Pollution* is the total annual toxic release for a plant-chemical pair. *Pollution Intensity* is the total annual toxic release scaled by the cumulative production ratio for a plant-chemical pair. *Divested* is an indicator variable that equals one if a plant has been divested by its parent during the sample period. *Post* is an indicator variable that equals one in the years following the divestiture. In both Panels A and B, we present estimates from generalized difference-in-difference regressions (columns (1) through (3) and (5) through (7)) and estimates from stacked regressions (columns (4) and (8)). The stacked samples consist of divested plants and matched never-divested plants within the same NAICS3 industry and state. In stacked regressions, all fixed effects are interacted with cohort indicators, where a cohort includes all divested plants sharing the same event year and their matched never-divested control plants. Standard errors are presented in parentheses and clustered by plant. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Pollution at Divested Plants

Dep. Var.:	*Total Pollution*				*Pollution Intensity*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Divested × *Post*	0.030	0.022	0.024	0.041	0.046	0.027	0.044	0.065
	(0.035)	(0.037)	(0.035)	(0.040)	(0.046)	(0.046)	(0.048)	(0.049)
Plant-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE		Yes	Yes	Yes		Yes	Yes	Yes
Industry-Year FE			Yes	Yes			Yes	Yes
Method	GDID	GDID	GDID	Stacked	GDID	GDID	GDID	Stacked
Observations	992,424	992,418	992,313	3,994,695	992,424	992,418	992,313	3,994,695
R^2	0.914	0.916	0.917	0.918	0.914	0.915	0.917	0.914

Panel B: Pollution at All Plants Owned by Buyers and Sellers

Dep. Var.:	*Total Pollution*				*Pollution Intensity*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Divested × *Post*	0.008	0.012	0.002	0.000	−0.009	−0.012	−0.012	−0.013
	(0.020)	(0.019)	(0.019)	(0.025)	(0.024)	(0.023)	(0.023)	(0.032)
Plant-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE		Yes	Yes	Yes		Yes	Yes	Yes
Industry-Year FE			Yes	Yes			Yes	Yes
Method	GDID	GDID	GDID	Stacked	GDID	GDID	GDID	Stacked
Observations	872,280	872,274	872,163	9,431,650	872,280	872,274	872,163	9,431,650
R^2	0.918	0.919	0.921	0.914	0.916	0.917	0.919	0.911

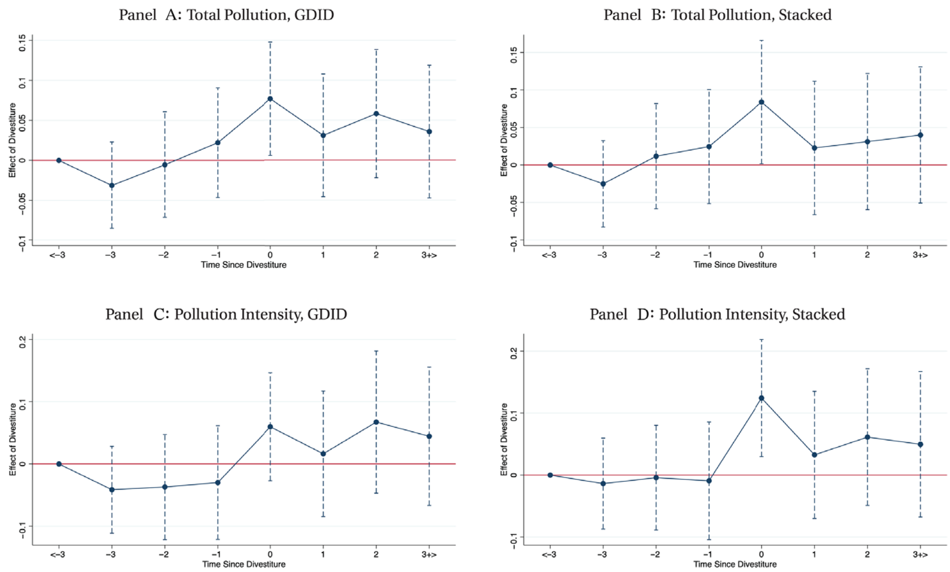

Figure 3. Changes in pollution around divestitures. This figure reports annual pollution levels and pollution intensities at the plant-chemical level around divestitures of pollutive plants. *Total Pollution* is the total annual toxic release for a plant-chemical pair. *Pollution Intensity* is the total annual toxic release scaled by the cumulative production ratio for a plant-chemical pair. We present estimates from generalized difference-in-difference (GDID) regressions in Panels A and C, and estimates from stacked regressions in Panels B and D. The stacked samples consist of divested plants and matched never-divested plants within the same NAICS3 industry and state. The regressions include plant-chemical, chemical-year, industry-year, and state-year fixed effects. In stacked regressions, all fixed effects are interacted with cohort indicators, where a cohort includes all divested plants sharing the same event year and their matched never-divested control plants. The dashed vertical lines represent 90% confidence intervals based on standard errors clustered by plant. All variable definitions appear in the Appendix. (Color figure can be viewed at wileyonlinelibrary.com)

where *Pollution* is total pollution or pollution intensity at the plant-chemical level, k is the number of years from the year of divestment (indexed by e_t), and $1_{i,t=e_t+k}$ denotes separate event time indicators. The regression includes plant-chemical, chemical-year, state-year, and industry-year fixed effects.

Figure 3 reports the results. Compared to never-sold plants, we do not find significant pollution changes at sold plants prior to divestment. Following divestment, emissions increase temporarily before falling back to preevent levels. These findings are consistent with our baseline regression estimates indicating that divestment is not accompanied by a decrease in emissions.

To further address concerns about selection and omitted variables, we focus on a subset of divestitures that follow quasi-exogenous Reprisk environmental risk incidents. The identifying assumption is that firms cannot fully predict the occurrence and timing of such incidents. Figure 4 presents estimates from a dynamic regression that traces pollution around such incident-driven divestitures. Consistent with the patterns in Figure 3, we do not find any evidence that pollution declines following these divestitures. Furthermore,

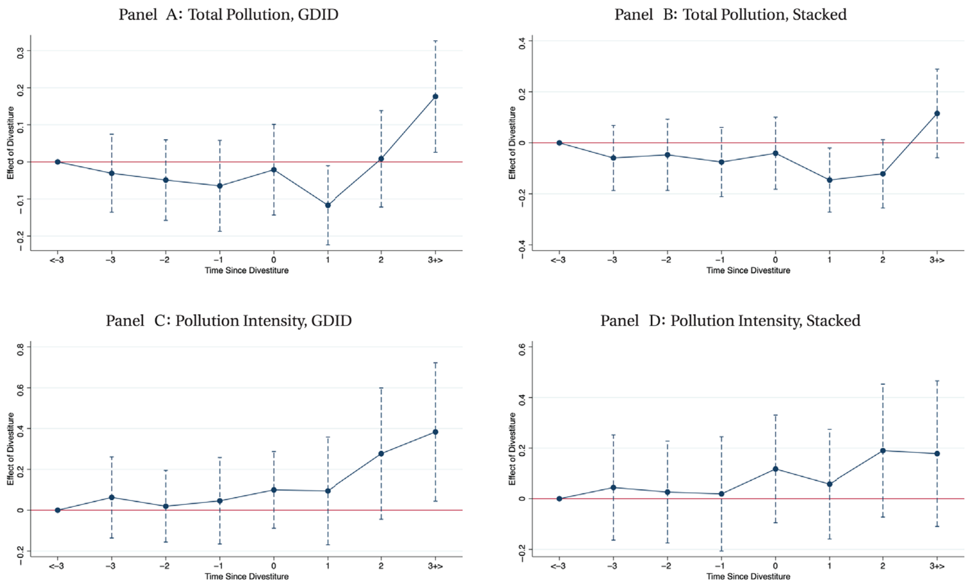

Figure 4. Changes in pollution around divestitures following environmental risk incidents. This figure reports annual pollution levels and pollution intensities at the plant-chemical level around divestitures that take place in the same year as or the year after environmental risk incidents. *Total Pollution* is the total annual toxic release for a plant-chemical pair. *Pollution Intensity* is the total annual toxic release scaled by the cumulative production ratio for a plant-chemical pair. We present estimates from generalized difference-in-difference (GDID) regressions in Panels A and C, and estimates from stacked regressions in Panels B and D. The stacked samples consist of divested plants and matched never-divested plants within the same NAICS3 industry and state. The regressions include plant-chemical, chemical-year, industry-year, and state-year fixed effects. In the stacked regressions, all fixed effects are interacted with cohort indicators, where a cohort includes all divested plants sharing the same event year and their matched never-divested control plants. The dashed vertical lines represent 90% confidence intervals based on standard errors clustered by plant. All variable definitions appear in the Appendix. (Color figure can be viewed at wileyonlinelibrary.com)

pollution does not change significantly in the years immediately preceding environmental risk incidents, mitigating concerns that environmental risk incidents can be fully predicted by firms' environmental practices and pollution.

Next, we examine pollution abatement activities at sold plants. In Table VII, we examine annual pollution abatement efforts, including source reduction and postproduction waste management (i.e., recycling, recovery, and treatment). In Panel A, we examine changes in abatement efforts at divested plants compared to control plants. In Panel B, we examine changes in the combined abatement efforts at all plants owned by buyers and sellers. Similar to Table VI, we report results from both generalized DID regressions and stacked regressions.

