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

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Abstract

This paper studies the asset market for pollutive plants. Firms divest their most pollutive plants following environmental risk incidents. The buyers face weaker environmental pressures, and have supply chain relationships or joint ventures with the sellers. Following these divestitures, total and scaled pollution levels do not decline. The sellers earn higher returns when they sell more pollutive plants, and their ESG ratings increase while their regulatory compliance costs decrease after divesting. Overall, the asset market allows firms to redraw their boundaries in a manner perceived as environmentally friendly without real consequences for pollution levels and with substantial gains from trade.

Keywords: Divestiture, ESG, Pollution, Greenwashing

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1 Introduction

A growing trend in corporate finance, a result of pressures from activists, regulators, and governments, is the divestment of polluting assets. A recent article in the Economist, for example, reports that: "the West's six biggest oil companies have shed $44bn of mostly fossil-fuel assets since the start of 2018."[1] Consistent with this trend, Panel A of Figure 1 shows that the average value of divestitures of polluting assets has increased considerably since 2015.

While this trend reflects mounting concerns about climate change, it has raised the question of how effective such divestment is. On the one hand, Environmental, Social, and Governance (ESG) supporters can point to successful pressures that have encouraged many firms to sell off dirty assets. On the other hand, as a recent article in the *Wall Street Journal* concludes: "Sadly, selling off assets or shares by itself does nothing to save the planet, because someone else bought them."[2] Moreover, as another recent article suggests, the effects on environmental efforts may even be negative: "Divesting can take away the option of engaging high-carbon companies to do better."[3] These views raise concerns that the divestment of polluting assets is a "greenwashing" strategy through which firms convey a false impression that they are more environmentally sound. Indeed, as Panel B of Figure 1 shows, attention to "greenwashing" has risen more than eight-fold since 2004 based on Google Trends.

In this paper, we aim to shed new light on this question by studying the reallocation of industrial pollution through acquisitions and sales of divested assets in the real asset market. Specifically, we examine how pollution levels change around the transfer of ownership, investigate who the buyers and sellers of pollutive assets are, and estimate the gains from trading these assets. Overall, the goal of the analyses is to help unveil the motives and economic forces behind the movement to divest pollution.

[1] "Who buys the dirty energy assets public companies no longer want?" The Economist, February 12th, 2022 edition.

[2] "Why the Sustainable Investment Craze Is Flawed?" by James Mackintosh, *The Wall Street Journal*, January 23rd, 2022.

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

We consider two possibilities. The first possibility is that divestitures of pollutive assets reallocate assets to owners most capable of treating pollution (Jovanovic and Rousseau 2002). Under this view, the divested assets will generate less pollution after the transfer of ownership. The second possibility is that divestitures of pollutive assets respond to external environmental pressures by transferring ownership from firms that face stronger pressures to firms that face weaker pressures (or are better at addressing those pressures). Under this view, divestitures allow sellers to gain from offloading pollutive assets to less scrutinized firms without having a real impact on pollution levels.

To evaluate these possibilities, we compile a novel dataset of 888 divestitures of pollutive industrial plants from 2000 to 2020, and investigate 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, plants' toxic release levels from the Environmental Protection Agency's (EPA) Toxic Release Inventory (TRI) database, plant-level employment data from the National Establishment Time-Series (NETS) database, ESG ratings from Kinder, Lydenberg, and Domini (KLD), Refinitive and MSCI, ESG-related incidents from Factset's RepRisk ESG Business Intelligence database, and supply-chain and joint ventures information from the Compustat Segment, Factset, and SDC databases.

We begin the empirical analyses by examining changes in pollution levels around divestitures. We measure chemical-by-chemical pollution using both the total amount of toxic release and emission intensity, defined as the ratio of toxic release to cumulative chemical production. In difference-in-difference 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-by-plant, chemical-by-year, industry-by-year, and state-by-year fixed effects. These findings continue to hold after weighing toxic release levels by the toxicity of each chemical, in collapsed plant-by-year panel regressions, in regressions estimated separately for divested and never-divested plants, and in stacked regressions that consider potential biases due to heterogeneous dynamic treatment effects (e.g., Gormley and Matsa 2011, Baker et al. 2022). In similar specifications, we also find no difference between pollution abatement efforts at sold and unsold plants.

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. Alternatively, buyers might adjust pollution at other plants upon acquiring new pollutive assets. To evaluate this possibility, we trace the pollution levels of seller and buyers' remaining plants around divestitures. We find that following divestitures, there is no reduction in the pollution levels of sellers and buyers' remaining plants. Therefore, the aggregate pollution across buyers and sellers remains stable post-divestitures. In addition, it is also possible that firms reallocate capital efficiently by divesting pollutive assets that become obsolete. We do not find empirical support for obsolescence or capital reallocation: productivity growth rates and survival rates are similar across sold and unsold plants, and divesting firms are not more likely to acquire new plants.

Taken together, the findings suggest that the allocation of assets resulting from divestitures does not entail reductions in pollution levels, and is unrelated to technological obsolescence or investment in new plants.

If pollution levels do not change around the divestitures of pollutive plants, what determines their reallocation and what are the gains from trading them? In the analyses of the sellers, we provide two key findings. First, firms are more likely to divest an asset if it pollutes more. Our estimates suggest that an inter-quartile change in a plant's total toxic release (from the least pollutive to the most pollutive quartile) leads to an increase of 45% in the likelihood of divestment relative to the average divestment rate in our sample. The same increase in a plant's emission intensity is associated with a 28% relative increase in divestment likelihood.

Second, we show that firms are more likely to divest pollutive assets following ESG risk exposure, particularly exposure to environmental risks. ESG risk exposure is measured based on publicly known, negative incidents related to a firm's business conduct, gathered by RepRisk.[4] Our estimates indicate that the occurrence of environmental risk incidents

[4] These incidents typically involve criticisms and fines related to climate change, greenhouse gas emissions, coal-fired power plants, gas flaring, carbon credits, etc. Gantchev et al. (2019) show that

increases the likelihood of divesting a pollutive asset by 1.3 percentage points, or 92% relative to the sample mean.

Importantly, divestitures of non-pollutive (non-TRI) assets, which do not release toxic substances, are uncorrelated with the occurrence of ESG risk incidents. This finding mitigates concerns about a mechanical relation between ESG risk incidents and divestitures that could be driven by confounding effects unrelated to environmental risks.

In the analyses of the buyers of pollutive assets, we investigate their exposure to public market scrutiny and environmental pressures. We find that, compared to the sellers, the buyers of pollutive plants are 7.9 percentage points more likely to be private, 5.1 percentage points less likely to be covered by ESG ratings, 4.8 percentage points more likely to have not experienced an environmental risk incident prior to the transactions, and 5.8 percentage points more likely to be headquartered in a Republican county. These effects are economically large, representing increases of 5-19% relative to the sample mean, and are nonexistent for divestitures of non-pollutive assets. Overall, they suggest that buyers of pollutive assets face considerably weaker pressures for owning and operating pollutive plants. We find no evidence, however, that the sellers gain from offloading their environmental liabilities to distressed firms that enjoy bankruptcy protection from environmental litigation. On average, the default probabilities of the buyers are lower than those of the sellers.

Combined, these results give rise to a segmenting real asset market equilibrium whereby public firms that face mounting ESG pressures sell their most pollutive assets to firms that face weaker ESG pressures. As such, Our findings identify a mechanism that realigns firms' ownership of pollutive assets with capital investors' dichotomous ESG preferences (e.g., Pástor et al. 2021, Piccolo et al. 2022, Heinkel et al. 2001, among others), and contribute to a related literature on the divestment of brown firms in capital markets by financial institutions and investment funds (Broccardo et al. 2020, Edmans et al. 2022, Green and Vallee 2022).

In the final set of analyses, we investigate the gains from trading pollutive assets.

Reprisk events put pressure on management and influence corporate policies.

We start by exploring the benefits to the sellers. These analyses provide three main results. First, following the divestment of pollutive assets, the ESG ratings of sellers increase by roughly 22% (relative to the sample standard deviation), and the improvement is particularly strong for environmental ratings (27% relative to the sample standard deviation). Second, following divestitures, the likelihood of being hit with an EPA enforcement action drops by about 6 percentage points (a large magnitude compared to a sample mean of 6 percentage points). Moreover, the costs of regulatory enforcement, including fines and cleanup costs, decline by over 70%.