The estimates across all outcome variables consistently suggest no differential changes in pollution abatement activities across divested and undivested plants following divestitures. The coefficient estimates on the interaction

Table VII

Changes in Abatement Activities around Divestitures

This table presents difference-in-difference OLS regression estimates of the abatement activities of divested plants (Panel A) and all plants owned by buyers and sellers (Panel B). We examine various pollution abatement efforts, including the total number of source reduction activities (*#Source Reduction*) in columns (1) and (2), the percentage of toxic chemicals reduced through recycling (*%Recycling*) in columns (3) and (4), energy recovery (*%Recovery*) in columns (5) and (6), and treatment (*%Treatment*) in columns (7) and (8). The unit of observation is a plant-chemical-year. The sample includes all plants in the Toxic Release Inventory Program of the U.S. Environmental Protection Agency. *Divested* is an indicator that equals one if a plant has been divested by its parent during the sample period. *Post* is an indicator that equals one in the years following divestiture. In Panels A and B, we present generalized difference-in-difference regression estimates (columns (1), (3), (5), and (7)) and stacked regression estimates (columns (2), (4), (6), and (8)). In stacked regressions, the samples consist of divested and matched never-divested plants within the same NAICS3 industry and state, and all fixed effects are interacted with cohort indicators where a cohort includes all divested plants sharing the same event year and their matched never-divested control plants. Standard errors are presented in parentheses and clustered by plant. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Abatement at Divested Plants

Dep. Var.:	*#Source Reduction*		*%Recycling*		*%Recovery*		*%Treatment*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Divested × *Post*	−0.005	−0.071	0.476	−0.010	−0.551	−0.177	0.438	0.834
	(0.079)	(0.101)	(0.560)	(0.635)	(0.615)	(0.707)	(0.755)	(0.885)
Plant-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Method	GDID	Stacked	GDID	Stacked	GDID	Stacked	GDID	Stacked
Observations	1,218,155	3,879,670	1,035,311	3,427,189	1,035,311	3,427,189	1,035,311	3,427,189
R^2	0.941	0.948	0.884	0.860	0.777	0.740	0.841	0.793

(*Continued*)

Table VII—*Continued*

Panel B: Abatement at All Plants Owned by Buyers and Sellers

Dep. Var.:	*#Source Reduction*		*%Recycling*		*%Recovery*		*%Treatment*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Divested × *Post*	−0.001	−0.028	0.534*	0.386	0.264	0.771**	0.066	−0.225
	(0.039)	(0.075)	(0.281)	(0.363)	(0.276)	(0.380)	(0.347)	(0.470)
Plant-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Method	GDID	Stacked	GDID	Stacked	GDID	Stacked	GDID	Stacked
Observations	1,069,201	11,122,028	909,339	9,723,698	909,339	9,723,698	909,339	9,723,698
R^2	0.942	0.947	0.884	0.869	0.774	0.756	0.842	0.813

Divested × *Post* are statistically insignificant at conventional levels and flip signs across specifications. Treating all plants of buyers and sellers together, we still do not find evidence consistent with improved abatement activities. While *Divested* × *Post* loads positively in columns (3) and (7), the estimates have relatively small economic magnitudes and become insignificant in a different specification. These results shed more light on the findings in Table VI. In particular, they imply that plants do not experience meaningful changes in their pollution levels in part because they do not materially change their pollution abatement activities.

In the Internet Appendix, we address concerns about our test specifications and sample composition. One concern is that the test specifications lack power to detect a significant effect of divestitures on pollution. To address this concern, in Table IA.II, we provide estimates of the minimum detectable effect size (MDES) following Bloom (1995). The estimates suggest that the test specifications have sufficient power to detect effects of approximately 2% to 3% of the sample standard deviation. This means that the muted effects of divestitures on pollution are not driven by weak or overly strict test specifications.

We also consider alternative regression specifications. Panel A of Internet Appendix Table IA.III provides estimates from OLS regressions instead of Poisson regressions. Panel B provides estimates from regressions that aggregate pollution across all chemicals in each plant. Panel C provides estimates from toxicity-weighted measures of chemical emissions. In IA.IV, we extend the sample to include deals that involve financial buyers such as private equity firms. Across all of these analyses, which are estimated using both generalized DID and stacked regressions, the coefficient estimates on the interaction *Divested* × *Post* are never negative nor statistically significant, suggesting that pollution levels do not decline following the divestment of pollutive plants.

Overall, the evidence in this section indicates that the buyers of pollutive plants maintain pollution levels similar to predivestment levels. These results do not support the hypothesis that divestitures transfer pollutive assets to new owners with higher capacity and better technology to reduce pollution. Instead, they suggest that the divestment of pollutive plants, often in response to environmental pressures, does not have any real impact on pollution levels. In the next section, we explore the strategic mechanisms that underlie the divestment of pollutive plants and the benefits and gains from trade.

IV. Strategic Mechanisms and Gains from Trade

In this section, we investigate the strategic mechanisms behind the divestment of pollutive assets. First, we investigate the role of information costs as an indirect proxy for misalignment between corporate managers and outside stakeholders. Second, we study the existence of business ties between the sellers of the assets and their buyers, which would allow the sellers to keep the assets as part of their value chain even after their divestment. Third, we investigate how firms exploit the divestment of pollutive plants to advertise their environmental policies by analyzing the text of earnings conference calls. Last, we consider the gains from trading pollutive assets, including improvements in ESG ratings, reductions in EPA enforcement costs, and the market's reaction to divestitures.

A. Information Costs

A possible interpretation of our findings thus far is that firms respond to environmental pressures through a greenwashing divestment strategy, whereby the company and its managers divest pollutive plants to mitigate environmental pressures without any real effects on pollution levels. In this subsection, we explore this interpretation by investigating the role of information costs as an indirect proxy for misalignment between corporate managers and outside stakeholders. This line of research is rooted in an extensive literature on corporate governance that considers the role of information asymmetry in agency conflicts and interest misalignment (e.g., Demsetz and Lehn (1985), Almazan and Suarez (2003), Duchin, Matsusaka, and Ozbas (2010)).

To explore the role of information frictions, we exploit cross-sectional variation in firms' organizational and ownership structures. We argue that more complex structures increase outsiders' costs of acquiring information about the firm (Cohen and Lou (2012)), including information about the firm's divestment policy and its consequences for pollution levels. We measure firm complexity in several ways: (i) number of business segments, (ii) number of NAICS three-digit industries, (iii) number of subsidiaries, and (iv) number of organizational layers based on the firm's ownership structure (Xu and Zwick (2024)).

We also consider the presence of blockholders, defined as institutional investors that own at least 5% of the firm. Blockholders have stronger incentives to acquire information about the firm than atomistic shareholders and therefore are considered external monitors (Edmans and Holderness (2017)). We measure the presence of blockholders as the total percentage of a firm's shares held by blockholders based on 13-F data.

In Table VIII, we examine whether higher information costs increase the likelihood that firms respond to environmental pressure by divesting pollutive assets. In particular, we provide estimates from regressions explaining the likelihood of divesting pollutive plants where the key independent variable is the interaction term *Pressure Index* × *Information Asymmetry*. The estimates suggest that firms with higher information costs, as measured by more complex organizational structures and lower presence of blockholders, are more likely to divest pollutive plants in response to environmental pressures. The coefficient estimates on the interaction *Pressure Index* × *Information Asymmetry* are statistically significant at conventional levels across all of the specifications in Table VIII.

Together, these findings provide indirect evidence in support of a greenwashing divestment strategy, whereby more opaque firms divest pollutive plants to falsely create the perception that the company is attempting to become more environmentally sound. Such a strategy is more likely to succeed when

Table VIII
Information Costs

This table reports estimates from regressions that explore the role of information frictions in firms' decisions to divest pollutive plants in response to environmental pressures. We consider the following measures of information frictions/costs: *#Segments*—the number of business segments, *#Industries*—the number of unique industries (NAICS3) that a firm operates in, *#Subsidiaries*—the number of subsidiaries, *#Layers*—the number of organizational layers, and *%Blockholders*—the percentage of shares owned by blockholders, defined as entities that each owns at least 5% of the company's shares. The unit of observation is a firm-year, and the sample includes all public firms owning plants in the Toxic Release Inventory Program of the U.S. Environmental Protection Agency. The dependent variable is *Sell (Pollutive)*, an indicator that equals one if the firm divests a pollutive plant in a given year, multiplied by 100. *Firm Char* includes *Q*, *Leverage*, *Cash Holdings*, and *Tangibility*. All variable definitions appear in the Appendix. Standard errors are clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Proxies for *Info. Asymmetry* Dep. Var.: *Sell (Pollutive)(%)*	*#Segments* (1)	*#Industries* (2)	*#Subsidiaries* (3)	*#Layers* (4)	*%Blockholders* (5)
Pressure Index × *Info. Asymmetry*	0.823**	2.102**	0.018*	1.773**	−5.610*
	(0.350)	(0.889)	(0.010)	(0.774)	(3.200)
Info. Asymmetry	0.028	−0.287	−0.004	−0.324	2.127
	(0.186)	(0.414)	(0.006)	(0.349)	(1.570)
Pressure Index	−1.003	−1.999	1.525**	−1.157	3.152***
	(1.006)	(1.366)	(0.706)	(1.681)	(0.858)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
Firm Char	Yes	Yes	Yes	Yes	Yes
Observations	14,790	12,449	10,311	10,114	18,826
R^2	0.063	0.072	0.077	0.079	0.060

outsiders face higher costs of becoming informed about the firm. These findings also highlight the role of divestment in balancing/resolving complex pressures from diffused owners with heterogeneous preferences. In disperse-owned and complex firms, managers likely face greater challenges in aggregating and navigating the preferences of all stakeholders. Divesting pollutive assets can help reduce the costs of "preference aggregation" in such firms.

B. Business Ties between Buyers and Sellers

Anecdotal evidence suggests that the divestitures of pollutive assets often occur between operationally related firms. For example, in 2002, Genencor International Inc acquired Enzyme Bio-System Ltd from its joint venture partners, CPC International Inc and Texaco Inc. As another example, Sumitomo Rubber acquired Goodyear Dunlop Tires North America from its joint venture partner, Goodyear Tire in 2015. Other deals lead to the start of cooperative relations between the buyer and the seller. For example, Outokumpu Oyj acquired the heat transfer business of Lennox International (LI) in 2002, and subsequently formed a joint venture with LI. Similarly, BASF Corp acquired a factory of Toda Kogyo Inc in 2018 to form a joint venture.

Motivated by such real-world examples, we investigate the nature of the relationship between sellers and buyers of pollutive assets to shed light on the incentives of the buyers and on the ability of the sellers to access the divested plants and their products postdivestiture. Specifically, we test whether firms with preexisting business ties with the sellers are more likely to purchase pollutive plants from the sellers. We consider two types of relationships: (i) customer-supplier relations and (ii) joint venture partnerships. We argue that the existence of such relationships reduces the frictions and costs associated with accessing the plant's output even when it is operated by a different parent company, allowing the seller to maintain its current operations and production processes.