Third, we find that the divested assets are sold to firms that have business ties with the sellers. Specifically, the buyers of divested assets tend to be firms with pre-existing supply chain relationships or joint ventures with the sellers. Such pre-existing connections likely reduce counter-party risk and information asymmetries, allowing sellers to maintain their access to the sold assets. Furthermore, the sellers are also likely to develop additional business relationships with the buyers after the sale, suggesting that the sellers begin transacting with the buyers of their pollutive assets.

Importantly, we show that the changes in ESG ratings, EPA enforcement actions, and buyer-seller business ties are only present following the divestment of pollutive assets, but are nonexistent following the divestment of non-pollutive assets. This result indicates that the benefits from divestitures are unique to the transfer of pollutive assets, and are not mechanical outcomes of any type of divestiture.

Do shareholders recognize the above benefits from offloading pollutive assets? To answer this question, we estimate sellers' cumulative abnormal returns (CAR) around the announcement of divestitures of pollutive assets. We find that the average CAR ranges from 1.6% to 1.8%, depending on the empirical specification, and is statistically significant at conventional levels. Moreover, the average CAR is significantly higher when the divested plant is more pollutive. Our estimates suggest that an inter-quartile increase in pollution is associated with a 3–4 percentage-point increase in the average CAR.

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. We estimate that in the divestitures of the most pollutive plants (top quartile of the sample), buyers earn roughly $400 million higher value gain relative to the sellers. This finding is consistent with buyers' comparative advantage in owning and operating pollutive assets insulated from ESG pressures.

The central contribution of this article 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 sell 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 divestitures. As such, our findings are more consistent with greenwashing, suggesting that ESG rating agencies, environmental regulators, and ESG-minded investors fail to recognize that divestitures of pollutive assets are ineffective conduits to reduce industrial pollution.

A policy implication of our findings is that regulators and ESG ratings should consider Scope 3 pollution, that is, pollution generated by assets along the firm's value chain such as suppliers and strategic partners. This can prevent ESG-rating arbitrage through asset transfers along a firm's value chain.[5]

Overall, our findings extend prior research on (1) industrial pollution, (2) ESG, and (3) divestitures. The literature on industrial pollution studies its determinants, which range from legal liability (e.g., Alberini and Austin 2002, Stafford 2002, Shapira and Zingales 2017, Akey and Appel 2021) to third-party auditors (Duflo et al. 2013), reputational penalties (Karpoff et al. 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 structure (Shive and Forster 2020, and political ideologies (Bisetti et al. 2021, among others). We add to this literature by showing that industrial firms react to scrutinized environmental risks by divesting their pollutive assets in a concerted effort to improve their ESG ratings and lower their regulatory compliance costs.

We also add to the growing literature on ESG (see Hong et al. 2020 and Gillan et al.

[5]Currently, the EPA does not require organizations to quantify scope 3 emissions. See: https://www.epa.gov/climateleadership/ghg-inventory-development-process-and-guidance

2021 for a review). One strand of this literature studies the benefits that better ESG performance helps firms mitigate downside risks (e.g., Lins et al. 2017, Hoepner et al. 2018, Albuquerque et al. 2020, Ding et al. 2021). A second strand of this literature studies ESG monitoring and its effect on corporate ESG performance (e.g., Dimson et al. 2015, Akey and Appel 2019, Dyck et al. 2019, Barko et al. 2021, Heath et al. 2021, Naaraayanan et al. 2021). A third strand of this literature focuses on impact investing, emphasizing the role of ESG performance in capital market allocation (e.g., Starks et al. 2017; Barber et al. 2021; Hartzmark and Sussman 2019; Zaccone and Pedrini 2020; Krueger et al. 2020; Ľuboš Pástor et al. 2021; Bolton and Kacperczyk 2021; Hong et al. 2021). We contribute to this literature by showing that the monitoring of ESG-related incidents pushes firms to divest pollutive assets in an attempt to improve their ESG ratings and enjoy their potential benefits, without fundamental changes to operation and environmental pollution. As such, our evidence complements several recent studies revealing the drawbacks of outstanding ESG rating schemes by showing that ratings from different agencies do not agree with one another, and do not reflect the true ESG initiatives of corporations (Chatterji et al. 2016, Gibson et al. 2019, Dimson et al. 2020, Berg et al. 2020).

Lastly, our paper contributes to the literature on divestitures. Several papers have studied the market for real assets and the resulting efficiency gains and resource allocation (e.g., Mulherin and Boone 2000, Maksimovic and Phillips 2001, Schlingemann et al. 2002, Bates 2005). Other studies have focused on divestitures that follow acquisitions as an ex-post measure of acquisition success (e.g., Kaplan and Weisbach 1992, Capron et al. 2001, Maksimovic et al. 2011, Arcot et al. 2020, Mavis et al. 2020). We add to this literature by documenting the important role of pollution in the divestiture market.

2 Data and Variables

2.1 Toxic Release Inventory (TRI) Data

We obtain data on chemical-by-chemical toxic emissions for each plant from the EPA's Toxic Release Inventory (TRI) Program over the period 2000-2020. Section 313 of the

Emergency Planning and Community Right-to-Know Act (EPCRA), which created the TRI program, requires industrial facilities to disclose the release of toxic chemicals. Toxic chemicals are defined as ones that cause one or more of the following: (a) cancer or other chronic human health effects, (b) significant adverse acute human health effects, and (c) significant adverse environmental effects.[6] The resultant list contains over 600 individually listed chemicals and chemical categories as of 2020, the last year of our data period. Reporting is mandatory if an establishment has at least 10 employees, operates in a specific list of NAICS codes, and emits one or more specified chemicals above a certain quantity threshold.

The TRI Program provides information regarding the level of each type of chemical released by a plant during a given year. It also provides plant address and NAICS industry classification code. We supplement the plant-level toxic release information from TRI with additional facility information from the National Establishment Time-Series (NETS) database using a crosswalk provided in the TRI program. The NETS database provides plant-level longitudinal data, including facility production measures such as the number of employees and the dollar amount of sales.

Using these data, we construct several measures of toxic release. In the main specifications, we study chemical-by-chemical toxic emissions. The benefit of doing so is threefold. First, it facilitates comparing toxic emissions separately for each chemical, thus avoiding comparisons across chemicals whose toxicity and emission consequences can be considerably different. Second, it allows us to include a strict set of fixed effects in the regressions, which include both plant-by-chemical fixed effects and chemical-by-year fixed effects. Third, it allows us to scale a chemical's toxic release by its production ratio, which is a quantity-based measure of output growth that is only available at the chemical level.[7]

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

[7] For chemicals directly used in the production process, the production ratio captures the ratio of $output_t$ relative to $output_{t-1}$. For chemicals that are used as support activities for production, this measure indicates the change in the 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 that are not between $[0, 3]$ are excluded due to apparent errors in the data, and missing observations are replaced with one (Akey and Appel 2021).

Specifically, we construct the variable *Total Release* as the total toxic emission of each chemical for each plant in a given year (Xu and Kim, 2022). We also calculate a measure of a chemical's *Emission Intensity* by dividing each chemical's *Total Release* by its production ratio.

In additional analyses, we consider two sets of alternative measures of pollution. First, we aggregate toxic release levels across all chemicals for a given plant in a given year. This measure captures the aggregate impact of a plant's production activities on the environment and public health. We also calculate a measure of a plant's toxic emission intensity (Copeland and Taylor, 2003; Shapiro and Walker, 2018) as the amount of toxic release per employee (*Release/Emp*).

Second, we use data on the toxicity of each chemical (RSEI) to construct toxicity-weighted measures of toxic release. In particular, we use *RSEI hazard*, a toxicity weighted pound measure of toxic release, and *RSEI Score*, which incorporates both toxicity weight and modeled population exposure, to gauge the impact of each chemical on public health. As before, we also calculate a toxicity weighted measure of emission intensity by dividing each chemical's toxicity weighted toxic release by its production ratio.