We design these analyses following the matching approach introduced by Bena and Li (2014). For each divestiture deal, we find five "pseudo buyers," that is, firms that operate in the same industry as the buyer. Pseudo buyers are sampled with replacement from a list of SDC acquirers. Such acquirers have both the propensity and the capacity to purchase assets from other firms. This matching approach generates six buyer-seller pairs for each deal, including the actual buyer and five pseudo buyers. We set *Buyer (Pollutive)* to one for the actual buyer and zero for the pseudo buyers.

Next, we investigate whether each pair of firms shares an ongoing supply chain relation at the time of the deal or starts a joint venture prior to the deal. If so, we set the indicator *Operationally Related* to one for this pair of firms.

We also consider the possibility that sellers maintain their access to products or services of divested plants after the deal by examining whether the seller is more likely to start a new business relationship with the actual buyer than with pseudo buyers after the deal takes place. This analysis sheds light on whether the divestiture represents a material operational or production change for the seller, or whether it simply reflects a change in the boundaries of the firm without material operational shifts.

Panel A of Table IX reports the results from this analysis. In column (1), we regress the *Buyer (Pollutive)* indicator on the indicator variable for business ties, *Operationally Related*. The regression model includes match group fixed effects, which allow us to compare each buyer-seller pair to its matched pseudo buyer-seller pairs and absorb deal-level variation, as well as macroeconomic trends, seller characteristics, and industry dynamics.

The results suggest that operationally related firms are 65 % more likely to purchase a pollutive plant from the seller, compared to unrelated firms. This magnitude is substantially larger than the sample average for *Buyer*, which is 0.167 (1/6) by construction.

The results in column (2) show that following divestitures, sellers are 7 percentage points more likely to establish business relations with the buyer, which likely allows buyers to maintain access to their divested plants. The magnitude is economically large since the average probability of establishing new business ties in the matched sample is slightly above 2 percentage points.

In Panel B of Table IX, we investigate whether the likelihood of transferring pollutive assets to connected firms increases when those connected firms face weaker environmental pressures. We hypothesize that pursuing a divestment strategy that transfers pollutive plants to connected firms in response to

Table IX

Business Ties between Buyers and Sellers of Pollutive Plants

This table provides regression estimates examining the business relations between buyers and sellers of pollutive plants. Panel A examines whether the buyers and sellers of pollutive plants are operationally related through supply chain relationships and joint ventures. Column (1) examines whether preexisting operational relations predict future participation in pollutive asset divestitures. The dependent variable, *Buyer (Pollutive)*, is an indicator that equals one if a firm purchases a pollutive asset from the seller. *Operationally Related* is an indicator that equals one if a firm has a preexisting supply chain relationship or a joint venture partnership with the seller. Column (2) examines whether buyers and sellers develop new supply chain or joint venture relations following divestiture. For each divestiture deal (or a buyer-seller pair), we generate five control pairs that match the buyer with randomly chosen pseudo acquirers from the SDC universe that operate in the same industry as the actual acquirer. The analyses use a matched-pair sample, each observation being a seller-buyer pair. As such, each deal has six observations, which consist of the actual buyer-seller pair and five potential buyer-seller pairs. The regressions include matched group fixed effects. Standard errors are double-clustered by matched group and deal year. In Panel B, we investigate whether the likelihood of selling pollutive assets to connected firms increases when those connected firms face weaker environmental pressures. The unit of analysis is a firm-year. The key independent variables are the focal firm's own pressure index (*Pressure Index, Own*) and the minimum pressure index of its connected firms (*Pressure Index, Connected Firms' Min*). Connected firms are those that share supply chain or joint venture relations with the focal firm. Standard errors are clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Buyers and Sellers of Pollutive Plants

Dep. Var.:	*Buyer (Pollutive)* (1)	*Develop New Relationship* (2)
Operationally Related	0.651***	
	(0.099)	
Buyer of Pollutive Assets		0.069***
		(0.013)
Matched Group FE	Yes	Yes
Observations	3,576	3,576
R^2	0.040	0.247

Panel B: Connected Firms' Pressure and Divestiture Likelihood

Dep. Var.: *Divested*	(1)	(2)	(3)
Pressure Index, Own	0.018***	0.018***	0.018***
	(0.005)	(0.005)	(0.005)
Pressure Index, Connected Firms' Min	−0.007*	−0.009**	−0.008*
	(0.004)	(0.004)	(0.004)
Year FE	Yes		
Industry FE	Yes		
Industry-Year FE		Yes	Yes
Firm Controls			Yes
Observations	11,824	11,514	11,107
R^2	0.015	0.075	0.080

environmental pressures becomes more feasible when those connected firms face weaker environmental pressures. To test this hypothesis, we estimate regressions explaining the likelihood of divesting pollutive plants (*Divested*). The key independent variables are (i) the focal firm's own pressure index (*Pressure Index, Own*), and (ii) the minimum pressure index of its connected firms (*Pressure Index, Connected Firms' Min*). Connected firms are those that share supply chain or joint venture relations with the focal firm.

The findings in Panel B of Table IX are twofold. First, the likelihood of divestment is positively related to a firm's own environmental pressure index, suggesting that firms are more likely to divest pollutive plants when they face stronger environmental pressures. Second, the likelihood of divestment is negatively related to the pressure indices of the company's connected firms, suggesting that being connected to low-pressure firms significantly increases the likelihood of divesting pollutive assets.

Taken together, the findings in this subsection are consistent with a greenwashing strategy, as they suggest that the divestment of pollutive plants reflects a cosmetic redrawing of firm boundaries whereby sellers respond to environmental pressures through divestitures along their value chains that maintain their access to the sold plants.

C. Conference Call Environmental Disclosures

In this subsection, we investigate whether firms publicly advertise their environmental progress after divestment. As discussed in Section I.E, we use a BERT language model to analyze the text of firms' conference calls with investors. The textual analysis generates a sentiment-based classification of firms' environmental disclosures in conference calls: *Positive Env. Disclosure* (*Negative Env. Disclosure*) is an indicator variable that equals one if the firm generally expresses positive (negative) sentiment when discussing its environmental performance during the conference call, and zero otherwise.

Specifically, we estimate regressions explaining the above sentiment indicators using the regression specification

$$Y_{f,t} = \beta Seller\,(Pollutive)_f \times Post_{f,t} + \gamma \cdot \mathbf{X}_{f,t} + \theta_f + \tau_t + \nu_{f,t}, \tag{4}$$

where f denotes a parent firm and t denotes the year. The dependent variables, $Y_{f,t}$, denote conference call disclosures. The variable $Seller\,(Pollutive)_f$ equals one if firm f sells any pollutive plant over the sample period, and zero otherwise, $Post_{f,t}$ equals one starting from the year of the divestiture, and $\mathbf{X}_{f,t}$ represents an array of firm characteristics, including firm size, leverage, profitability, and asset tangibility. Our regression model includes firm fixed effects (θ_f) and year fixed effects (τ_t). More stringent specifications also include industry-year fixed effects. Standard errors are clustered by firm.

Similar to the analyses of pollution, we estimate these effects using the generalized DID regression method and the stacked regression method. The stacked regression sample is constructed by matching each seller firm to other

Table X

Conference Call Environmental Disclosures

This table reports estimates from regressions explaining changes in sellers' conference call environmental disclosures around divestitures of pollutive plants. The sample includes all firm-year observations with at least one conference call transcript. The dependent variable in columns (1) through (4) is *Positive Env. Disclosure*, defined as an indicator that equals one if a firm discusses improvements in its environmental performance during its earnings conference calls in a given year. The dependent variable in columns (5) through (8) is *Negative Env. Disclosure*, defined analogously with respect to disclosures of declines in the firm's environmental performance. *Seller (Pollutive)* is an indicator that equals one if a firm divests a pollutive plant during the sample period. *Post* is an indicator that equals one in the years following the divestiture. *Firm Char* includes *Q*, *Leverage*, *Cash Holdings*, and *Tangibility*. All variable definitions appear in the Appendix. Columns (1) through (3) and (5) through (7) report estimates from generalized difference-in-difference (GDID) regressions. Columns (4) and (8) report results from stacked regressions. The stacked sample consists of sellers and matched control firms within the same NAICS3 industry that have not sold a plant during the sample period. In the stacked regressions, all fixed effects are interacted with cohort indicators, where a cohort includes all divesting firms sharing the same event year and their matched never-divest control firms. Standard errors are reported in parentheses and clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dep. Var.:	*Positive Env Disclosure*				*Negative Env Disclosure*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Seller (Pollutive) × *Post*	0.060**	0.051*	0.056*	0.062**	−0.003	−0.008	0.002	0.005
	(0.030)	(0.031)	(0.031)	(0.031)	(0.021)	(0.022)	(0.021)	(0.021)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes				Yes			
Industry-Year FE		Yes	Yes	Yes		Yes	Yes	Yes
Firm Char			Yes	Yes			Yes	Yes
Method	GDID	GDID	GDID	Stacked	GDID	GDID	GDID	Stacked
Observations	37,923	37,796	33,873	237,867	37,923	37,796	33,873	237,867
R^2	0.468	0.499	0.520	0.496	0.659	0.688	0.711	0.712

publicly listed firms that never divested a plant during the sample period and that operate in the same industry (NAICS3) when the divestiture takes place. We again control for interactive fixed effects between cohorts and firms as well as cohort-industry-year fixed effects.

Table X presents the results. The sample includes all public firm-year observations with at least one conference call. Columns (1) through (4) present the results for positive environmental disclosures, while columns (5) through (8) report the results for negative environmental disclosures. For each outcome variable, we first provide estimates from a generalized DID specification, followed by results from a stacked regression specification (columns (4) and (8)).