In addition to monitoring toxic releases, the EPA also records pollution abatement activities. Appendix A provides an overview of the abatement process. We measure abatement in two ways. The first measure considers source reduction practices, which reduce or eliminate pollutants by modifying the production processes, promoting the use of nontoxic or less toxic substances, etc. To construct this measure, we count the total number of source reduction practices (*#Source Reduction*) across all chemicals in a plant-year based on the EPA's Pollution Prevention (P2) database. The second measure considers post-production waste management activities, which are used to manage pollutants after they were created. To assess plants' engagement in post-production activities, we trace the percentage of total generated toxic waste that is reduced through recycling (*%Recycling*), energy recovery (*%Recovery*), and treatment (*%Treatment*), respectively.

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, which can change over time following incidents such as ownership changes and 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 CRSP and match those names to the names of plant owners.[8]

2.2 Divestitures

We collect data on divestiture transactions completed between 2000 and 2020 from the SDC M&A database. For each transaction, SDC provides the effective date, the names of the buyer and the seller, and the percentage of stakes transferred, among other details. In cases where the buyer or the seller is recorded at the subsidiary firm level, SDC also reports the ultimate parent company's names and CUSIP identifiers. We only retain deals classified as "divestiture" or "spin-off" by SDC. We also require the deal to represent a significant transfer of control rights. In other words, the buyer must own more than 50% of the stake after the transaction. Next, we 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 where the buyer or the seller is a financial company, including private equity firms, banks, investment firms, funds, etc. We also exclude cases where the buyer or the seller is majority-owned by a financial firm.

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

In addition, we collect data on 41,001 divestitures of non-pollutive assets over the

[8] We remove all punctuation marks, delete corporate designators such as "corporation," "company," "inc," or "llc," standardize the most common words to a consistent format, and generate a similarity score between the deduplicated TRI parent names 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 go through the matches to verify whether they are correct.

period 2000–2020. Non-pollutive assets include assets 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 between the effects of divesting pollutive plants and the effects of divesting non-pollutive assets.

2.3 ESG Risk Incidents

The ESG research provider RepRisk compiles data on business-conduct risk by combining machine-learning and human analysis. 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 these events into 28 categories such as pollution, waste management issues, human rights abuses, occupational health issues, child labor, and discrimination in social and employment settings. It also assigns each event into one of three broad categories: "environmental", "social", or "governance."

Using these data, we define an indicator variable *Have ESG Event*, which equals one if RepRisk reports an ESG risk event for a given firm in a given year, and zero otherwise. Similarly, we also define *Have Environmental Event* to be an indicator for a firm having an environment-related risk event in a year. Analogously, *Have Social, Governance Event* is an indicator variable that equals one for a firm with a social or governance issue in a year.

2.4 ESG Ratings

We obtain ESG ratings of U.S. public firms from the Kinder, Lydenberg, and Domini (KLD) database to empirically examine the effects of divestitures on sellers' (parent-level) ESG performance. 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 for the firm. Following Cronqvist and Yu (2017), among others, we create an aggregate *CSR score* by netting the total number of strengths and the total number of weaknesses across all categories. In other words, each strength adds one point while each weakness subtracts one point from the aggregate CSR score. Similar to the RepRisk event measure, we also separately compute the net strength in the environment category and create *Environmental Score* to track firms' environmental ratings. In addition, we also use ESG ratings from the Refinitive and MSCI to argument the KLD data.

2.5 EPA Enforcement Actions and Compliance Costs

In addition to toxic emissions data from the TRI program, the EPA also records government agency investigations and enforcement activities in its comprehensive Enforcement and Compliance History Online (ECHO) database. ECHO provides exact filing dates, detailed violation information, milestone dates, and final enforcement actions for each investigation initiated by the EPA or by state and local agencies. Further, it also reports the dollar amount of federal and local penalties, compliance actions, cost recovery, and supplemental environmental projects. We aggregate these items to evaluate the total legal liability and compliance costs for each case. Using these estimates, we analyze the changes in enforcement actions and compliance costs for sellers of pollutive plants.

2.6 Supply-Chain and Joint Venture Relationships

We examine whether firms with prior business connections are more likely to offload polluting plants to each other, and whether divestitures of pollutive plants lead to the establishment of future business connections. Business connections refer to supply-chain relations and joint venture partnerships. We obtain supply-chain relations data from Factset and Compustat Segment databases. We obtain Information on joint ventures from SDC (see also Allen and Phillips 2000 and Schilling 2009). As explained in Section 6.3, we compile a matched sample of acquirer-target pairs and define a pair to be "operationally related" if the acquirer and the target shared either a supply-chain connection or a joint venture connection in the past.

2.7 Announcement CARs

We compute the cumulative abnormal returns (CARs) around deal announcement for sellers during a 3-day window centered around the announcement date (i.e., $CAR[-1,+1]$).

We define abnormal returns both relative to the market benchmark (*CAR, Market*) and relative to the Fama-French 3-factor benchmark (*CAR, FF*). Data come from CRSP.

We also calculate the differential market value gain between buyers and sellers. This measure aims to evaluate buyers' rent extraction relative to the sellers. 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 during the $[-1,+1]$-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.

2.8 Other Data Sources

We use county-level vote share data compiled by MIT Election Data and Science Lab to compute the share of a county's votes in support of Republican candidates during general presidential elections. We then match this measure to a firm's headquarters location. We use this measure as a proxy for environmental political pressures that firms face. We conjecture that firms face weaker pressures in Republican counties than in Democratic counties.

In addition, we obtain corporate hierarchy data from the National Establishment Time-Series (NETS) database to supplement and cross-reference the information on parent companies from the TRI database. This dataset helps identify the owners of pollutive plants and their "peers," i.e., plants owned by the same parent firm but not divested in a deal. We use these data to trace toxic emissions in peer plants around divestitures.

Lastly, we collect financial data from Compustat to compute several control variables for public firms, including asset size, cash, leverage, market-to-book, and asset tangibility.

3 Empirical Strategy

We provide analyses both at the plant-chemical (or plant) level and the parent-firm level. The plant-chemical-level analyses investigate whether plants generate less pollution after being sold to another firm. The firm-level analyses investigate the determinants and consequences of divesting pollutive plants for the sellers and buyers.

Throughout all the analyses, we consider two test specifications. First, we estimate generalized difference-in-difference (DID) regression specifications using two-way fixed effects. In the plant-chemical-year panel, these include plant-by-chemical, chemical-by-year, state-by-year, and industry-by-year fixed effects. In the firm-year panel, these include firm and industry-by-year fixed effects. Second, we address concerns related to the heterogeneous treatment timing effects in generalized DID regressions by estimating stacked event regressions.[9] To estimate the stacked regressions, we match each treated unit (plant-chemical or firm) with similar, never-treated units, and track both the treated and control units around the event. The combined set of treated and control units sharing the same event year is labeled as a "cohort." We then stack all such cohort groups together to form our testing sample.

3.1 Plant-by-Chemical Analyses

We compile a plant-by-chemical-by-year panel that contains all plants reported in the TRI database. The key variable of interest is *Divested* $\times$ *Post*, which equals one following the sale of a plant through a divestiture, and zero prior to the sale and for all plants that are never sold.

In these analyses, we separately track the emission of each type of chemical from a plant over time. By doing so, we account for the concern that the same weight of different types of chemicals may generate different environmental externalities.

We estimate the following regression:

$$Y_{i,t} = \beta Divested_i \times Post_{i,t} + \alpha_i + \tau_t + \epsilon_{i,t}, \tag{1}$$

where i represents a plant-chemical pair and t represents a year. $Y_{i,t}$ includes total

[9]See: De Chaisemartin and d'Haultfoeuille (2020), Borusyak et al. (2021), Callaway and Sant'Anna (2021), Goodman-Bacon (2021), Imai and Kim (2021), Sun and Abraham (2021), Athey and Imbens (2022), Baker et al. (2022), among others.

release and toxic emission intensity, and pollution abatement activities, including source reduction, the percentage of waste being recycled, recovered, and treated, etc. When estimating the effects for variables with a skewed distribution, such as total quantity of emission, we use the Poisson regression approach (Cohn et al. (2021)). Our regressions include plant-by-chemical fixed effects (α_i) and chemical-by-year fixed effects (τ_t). In more stringent specifications, we control for industry-year interactive fixed effects and state-year interactive fixed effects. These controls help rule out confounding explanations related to industry dynamics, local economic conditions, or state-level policies. Standard errors are clustered by plant.