The results suggest that sellers of pollutive assets are more likely to highlight an improvement in their environmental performance. Based on the regression estimates in column (3), which include both firm and industry-year fixed effects, firms are roughly 5.6 percentage points more likely to advertise their environmental progress during conference calls following pollutive plant divestitures. This represents a 47% increase compared to the average

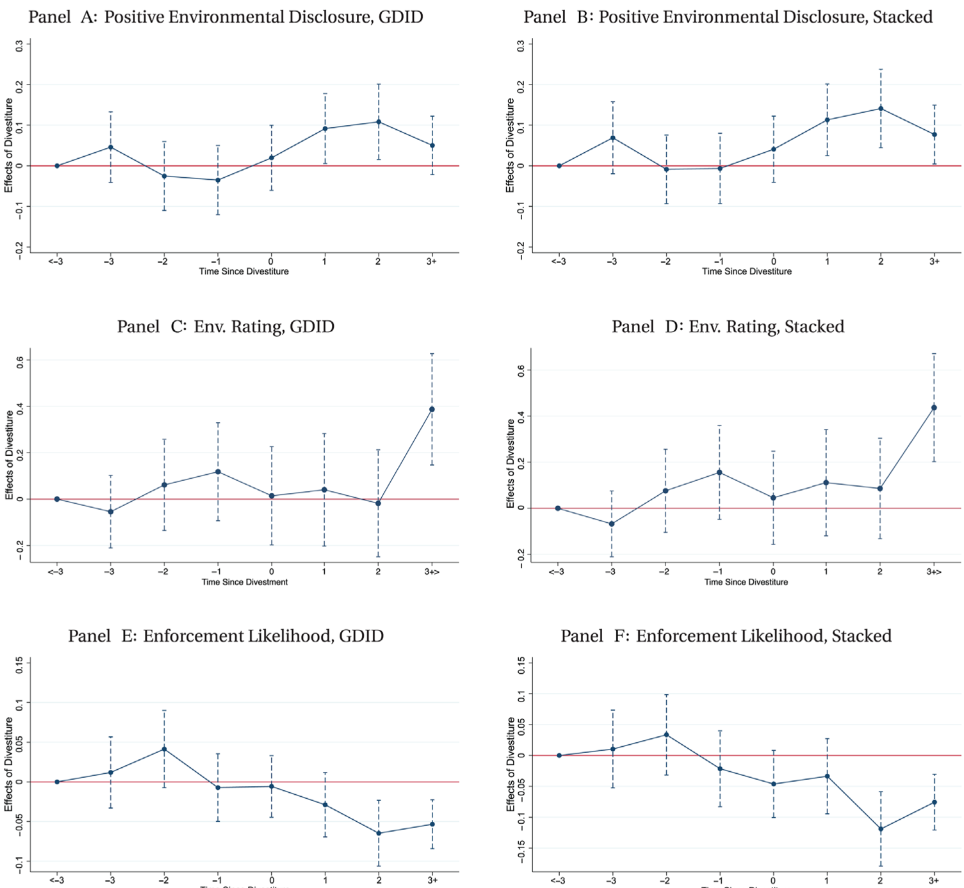

Figure 5. Changes in environmental disclosures, ESG ratings, and regulatory enforcement actions around divestitures. This figure reports annual environmental disclosures in earnings conference calls (Panels A and B), environmental ratings (Panels C and D), and EPA enforcement actions (Panels E and F) around divestitures of pollutive plants. We present estimates from generalized difference-in-difference (GDID) regressions in Panels A, C, and E, and estimates from stacked regressions in Panels B, D, and F. The stacked samples consist of divested plants and matched never-divested plants within the same NAICS3 industry. The regressions include firm fixed effects, industry-year fixed effects, and firm controls. In stacked regressions, all fixed effects are interacted with cohort indicators, where a cohort includes all divesting firms sharing the same event year and their matched never-divesting control firms. The dashed vertical lines represent 90% confidence intervals based on standard errors clustered by firm. All variable definitions appear in the Appendix. (Color figure can be viewed at wileyonlinelibrary.com)

likelihood of providing positive environmental disclosures in the sample (12 percentage points). In contrast, sellers exhibit no difference in the likelihood of providing negative environmental disclosures.

Panels A and B of Figure 5 explore the dynamics of positive environmental disclosures in generalized DID regressions and stacked regressions, respectively. The figure shows an increase in the likelihood of positive environmental disclosures following divestitures without any noticeable preevent trends.

In the Internet Appendix, we provide two additional analyses. First, in Internet Appendix Figure IA.2, we estimate changes in pollution surrounding divestitures accompanied by positive conference call environmental disclosures. We find that pollution levels do not decline following divestitures accompanied by positive environmental disclosures. This finding is consistent with the view that firms divest pollutive assets and advertise their consequent environmental performance to alleviate environmental pressures without reducing pollution levels.

Second, we explore whether firms are more likely to advertise their environmental performance when they have divested pollutive assets in response to environmental pressures. To address this question, we separately analyze the effects of divestitures that are more and less likely to be motivated by environmental pressures. Specifically, we define *High (Low) Env Pressures* as a dummy variable that equals one if the seller faces above-median (below-median) environmental pressures, and zero otherwise. We then regress positive environmental disclosures on the triple-interaction terms *Seller (Pollutive)* × *Post* × *High Env Pressure* and *Seller (Pollutive)* × *Post* × *Low Env Pressure*. The results, reported in Table IA.V, suggest that when environmental pressures are high, sellers of pollutive plants are significantly more likely to provide positive environmental disclosures compared to nonsellers. Conversely, when environmental pressures are low, the sellers are not more likely to provide such disclosures compared to nonsellers. We note, however, that the differences between these coefficients are not statistically significant at conventional levels.

Overall, the findings in this subsection suggest that sellers of pollutive assets highlight their environmental policies in subsequent conference calls. Doing so allows them to strengthen their public image as being environmentally friendly, despite the muted impact of divestitures on pollution levels and abatement efforts.

D. Gains from Divestitures

In this subsection, we explore the benefits from divestment, focusing on changes in sellers' ESG ratings and EPA regulatory actions and enforcement costs. These analyses can shed light on the motives driving divestment activities.

Similar to the analyses of conference calls, we estimate the specification in equation (4) to compare changes in ESG ratings and regulatory enforcement actions or costs between sellers and nonsellers. Panel A of Table XI presents results on the changes in sellers' ESG ratings following pollutive asset divestitures. Columns (1) through (4) present results for firms' overall CSR scores, and columns (5) through (8) report results for their environmental scores. We provide estimates from both generalized DID regressions and from stacked

Table XI

Changes in ESG Ratings and Regulatory Costs

This table reports regression estimates explaining changes in sellers' ESG ratings (Panel A) and enforcement costs (Panel B) around pollutive plant divestitures. In Panel A, the sample includes all public firms covered by the KLD database. In Panel B, the sample includes all public firms owning plants in the Toxic Release Inventory Program of the U.S. Environmental Protection Agency (EPA). *Enforcement Action* is an indicator that equals one if a firm receives an EPA enforcement action in a given year. *Enforcement Cost* is the dollar amount (in millions) of regulatory costs incurred by the firm due to EPA enforcement actions, including fines and cleanup costs. The latter is defined only for firm-years with at least one enforcement action. *Seller (Pollutive)* is an indicator that equals one if a firm divests a pollutive plant during the sample period. *Post* is an indicator that equals one in the years following the divestiture. *Firm Char* includes *Q*, *Leverage*, *Cash Holdings*, and *Tangibility*. All variable definitions appear in the Appendix. In each panel, we report results from generalized difference-in-difference (GDID) regressions in columns (1) to (3) and (5) to (7), and from stacked regressions in columns (4) and (8). In the stacked regressions, all fixed effects are interacted with cohort indicators where a cohort includes all divesting firms sharing the same event year and their matched never-divesting firms. Standard errors are reported in parentheses and clustered by firm. For the Poisson regressions, we report pseudo R^2s. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Changes in ESG Ratings

Dep. Var.:	*Overall CSR Scores*				*Environment Scores*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Seller (Pollutive) × *Post*	0.461**	0.302*	0.302*	0.341*	0.385***	0.234***	0.234***	0.245***
	(0.187)	(0.178)	(0.180)	(0.187)	(0.087)	(0.086)	(0.087)	(0.091)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes				Yes			
Industry-Year FE		Yes	Yes	Yes		Yes	Yes	Yes
Firm Char			Yes	Yes			Yes	Yes
Method	GDID	GDID	GDID	Stacked	GDID	GDID	GDID	Stacked
Observations	29,683	29,536	29,273	133,621	29,683	29,536	29,273	133,621
R^2	0.672	0.709	0.709	0.710	0.574	0.630	0.630	0.621

(*Continued*)

Table XI—*Continued*

Panel B: Changes in Enforcement Costs

Dep. Var.:	*Enforcement Action*				*Enforcement Cost*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Seller (Pollutive) × *Post*	−0.048***	−0.048***	−0.050***	−0.073***	−2.140***	−2.708***	−3.332***	−4.376***
	(0.012)	(0.013)	(0.013)	(0.018)	(0.695)	(0.676)	(1.016)	(1.033)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes				Yes			
Industry-Year FE		Yes	Yes	Yes		Yes	Yes	Yes
Firm Char			Yes	Yes			Yes	Yes
Method	GDID	GDID	GDID	Stacked	GDID	GDID	GDID	Stacked
Observations	18,620	18,333	17,129	129,439	7,261	5,924	5,495	52,347
R^2	0.283	0.314	0.320	0.289	0.701	0.787	0.815	0.876

regressions. The sample includes all firms with available ESG scores from the KLD database.

We find that sellers of pollutive plants experience a significant improvement in their ESG ratings following divestitures. Based on the estimates in column (3), sellers' overall ESG scores increase by approximately 0.34 relative to nonsellers, a substantial change compared to the sample mean of 0.33. Furthermore, the divestment of pollutive plants is associated with a significant improvement in sellers' environmental scores. The estimates in column (7) of Panel A suggest that sellers' environmental scores increase by approximately 0.23, or 160% of the sample mean. We obtain similar estimates in stacked regressions.[12]

Panels C and D of Figure 5 explore the dynamics of ESG ratings in generalized DID regressions and stacked regressions, respectively. The figure shows an increase in sellers' ESG ratings following divestitures without any noticeable preevent trends.

In Panel B of Table XI, we investigate gains in regulatory compliance costs from divesting pollutive assets. Specifically, we analyze changes in the likelihood of EPA violations and in compliance costs following the divestitures of pollutive plants. We estimate equation (4) with two dependent variables. In columns (1) through (4), the dependent variable is an indicator variable that equals one if the company receives an enforcement action and zero otherwise (*Enforcement Action*). In these analyses, the sample includes publicly traded firms that own TRI plants since nonowners are not subject to EPA regulation. In columns (5) through (8), the dependent variable is the dollar value of EPA enforcement costs (*Enforcement Cost*). Given that *Enforcement Cost* follows a skewed distribution, we use a Poisson regression to estimate its changes around divestitures. In these analyses, the sample includes firm-year observations with at least one enforcement action because enforcement costs are undefined absent enforcement actions.

We find that pollutive plant divestitures are associated with significant reductions in sellers' enforcement actions and costs. The effects are economically large. Based on column (3), following the divestment of pollutive plants, sellers are roughly 5 percentage points less likely to receive an EPA enforcement action. This decline is on par with the sample standard deviation of 7 percentage points. Moreover, the estimates suggest that divestment eliminates the majority of sellers' enforcement costs. Based on column (7), following divestitures, the average enforcement costs of the sellers drop to roughly 3.6% of their original level ($e^{-3.33}$)—an average decline of \$0.1 million in enforcement costs. These results provide evidence that sellers of pollutive plants gain from increasing their compliance with environmental regulations and reducing the costs associated with enforcement actions.

Panels E and F of Figure 5 explore the dynamics of enforcement actions in generalized DID and stacked regressions, respectively. The figure shows a

[12] In Table IA.VI, we consider alternative sources of ESG ratings, such as those provided by Refinitive and MSCI, and find similar results.

decline in sellers' enforcement actions following divestitures without any noticeable preevent trends.

Both anecdotal evidence and academic research suggest that EPA enforcement tends to target heavy emitters and larger firms (Becker, 2005). Thus, the decline in enforcement costs following divestitures can arise due to not only directly offloading the toxic release of the sold plant, but also to indirect declines in regulatory scrutiny as the parent company becomes less pollutive. In Table IA.VII, we separately estimate changes in regulatory costs of unsold plants, and find that they decline significantly following the divestment of peer plants. This finding suggests that regulatory scrutiny also declines for unsold assets following the sale of pollutive plants. We note, however, that the decline in regulatory costs may also result from other firm responses, such as enhanced pollution abatement or closure of pollutive plants (see Table II).

Taken together, the results in this subsection suggest that firms gain from divesting pollutive assets. They enjoy improvements in both their ESG ratings and their EPA enforcement costs. These results suggest that divesting pollutive assets in response to environmental pressures carries considerable benefits despite the muted effect on pollution levels.

E. Divestiture Announcement Returns

As sellers obtain various benefits from divesting pollutive assets, it is natural to ask whether shareholders recognize these benefits and adjust their valuations of the divesting firms. To answer this question, we investigate the relationship between deal announcement CARs and the pollution of sold plants.

Since CARs are measured at the deal level, we compute the total amount of pollution and pollution intensity across all plants sold in a given deal. As before, we sort pollution levels into quartiles and regress sellers' CARs on each deal's pollution quartile, controlling for sellers' industry and year fixed effects. We compute CARs relative to both the market model and the Fama-French three-factor model.

Table XII reports the results. Across all measures of abnormal returns and pollution, we observe a significant, positive relation between the level of pollution of the sold plants and announcement returns. The estimates suggest that an interquartile increase in pollution is associated with 3- to 4 percentage point higher CARs. These magnitudes are economically large compared to the sample average CAR of 2.5 percentage points. The results are consistent with investors rewarding firms for divesting their most pollutive assets.

We also investigate the role of positive environmental disclosures in divestiture announcement returns. These tests aim to explore whether a disclosure strategy that emphasizes environmental performance following pollutive asset divestitures affects investors' responses. Table XIII provides estimates from regressions explaining conference call announcement returns. In Panel A, the sample includes all conference calls, and the key independent variable is the interaction term *Positive Env. Disclosure* × *Divest*, which captures the

Table XII

Divestiture Announcement Returns

This table provides estimates from regressions that examine the relation between the pollution from divested plants and sellers' cumulative abnormal returns (CARs) in the three-day window surrounding the divestiture announcement date. The unit of observation is a divestiture deal, and the sample includes all publicly traded sellers. We compute abnormal returns in two ways. First, we subtract the market return from firms' equity returns ("Market" benchmark). Second, we compute the residuals from regressing total returns on the Fama-French three-factor model ("FF" benchmark). We consider two measures of pollution. *Quantity* is the total amount of toxic release generated by all plants sold in the deal in the year preceding the deal. *Intensity* is the ratio of total toxic release to total employment at the sold plants in the year preceding the deal. We sort deals into pollution quartiles ranging from one (least pollutive) to four (most pollutive). All regressions include industry fixed effects and year fixed effects. Standard errors are reported in parentheses and are double-clustered by year and industry. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Benchmark *Past Pollution* Measured By: Dep. Var.: Seller $CAR[-1, +1]$	Market Quantity (1)	Market Intensity (2)	FF Quantity (3)	FF Intensity (4)
Past Pollution (Quartile)	0.010**	0.011**	0.012**	0.013**
	(0.004)	(0.005)	(0.005)	(0.006)
Seller Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	277	246	278	246
R^2	0.307	0.410	0.307	0.429
Model	OLS	OLS	OLS	OLS

incremental announcement returns when the company reports positive environmental progress following the divestment of pollutive assets. The estimates suggest that disclosing environmental progress following the sale of pollutive assets leads to an increase in shareholder value of around 0.5 percentage points. In Panel B, we restrict the sample to conference calls that occurred during and immediately after the year of a pollutive plant divestiture. The key independent variable is *Positive Env. Disclosure*, which captures the difference in announcement returns when sellers of pollutive plants report positive environmental progress. The results show that in the subsample of conference calls held after divesting a pollutive plant, equity values increase 0.6 percentage points more when firms advertise their environmental progress compared to divestitures for which firms do not advertise such progress. These results show that advertising the firm's environmental performance after divesting pollutive plants is an effective strategy to increase shareholder value.

We also examine the relative gains from trade between buyers and sellers. If firms with a comparative advantage in operating and owning pollutive plants are relatively scarce, we would expect them to have more bargaining power and consequently capture a higher share of the gains when they purchase more pollutive assets. In contrast, sellers may capture a greater share of the gains if the technology or production capacity of their plants is in high demand.

We measure the relative gains of asset buyers and sellers using the differential changes in their market value of equity in the three-day window

Table XIII

Conference Call Announcement Returns

This table provides estimates from regressions explaining conference call announcement returns. The unit of analysis is a conference call. The dependent variable is the cumulative abnormal return during the three-day window centered on a conference call. *Positive Env. Disclosure* is an indicator that equals one if the firm reports positive environmental progress during its earnings conference call. *Divest* is an indicator that equals one if the firm divested pollutive plants in the current or previous year. In Panel A, the sample includes all conference calls, and the key independent variable is the interaction *Positive Env. Disclosure* × *Divest*, which captures the difference in announcement returns when the company reports positive environmental progress following the divestment of pollutive assets. In Panel B, the sample only includes conference calls following the divestment of pollutive assets, and the key independent variable is *Positive Env. Disclosure*, which captures the difference in announcement returns when sellers report positive environmental progress. Standard errors are reported in parentheses and clustered by industry. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Full Conference Calls Sample

Benchmark	Market		FF	
Dep. Var.: $CAR[-1, +1]$	(1)	(2)	(3)	(4)
Positive Env. Disclosure × *Divest*	0.005**	0.005*	0.005*	0.004
	(0.002)	(0.003)	(0.002)	(0.003)
Positive Env. Disclosure	0.000	0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Divest	−0.001	−0.000	−0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Industry FE		Yes		Yes
Year FE		Yes		Yes
Observations	174,531	174,531	174,531	174,531
R^2	0.000	0.002	0.000	0.001

Panel B: Conference Calls Following Divestment

Benchmark	Market	FF
Dep. Var.: $CAR[-1, +1]$	(1)	(2)
Positive Env. Disclosure	0.006**	0.006**
	(0.002)	(0.002)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Observations	2,144	2,144
R^2	0.030	0.030

around deal announcement. Higher values of this measure indicate that the buyer captures a higher dollar amount gain in equity value compared to the seller. As outlined in Section I.G, the gain in market value is computed by multiplying the sum of the buyer's and seller's market values of equity by their respective deal announcement returns (i.e., *CAR[−1, +1]*). We partition all of the divestiture deals into quartiles based on the pollution levels of the sold plants, in terms of both total emission quantity and emission intensity. We then compute the differential gains from trade for buyers relative to sellers

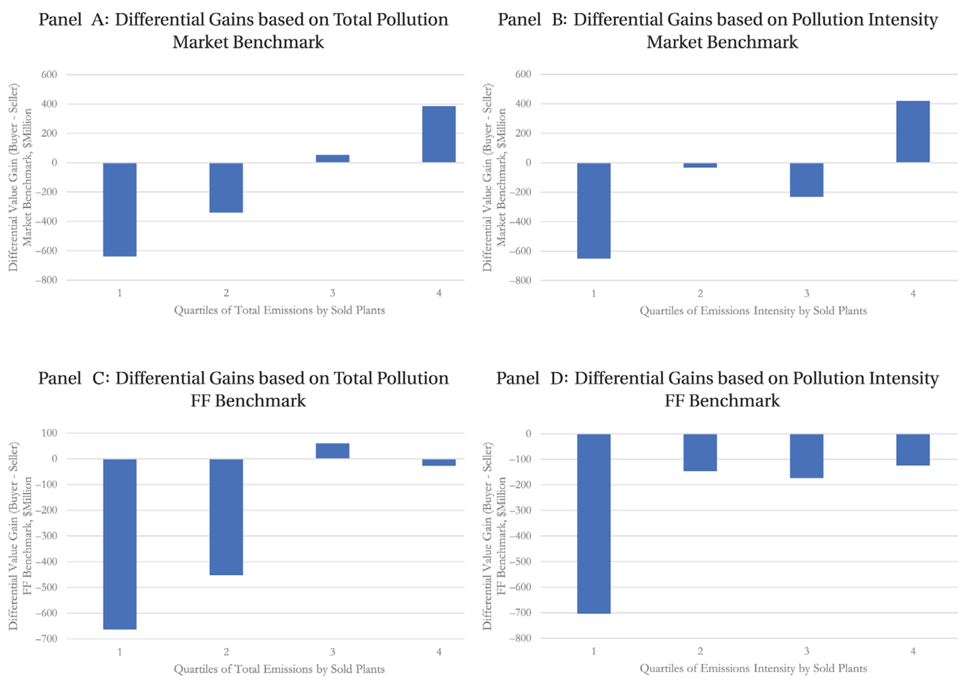

Figure 6. Relative gains from divesting pollutive plants. This figure presents the difference in market value gains between buyers and sellers of pollutive plants around deal announcement (*Buyer* − *Seller*). Market value gains are given as the product of a firm's market capitalization and its $CAR[-1, +1]$ around the deal announcement. Market capitalization is the product of a firm's shares outstanding and share price at the end of the year prior to the deal announcement. $CAR[-1, +1]$ represents cumulative abnormal equity returns during the three days surrounding the deal's announcement date. In Panels A and B, we calculate abnormal returns based on the market model. In Panels C and D, we use the Fama-French three-factor model. We consider two measures of pollution, the total quantity of emissions and emission intensity, which scales total emissions by employment at the plant level. All variable definitions appear in the Appendix. (Color figure can be viewed at wileyonlinelibrary.com)

for deals in each pollution quartile. Note that this analysis requires that both the buyers and the sellers be public firms, which reduces the sample size to just around 100 deals.