As mentioned above, we estimate these regressions in generalized difference-in-differences specifications and in stacked regressions. To construct the stacked sample, we match each sold plant to never-sold plants in the same industry (NAICS3) and state. We then estimate Equation (1) on the stacked sample composed of all such cohorts. In the stacked regressions, our control plants are sampled with replacement. We thus interact all our fixed effects with cohort fixed effects, augmenting the regression 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.

3.2 Firm-Level Analyses

The firm-level analyses primarily center around sellers. We construct a sample including all ultimate parent firms of TRI plants. For some analyses where the dependent variable is available only for public firms, we restrict the sample to publicly traded parents. We estimate the following regression:

$$Y_{f,t} = \beta Seller\,(Pollutive)_f \times Post_{f,t} + \gamma \cdot \mathbf{X}_{f,t} + \theta_f + \tau_t + \nu_{f,t}, \qquad (2)$$

where f represents a parent firm and t represents a year. $Y_{f,t}$ includes ESG scores, enforcement actions, enforcement costs, etc. Poisson regressions are used when the dependent variable is highly skewed, such as the amount of enforcement costs. $Seller\,(Pollutive)_f$ equals one if firm f sells any pollutive plant over our sample period, and zero otherwise. $Post_{f,t}$ equals one starting from the year of the transaction. $\mathbf{X}_{f,t}$ represents an array of firm characteristics, including firm size, leverage, profitability, and tangibility. Our estimation 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 plant-chemical-level analyses, we estimate these effects using the generalized difference-in-difference regression method and the stacked regression method. The stacked regression sample is constructed by matching each seller firm to other publicly listed firms who never sold a plant over our sample period that operate in the same industry (NAICS3) at the time of the divestiture of interest. We again control for interactive fixed effects between cohorts and firms as well as industry-by-year fixed effects.

We use the divestiture of non-pollutive assets as a benchmark of comparison, and repeat the seller-level tests above. Specifically, we examine:

$$Y_{f,t} = \beta Seller\,(NonPollutive)_f \times Post_{f,t} + \gamma \cdot \mathbf{X}_{f,t} + \theta_f + \tau_t + \nu_{f,t}, \tag{3}$$

where $Seller\,(NonPollutive)_f$ equals one if firm f sells any non-pollutive asset over our sample period, and zero otherwise. In these analyses, we utilize a firm-year panel that includes all observations for publicly traded firms, except those that sold TRI plants. This filter removes from the control group treated firms that sold pollutive plants.

3.3 Summary Statistics

Table 1 presents summary statistics for the variables used in our paper. Appendix D provides detailed definitions of the variables. Panel A and B provide statistics for the plant-chemical-level sample and plant-level sample. Our sample consists of 37,564 unique plants with 352,938 plant-year observations, and 1,056,361 plant-chemical-year observations. At the plant-chemical level, the distribution of pollution emission is skewed. The average toxic emission of our sample plant-chemical-year is around 16,893 pounds with the median being 483 pounds. On pollution abatement, an average plant-chemical-year adopts about 2 source reduction practices, and the percentage of total generated toxic chemicals reduced through recycling, recovery, and treatment is 24.4%, 8.4%, and 26%, respectively.

Table 1 About Here

Panel C provides information for the firm-level sample. In this sample, the average firm in our sample emits 626 thousand pounds of toxic chemicals, with the median being 22 thousand pounds. Firms included in the KLD rating data on average have a CSR score of 0.32 and environmental score of 0.15. Our sample firms faces around a 7% probability of ESG risk incidents and 4% of environmental risk incidents on average. It also faces a 1% likelihood of being targeted for EPA regulatory enforcement. The associated enforcement cost is about $4 million on average.

Panel D provides statistics for the announcement cumulative abnormal returns (CARs) for the divestiture deals in our sample. The average seller has a CAR around 3%. CARs follow a skewed distribution, as the median value is much lower, less than 1%. Buyers experience a slightly lower announcement return compared to buyers, with the average being 2%.