Figure 6 reports the results. Panels A and B plot the relative gains from trade based on the market model, and Panels C and D plot the relative gains based on the Fama-French three-factor model. The main takeaways are twofold. First, the relative gains (buyer − seller) are generally negative, suggesting that sellers earn higher market value growth upon deal announcement compared to buyers. This result is broadly consistent with the findings in the M&A literature. Second, and more importantly, the relative gains tilt toward the buyers when the sold assets are more pollutive.

These effects are economically nontrivial. Based on the market model, buyers capture roughly \$400 million higher value gains than sellers in divestitures involving plants in the highest pollution quartile. In contrast, buyers capture \$600 million to \$700 million lower gains than sellers for deals involving plants in the lowest pollution quartile. These results suggest that buyers of the most pollutive plants possess unique advantages in operating and owning those assets. As shown in Table V, these advantages include exposure to weaker environmental pressures. We note, however, that the evidence is based on the limited sample of public-to-public divestitures. To the extent that private firms' advantages cannot be gauged through market-based metrics, we may be underestimating buyers' relative gains from trading pollutive assets.

Overall, the evidence points to significant gains from trading pollutive assets. These gains can arise if the reallocation of pollutive assets through the real asset market caters both to investors with stronger ESG preferences, who gravitate toward green assets, and to those with weaker ESG preferences, who are more likely to hold brown assets (e.g., Heinkel, Kraus, and Zechner (2001), Pástor, Stambaugh, and Taylor (2021), Piccolo, Schneemeier, and Bisceglia (2022)).

V. Robustness and Extensions

A. Divestitures of Nonpollutive Assets

In this subsection, we provide estimates from tests that focus on the divestment of nonpollutive assets. These analyses aim to alleviate concerns that our estimates capture generic effects of divestitures, such as reductions in the scale of operations, capital influx/reallocation, or changes in production inputs, rather than effects specific to environmental pressures and the divestment of pollutive plants. Our logic is simple. If our results are driven by forces common to all divestitures rather than those of pollutive assets, the findings should be similar for divestitures of pollutive and nonpollutive assets. However, if our findings capture the unique consequences of divesting pollutive assets, we expect the effects not to be present for divestitures of nonpollutive assets.

Table XIV reestimates the previous analyses for divestitures of nonpollutive assets. Specifically, we estimate

$$Y_{f,t} = \beta Seller\,(NonPollutive)_f \times Post_{f,t} + \gamma \cdot \mathbf{X}_{f,t} + \theta_f + \tau_t + \nu_{f,t}, \tag{5}$$

where $Seller\,(NonPollutive)_f$ equals one if firm f divests any nonpollutive assets during the sample period, and zero otherwise. In these analyses, we use a firm-year panel that includes all observations for publicly traded firms, except those that sold TRI plants.

Panel A compares buyers' and sellers' exposures to environmental pressures. Panel B investigates the existence of business ties between buyers and sellers. Panel C explores environmental disclosures in earnings conference calls. Panel D traces changes in sellers' ESG ratings around divestitures of nonpollutive plants. Panel E studies sellers' enforcement actions and costs.

Across all of these analyses, we do not find similar effects following divestitures of nonpollutive assets. More specifically, we do not find that buyers face significantly less environmental pressures compared to sellers of nonpollu-

Table XIV

Divestitures of Nonpollutive Plants

This table reestimates the previous analyses for divestitures of nonpollutive plants. Nonpollutive plants are plants that are not reported in the Toxic Release Inventory Program of the U.S. Environmental Protection Agency. Panel A compares buyers' and sellers' exposures to environmental pressures. Panel B investigates the existence of business ties between buyers and sellers of nonpollutive plants. Panel C explores environmental disclosures in earnings conference calls. Panel D traces changes in sellers' ESG ratings around divestitures of nonpollutive plants. Panel E studies sellers' enforcement actions and costs. The specifications are similar to those in the corresponding analyses of pollutive asset divestitures. All variable definitions appear in the Appendix. Standard errors are reported in parentheses and clustered by firm. For the Poisson regressions, we report pseudo R^2s. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Environmental Pressures of Sellers and Buyers

Pressure Measure:	*Public*	*Rated*	*Pension Holdings*	*Democratic HQ*	*Env. Event*	*Pressure Index*
	(1)	(2)	(3)	(4)	(5)	(6)
Buyer	−0.000	0.011***	−0.000	0.019***	−0.019***	0.001
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Observations	89,994	89,994	89,994	63,049	63,284	89,994
R^2	0.000	0.000	0.000	0.000	0.002	0.000

Panel B: Business Ties

Dep. Var.:	*Buyer (NonPollutive)*	*Develop New Relationship*
	(1)	(2)
Operationally Related	−0.010	
	(0.014)	
Buyer of Nonpollutive Assets		0.003
		(0.002)
Matched Group FE	Yes	Yes
Observations	265,003	265,003
R^2	0.003	0.207

Panel C: Environmental Disclosures in Earnings Conference Calls

Dep. Var.:	*Positive Env Disclosure*			*Negative Env Disclosure*		
	(1)	(2)	(3)	(4)	(5)	(6)
Seller (NonPollutive) × *Post*	−0.000	−0.000	0.000	0.011**	0.009**	0.010**
	(0.007)	(0.007)	(0.007)	(0.005)	(0.004)	(0.005)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes			Yes		
Industry-Year FE		Yes	Yes		Yes	Yes
Firm Char			Yes			Yes
Observations	37,816	37,689	33,815	37,816	37,689	33,815
R^2	0.466	0.498	0.520	0.660	0.689	0.711

(Continued)

Table XIV—*Continued*

Panel D: ESG Ratings

Dep. Var.:	*Overall CSR Scores*			*Environment Scores*		
	(1)	(2)	(3)	(4)	(5)	(6)
Seller (NonPollutive) × Post	0.068	0.050	0.047	−0.003	−0.001	−0.001
	(0.062)	(0.062)	(0.063)	(0.029)	(0.028)	(0.029)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes			Yes		
Industry-Year FE		Yes	Yes		Yes	Yes
Firm Char			Yes			Yes
Observations	29,687	29,539	29,276	29,687	29,539	29,276
R^2	0.670	0.708	0.708	0.574	0.630	0.631

Panel E: EPA Regulatory Enforcement

Dep. Var.:	*Enforcement Action*			*Enforcement Cost*		
	(1)	(2)	(3)	(4)	(5)	(6)
Seller (NonPollutive) × Post	−0.011	−0.009	−0.010	0.149	0.819	1.246
	(0.008)	(0.008)	(0.008)	(0.791)	(1.095)	(1.100)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes			Yes		
Industry-Year FE		Yes	Yes		Yes	Yes
Firm Char			Yes			Yes
Observations	17,393	17,041	15,916	6,698	5,568	5,188
R^2	0.280	0.314	0.321	0.692	0.776	0.801

tive plants (Panel A). Sellers and buyers of nonpollutive assets are also not more likely to have preexiting business ties or to develop new ties compared to matched pairs of sellers and pseudobuyers (Panel B). Sellers are not more likely to discuss their environmental progress in earnings conference calls compared to nonsellers (Panel C), and they do not experience significant changes in their ESG scores (Panel D) or EPA enforcement costs (Panel E) compared to nonsellers.

Overall, the results suggest the documented benefits and effects are specific to divesting pollutive assets and are unlikely driven by mechanical changes common across all divestitures.

B. Alternative Explanations

In this section, we discuss several alternative explanations for our findings. One alternative interpretation of our findings is that firms divest pollutive assets to retire obsolete plants. Under this view, divestitures can reallocate capital toward newer technology through creative destruction, with the divested plants gradually becoming obsolete. Our findings that pollution levels do not decline postdivestiture are consistent with the obsolescence view—firms are unlikely to invest in pollution abatement efforts at plants being retired.

To test this idea, we construct both an ex ante measure and an ex post measure of obsolescence. Ex ante, before being divested, obsolete plants should experience a decline in productivity growth rates. Ex post, after being divested, obsolete plants should have lower survival rates compared to nondivested plants.

In generalized DID and stacked regressions presented in Table IA.VIII, we do not find significant differences in predivestiture sales growth rates between divested and nondivested plants. In particular, sales growth rates are indistinguishable across divested and nondivested plants over each of the five years prior to being divested. Furthermore, in Figure IA.3, we compare postdivestiture Kaplan-Meier survival rates across divested and matched never-divested plants (within the same NAICS3 industry and state) and find that divested plants do not have lower survival rates than never-divested plants. Together, these findings are inconsistent with the view that sellers choose to divest obsolete plants.

In Table IA.IX, we also investigate whether divestitures of pollutive plants coincide with the acquisition of new plants. The estimates suggest that firms are less likely to acquire new plants after divesting pollutive plants. This result holds only for divestitures of pollutive assets, and is not a general feature of divesting nonpollutive plants. As such, our findings are less consistent with the view that divestitures of pollutive assets reflect creative destruction, whereby firms divest pollutive assets to reallocate capital to new and potentially greener plants.

We note, however, that it is possible that pressuring firms to divest pollutive plants will lead them to build new production capacity that is greener. Furthermore, pushing for the sale of pollutive plants may drive down the price of such assets, ultimately reducing their supply in the market through pricing equilibrium effects. The evidence that divestitures are not correlated with the introduction of new plants or with shorter survival rates of pollutive plants does not support this possibility. Nevertheless, the growing trend to divest pollutive assets in more recent years can generate long-term effects that we cannot yet observe during our sample period.

VI. Conclusion

We study the real asset market for industrial pollution. In a sample of 888 divestitures of pollutive plants over the period 2000 to 2020, we find that chemical-by-chemical total and scaled toxic emissions, as well as pollution abatement efforts, do not materially change at divested plants. The estimates of pollution and abatement changes are statistically indistinguishable from zero, persist across different test windows, and remain largely unchanged after the inclusion of alternating sets of fixed effects. They also remain unchanged after weighing toxic release levels by the toxicity of each chemical, in collapsed plant-year panel regressions, and in stacked regressions that consider potential biases due to heterogeneous dynamic treatment effects.

We explore the determinants, attributes, and consequences of pollutive plant divestitures, and provide several key findings. First, firms divest pollutive plants in response to environmental pressures from their stakeholders. While the sellers of pollutive plants tend to be firms that face strong environmental pressures, the buyers of pollutive plants face weaker environmental pressures. They tend to be private, non-ESG-rated firms, firms with relatively lower pension fund ownership, firms headquartered in Republican-leaning counties, and firms that have not experienced environmental risk incidents.

Second, firms are more likely to divest pollutive plants in response to environmental pressures when their organizational and ownership structures are more complex. This evidence suggests that information frictions play a role in the divestment of pollutive plants, providing indirect evidence for misalignment between corporate managers and their stakeholders. Nevertheless, after divesting pollutive plants, the sellers advertise their environmental progress in conference calls with investors and analysts.

Third, the buyers of pollutive plants tend to have preexisting business ties with the sellers or to develop new ties following the divestment of pollutive plants. These findings suggest that divestitures of pollutive plants reflect a cosmetic redrawing of the firm's boundaries that exploits the failure of environmental ratings to account for scope-3 toxic emissions along the firm's entire value chain.

Lastly, there are considerable gains from trading pollutive assets. The sellers gain higher ESG and environmental ratings and eliminate the majority of their environmental regulatory compliance costs. Furthermore, sellers' announcement returns and the relative value gains captured by the buyers are higher for divestitures of more pollutive assets.

Overall, the evidence indicates that the value gains from divesting pollutive assets arise through a combination of several nonmutually exclusive sources, including declines in regulatory costs and information acquisition costs by stakeholders, as well as a reallocation of pollutive assets away from investors with stronger prosocial preferences and into the hands of those with weaker prosocial preferences. Assessing the relative importance of each of these channels, however, requires more structure, and thus we leave this for future research.

Taken together, our findings suggest that regulators and rating agencies reward the divestment of pollutive assets, even though these divestitures reflect only a cosmetic redrawing of the firm's boundaries without any real effects on abatement efforts or overall pollution levels. This evidence is consistent with a greenwashing strategy whereby firms exploit information frictions to respond to environmental pressures through cosmetic divestitures. As such, our findings provide novel evidence on the role of the real asset market in firms' greenwashing strategies.

Initial submission: February 15, 2023; Accepted: March 15, 2024
Editors: Antoinette Schoar, Urban Jermann, Leonid Kogan, Jonathan Lewellen, and Thomas Philippon

Appendix: Variable Definitions

Plant-Chemical-Level Variables:

- *Total Pollution*: The amount of total toxic releases
- *Pollution Intensity*: Total toxic releases divided by the cumulative production ratio
- #*Source Reduction*: The total number of source reduction activities
- %*Recycling*: The percentage of produced toxic chemicals reduced through recycling
- %*Recovery*: The percentage of produced toxic chemicals reduced through energy recovery
- %*Treatment*: The percentage of produced toxic chemicals reduced through treatment

Plant-Level Variables:

- *Total Pollution*: The total amount of toxic releases
- *Pollution Intensity*: Total toxic releases divided by the number of employees
- *RSEI Hazard*: The toxicity-weighted pollution amount
- *RSEI Score*: A value that accounts for toxic release amount, modeled population exposure, and the chemical's toxicity.

Firm-Level Variables:

- *Public*: A dummy variable indicating whether a firm is public
- *Rated*: A dummy variable indicating whether a firm is rated by KLD
- *Pension Holdings*: A dummy variable indicating whether a firm has Pension Holdings above the sample average
- *Env. Event*: A dummy variable indicating whether the firm experiences an environmental risk incident
- *Democratic HQ*: A dummy variable indicating whether the company is headquartered in a Democratic-leaning county (i.e., where the majority of the county's votes went to a Democratic presidential candidate in the most recent presidential elections).
- *Pressure Index*: The average of *Public*, *Rated*, *Pension Holdings*, *Env. Event*, and *Democratic HQ*
- #*Segments*: The number of business segments
- #*Industries*: The number of NAICS3 industries that the firm operates in
- #*Subsidiaries*: The total number of subsidiaries owned by the firm
- #*Layers*: The number of organization layers by direct ownership
- %*Blockholders*: The total percentage of shares owned by blockholders (each with $\geq$5%)
- *CSR Score* (KLD): Net strengths and concerns across six dimensions in KLD

- *Env. Score* (KLD): Net strengths and concerns of the KLD environmental dimension
- *Q*: $(at - ceq + csho * prcc_f)/at$
- *Leverage*: $(dlc + dltt)/(dlc + dltt + ceq)$
- *Cash Holdings*: $Cash/at$
- *Tangibility*: $PPENT/at$
- *Enforcement Action*: A dummy variable indicating whether a firm has experienced a regulatory enforcement event
- *Enforcement Cost* (in $M): The total dollar amount of regulatory enforcement costs
- *Positive Env Disclosure*: Firm management discusses improvement in the firm's environmental performance during conference calls in the given year
- *Negative Env Disclosure*: Firm management discusses deterioration in the firm's environmental performance during conference calls in the given year
- *Operationally Related*: A dummy variable indicating whether a firm has been a supply chain or joint venture partner with the seller in the past
- *Develop New Relationship*: A dummy variable indicating whether a firm is developing a new supply chain or joint venture relation with the seller

REFERENCES

Akey, Pat, and Ian Appel, 2019, Environmental externalities of activism, Working paper.

Akey, Pat, and Ian Appel, 2021, The limits of limited liability: Evidence from industrial pollution, *Journal of Finance* 76, 5–55.

Akey, Pat, Stefan Lewellen, Inessa Liskovich, and Christoph Schiller, 2021, Hacking corporate reputations, Rotman School of Management Working Paper 3143740.

Alberini, Anna, and David Austin, 2002, Accidents waiting to happen: Liability policy and toxic pollution releases, *Review of Economics and Statistics* 84, 729–741.

Albuquerque, Rui, Yrjo Koskinen, Shuai Yang, and Chendi Zhang, 2020, Resiliency of environmental and social stocks: An analysis of the exogenous COVID-19 market crash, *Review of Corporate Finance Studies* 9, 593–621.

Allen, Jeffrey W., and Gordon M. Phillips, 2000, Corporate equity ownership, strategic alliances, and product market relationships, *Journal of Finance* 55, 2791–2815.

Almazan, Andres, and Javier Suarez, 2003, Entrenchment and severance pay in optimal governance structures, *Journal of Finance* 58, 519–547.

Arcot, Sridhar, Nickolay Gantchev, and Merih Sevilir, 2020, Divest to acquire, Kelley School of Business Research Paper 2020-63.

Athey, Susan, and Guido W. Imbens, 2022, Design-based analysis in difference-in-differences settings with staggered adoption, *Journal of Econometrics* 226, 62–79.

Baker, Andrew C., David F. Larcker, and Charles C. Y. Wang, 2022, How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics* 144, 370–395.

Barber, Brad M., Adair Morse, and Ayako Yasuda, 2021, Impact investing, *Journal of Financial Economics* 139, 162–185.

Barko, Tamas, Martijn Cremers, and Luc Renneboog, 2022, Shareholder engagement on environmental, social, and governance performance, *Journal of Business Ethics* 180, 777–812.

Bates, Thomas W., 2005, Asset sales, investment opportunities, and the use of proceeds, *Journal of Finance* 60, 105–135.

Becker, Randy A., 2005, Air pollution abatement costs under the Clean Air Act: Evidence from the PACE survey, *Journal of Environmental Economics and Management* 50, 144–169.

Beland, Louis-Philippe, and Vincent Boucher, 2015, Polluting politics, *Economics Letters* 137, 176–181.

Bellon, Aymeric, 2021, Fresh start or fresh water: The impact of environmental lender liability, Jacobs Levy Equity Management Center for Quantitative Financial Research Paper.

Bena, Jan, and Kai Li, 2014, Corporate innovations and mergers and acquisitions, *Journal of Finance* 69, 1923–1960.

Berg, Florian, Julian F. Koelbel, and Roberto Rigobon, 2022, Aggregate confusion: The divergence of ESG ratings, *Review of Finance* 26, 1315–1344.

Bisetti, Emilio, Stefan Lewellen, Arkodipta Sarkar, and Xiao Zhao, 2022, Smokestacks and the swamp, Working paper.

Bloom, Howard S., 1995, Minimum detectable effects: A simple way to report the statistical power of experimental designs, *Evaluation Review* 19, 547–556.

Bochkay, Khrystyna, Seungju Choi, and Jeffrey Hales, 2022, Credible disclosure or mere puffery? The real effects of adopting voluntary ESG disclosure standards, Working paper.

Bolton, Patrick, and Marcin Kacperczyk, 2021, Do investors care about carbon risk? *Journal of Financial Economics* 142, 517–549.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess, 2024, Revisiting event-study designs: Robust and efficient estimation, *Review of Economic Studies* 91, 3253–3285.

Broccardo, Eleonora, Oliver Hart, and Luigi Zingales, 2022, Exit versus voice, *Journal of Political Economy* 130, 3101–3145.

Callaway, Brantly, and Pedro H. C. Sant'Anna, 2021, Difference-in-differences with multiple time periods, *Journal of Econometrics* 225, 200–230.

Capron, Laurence, Will Mitchell, and Anand Swaminathan, 2001, Asset divestiture following horizontal acquisitions: A dynamic view, *Strategic Management Journal* 22, 817–844.

Chang, Xin Simba, Kangkang Fu, Tao Li, Lewis Tam, and George Wong, 2021, Corporate environmental liabilities and capital structure, Working paper, Nanyang Technological University.

Chatterji, Aaron K., Rodolphe Durand, David I. Levine, and Samuel Touboul, 2016, Do ratings of firms converge? Implications for managers, investors and strategy researchers, *Strategic Management Journal* 37, 1597–1614.

Coase, R. H., 1937, The nature of the firm, *Economica* 4, 386–405.

Cohen, Lauren, and Dong Lou, 2012, Complicated firms, *Journal of Financial Economics* 104, 383–400.

Cohn, Jonathan B., Zack Liu, and Malcolm I. Wardlaw, 2022, Count (and count-like) data in finance, *Journal of Financial Economics* 146, 529–551.

Cronqvist, Henrik, and Frank Yu, 2017, Shaped by their daughters: Executives, female socialization, and corporate social responsibility, *Journal of Financial Economics* 126, 543–562.

De Chaisemartin, Clément, and Xavier d'Haultfoeuille, 2020, Two-way fixed effects estimators with heterogeneous treatment effects, *American Economic Review* 110, 2964–2996.

Demsetz, Harold, and Kenneth Lehn, 1985, The structure of corporate ownership: Causes and consequences, *Journal of Political Economy* 93, 1155–1177.

Derrien, François, Philipp Krueger, Augustin Landier, and Tianhao Yao, 2021, ESG news, future cash flows, and firm value, Swiss Finance Institute Research Paper 21-84.

Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova, 2019, BERT: Pre-training of deep bidirectional transformers for language understanding, in *North American Chapter of the Association for Computational Linguistics*.

Dimson, Elroy, Oğuzhan Karakaş, and Xi Li, 2015, Active ownership, *Review of Financial Studies* 28, 3225–3268.

Dimson, Elroy, Paul Marsh, and Mike Staunton, 2020, Divergent ESG ratings, *Journal of Portfolio Management* 47, 75–87.

Ding, Wenzhi, Ross Levine, Chen Lin, and Wensi Xie, 2021, Corporate immunity to the COVID-19 pandemic, *Journal of Financial Economics* 141, 802–830.

Duchin, Ran, John G. Matsusaka, and Oguzhan Ozbas, 2010, When are outside directors effective? *Journal of Financial Economics* 96, 195–214.

Duflo, Esther, Michael Greenstone, Rohini Pande, and Nicholas Ryan, 2013, Truth-telling by third-party auditors and the response of polluting firms: Experimental evidence from India, *Quarterly Journal of Economics* 128, 1499–1545.

Dyck, Alexander, Karl V. Lins, Lukas Roth, and Hannes F. Wagner, 2019, Do institutional investors drive corporate social responsibility? International evidence, *Journal of Financial Economics* 131, 693–714.

Edmans, Alex, and Clifford G. Holderness, 2017, Blockholders: A survey of theory and evidence, in Benjamin E. Hermalin, and Michael S. Weisbach, eds.: *The Handbook of the Economics of Corporate Governance* (North-Holland).

Edmans, Alex, Doron Levit, and Jan Schneemeier, 2022, Socially responsible divestment, European Corporate Governance Institute–Finance Working Paper 823.

Fredriksson, Per G., Eric Neumayer, Richard Damania, and Scott Gates, 2005, Environmentalism, democracy, and pollution control, *Journal of Environmental Economics and Management* 49, 343–365.

Gantchev, Nickolay, Mariassunta Giannetti, and Rachel Li, 2019, Does money talk? Market discipline through selloffs and boycotts, European Corporate Governance Institute–Finance Working Paper 634.

Gibson, Rajna, Philipp Krueger, and Peter Steffen Schmidt, 2019, ESG rating disagreement and stock returns, Swiss Finance Institute Research Paper 19-67.

Gillan, Stuart L., Andrew Koch, and Laura T. Starks, 2021, Firms and social responsibility: A review of ESG and CSR research in corporate finance, *Journal of Corporate Finance* 66, 101889.

Goodman-Bacon, Andrew, 2021, Difference-in-differences with variation in treatment timing, *Journal of Econometrics* 225, 254–277.

Gormley, Todd A., and David A. Matsa, 2011, Growing out of trouble? Corporate responses to liability risk, *Review of Financial Studies* 24, 2781–2821.

Green, Daniel, and Boris Vallee, 2022, Can finance save the world? Measurement and effects of coal divestment policies by banks, Working paper.

Harold Mulherin, J., and Audra L. Boone, 2000, Comparing acquisitions and divestitures, *Journal of Corporate Finance* 6, 117–139.

Hart, Oliver, and Luigi Zingales, 2017, Companies should maximize shareholder welfare not market value, *Journal of Law, Finance, and Accounting* 2, 247–274.

Hartzmark, Samuel M., and Abigail B. Sussman, 2019, Do investors value sustainability? A natural experiment examining ranking and fund flows, *Journal of Finance* 74, 2789–2837.

Heath, Davidson, Daniele Macciocchi, Roni Michaely, and Matthew C. Ringgenberg, 2023, Does socially responsible investing change firm behavior? *Review of Finance* 27, 2057–2083.

Heinkel, Robert, Alan Kraus, and Josef Zechner, 2001, The effect of green investment on corporate behavior, *Journal of Financial and Quantitative Analysis* 36, 431–449.

Hoepner, Andreas G. F., Ioannis Oikonomou, Zacharias Sautner, Laura T. Starks, and Xiaoyan Zhou, 2024, ESG shareholder engagement and downside risk, *Review of Finance* 28, 483–510.

Scott Holladay, J., 2016, Exporters and the environment, *Canadian Journal of Economics/Revue canadienne d'économique* 49, 147–172.

Hong, Harrison, G. Andrew Karolyi, and José A. Scheinkman, 2020, Climate finance, *Review of Financial Studies* 33, 1011–1023.

Hong, Harrison, Neng Wang, and Jinqiang Yang, 2021, Welfare consequences of sustainable finance, Technical report, National Bureau of Economic Research.

Imai, Kosuke, and In Song Kim, 2021, On the use of two-way fixed effects regression models for causal inference with panel data, *Political Analysis* 29, 405–415.

Jovanovic, Boyan, and Serguey Braguinsky, 2004, Bidder discounts and target premia in takeovers, *American Economic Review* 94, 46–56.

Kaplan, Steven N., and Michael S. Weisbach, 1992, The success of acquisitions: Evidence from divestitures, *Journal of Finance* 47, 107–138.

Karpoff, Jonathan M., John R. Lott, Jr, and Eric W. Wehrly, 2005, The reputational penalties for environmental violations: Empirical evidence, *Journal of Law and Economics* 48, 653–675.

Krueger, Philipp, Zacharias Sautner, and Laura T. Starks, 2020, The importance of climate risks for institutional investors, *Review of Financial Studies* 33, 1067–1111.

Li, Wei, Qiping Xu, and Qifei Zhu, 2021, CEO hometown favoritism in corporate environmental policies, Working paper.

Li, Xiaoyang, and Yue M. Zhou, 2017, Offshoring pollution while offshoring production? *Strategic Management Journal* 38, 2310–2329.

Lins, Karl V., Henri Servaes, and Ane Tamayo, 2017, Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis, *Journal of Finance* 72, 1785–1824.

Maksimovic, Vojislav, and Gordon Phillips, 2001, The market for corporate assets: Who engages in mergers and asset sales and are there efficiency gains? *Journal of Finance* 56, 2019–2065.

Maksimovic, Vojislav, Gordon Phillips, and Nagpurnanand R. Prabhala, 2011, Post-merger restructuring and the boundaries of the firm, *Journal of Financial Economics* 102, 317–343.

Mavis, Christos P., Nathan P. McNamee, Dimitris Petmezas, and Nickolaos G. Travlos, 2020, Selling to buy: Asset sales and acquisitions, *Journal of Corporate Finance* 62, 101587.

Naaraayanan, S. Lakshmi, Kunal Sachdeva, and Varun Sharma, 2021, The real effects of environmental activist investing, European Corporate Governance Institute–Finance Working Paper 743.

Oehmke, Martin, and Marcus M. Opp, 2022, A theory of socially responsible investment, Swedish House of Finance Research Paper 20-2.

Pástor, L'uboš, Robert F. Stambaugh, and Lucian A. Taylor, 2021, Sustainable investing in equilibrium, *Journal of Financial Economics* 142, 550–571.

Piccolo, Alessio, Jan Schneemeier, and Michele Bisceglia, 2022, Externalities of responsible investments, Working paper.

Schiller, Christoph, 2018, Global supply-chain networks and corporate social responsibility, 13th Annual Mid-Atlantic Research Conference in Finance (MARC) Paper.

Schilling, Melissa A., 2009, Understanding the alliance data, *Strategic Management Journal* 30, 233–260.

Schlingemann, Frederik P., René M. Stulz, and Ralph A. Walkling, 2002, Divestitures and the liquidity of the market for corporate assets, *Journal of Financial Economics* 64, 117–144.

Shapira, Roy, and Luigi Zingales, 2017, Is pollution value-maximizing? The DuPont case, Working Paper 23866, National Bureau of Economic Research.

Shive, Sophie A., and Margaret M. Forster, 2020, Corporate governance and pollution externalities of public and private firms, *Review of Financial Studies* 33, 1296–1330.

Simon, Daniel H., and Jeffrey T. Prince, 2016, The effect of competition on toxic pollution releases, *Journal of Environmental Economics and Management* 79, 40–54.

Stafford, Sarah L., 2002, The effect of punishment on firm compliance with hazardous waste regulations, *Journal of Environmental Economics and Management* 44, 290–308.

Starks, Laura T., Parth Venkat, and Qifei Zhu, 2017, Corporate ESG profiles and investor horizons, Working paper, University of Texas - Austin.

Sun, Liyang, and Sarah Abraham, 2021, Estimating dynamic treatment effects in event studies with heterogeneous treatment effects, *Journal of Econometrics* 225, 175–199.

Xu, Qiping, and Taehyun Kim, 2022, Financial constraints and corporate environmental policies, *Review of Financial Studies* 35, 576–635.

Xu, Qiping, and Eric Zwick, 2024, Tax policy and abnormal investment behavior, *Review of Financial Studies* 37, 2971–3023.

Zaccone, Maria Cristina, and Matteo Pedrini, 2020, ESG factor integration into private equity, *Sustainability* 12, 5725.

Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.