In Table 2, we compare between the buyers and sellers of pollutive assets in the sample. To start, we look at the public trading status and ESG rating coverage for all buyers and sellers in our sample deals. Relative to the sellers, buyers are 6% less likely to be publicly traded and 5% less likely to have an ESG rating. Buyers are also less likely to have experienced a negative environmental incidence in the current or past year compared to the sellers. Additionally, we note that buyers are more likely to be headquartered in a Republican-leaning county, i.e., counties where the majority votes went to the Republican presidential candidate in the most recent general election. Collectively, these patterns suggest that pollutive assets tend to transfer to firms facing weaker ESG pressures. Next, we restrict the comparison to publicly traded buyers and sellers, for whom detailed information on firm characteristics is available. Interestingly, buyers are significantly smaller than sellers, suggesting that in the sample divestitures of pollutive assets, smaller firms purchase assets from larger ones. Buyers also generate lower quantities of toxic release than sellers and have higher environmental pillar ratings based on the KLD database.

We also compare between buyers' and sellers' leverage ratios and default probabilities. We find that, on average, buyers have lower leverage ratios and default probabilities compared to sellers. These estimates show that our sample divestitures do not transfer assets to heavily-distressed firms. As such, they are less consistent with the possibility that sellers offload their pollution liabilities to distressed firms to gain from limited liability in bankruptcy and default.

TABLE 2 ABOUT HERE

4 Changes in Pollution Around Divestitures

4.1 Pollution at Sold Plants

We examine the changes in plant-level pollution following divestitures by estimating Equation (1) in an annual chemical-by-plant panel. Table 3 presents the results. In Panel A we examine changes in the pollution of sold plants compared to unsold plants in a generalized DID framework, and in Panel B, we compare the changes in pollution generated by sold plants relative to those by never-sold plants using stacked regressions. Given the skewness of the pollution variables, we estimate all the analyses in Poisson regressions. In each panel, columns (1) through (3) report results for total toxic releases and columns (4) through (6) report results for emission intensity. For each regression framework and pollution measure, we impose progressively stringent fixed effects, starting with plant-by-chemical and year-by-chemical fixed effects, then augmenting them with state-by-year and industry-by-year interactive fixed effects. In the stacked regressions, we interact these fixed effects with cohort indicators.

TABLE 3 ABOUT HERE

The estimates across all the specifications in Table 3 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 term *Divested* $\times$ *Post* are positive and statistically insignificant across all the specifications.

We obtain similar results in alternative regression specifications, and report the estimates in Appendix E. In particular, Panels A and B of Table E.1 provide estimates from OLS regressions instead of Poisson regressions. Panels C and D of Table E.1 provide estimates from regressions that aggregate annual toxic releases across all the chemicals in each plant. Lastly, Panels E and F of Table E.1 provide estimates from toxicity-weighted measures of chemical emissions. Across all the analyses, estimated in both generalized DID and stacked regressions, the coefficient estimates on the interaction term *Divested* $\times$ *Post* are never negative and statistically significant, suggesting that pollution levels do not decline following the divestment of pollutive plants.

A limitation of the difference-in-differences estimates is that they obscure the underlying pollution trends in divested and undivested plants, which may diverge in meaningful ways. For instance, it is possible that pollution levels at divested plants do decline, but are offset by parallel declines in pollution at undivested plants. Such parallel declining trends in pollution might arise, for example, if firms sell pollutive plants whose pollution they cannot treat to buyers who can, and keep those pollutive assets whose pollution they can treat.

To investigate this possibility, in Table 4, we separately estimate the changes in emissions at divested plants and at their never-sold matched counterparts in the same state and industry around the divestiture year. Panel A corresponds to divested plants whereas Panel B corresponds to never-divested plants. The estimates in Panels A and B suggest that toxic release levels and intensity do not meaningfully change either at divested plants or at undivested plants following divestitures. As such, these findings suggest that the difference-in-differences results are not driven by parallel declining trends in pollution at divested and undivested plants.

Next, we turn to examine pollution abatement efforts at sold plants. In Table 5, we examine annual pollution abatement efforts at the chemical-plant level, including source reduction (*#Source Reduction*) and post-production waste management (*%Recycling, %Recovery, and %Treatment*). Similar to Table 3, we report results from both generalized DID regressions (Panel A) and stacked regressions (Panel B). The estimates in both panels consistently show insignificant differences between changes in pollution abatement activities across divested and undivested plants following divestitures. The coefficient estimates on the interaction term *Divested* $\times$ *Post* are statistically insignificant at conventional levels and change signs across specifications.

These results shed more light on the findings in Table 3. They imply that plants do not experience meaningful changes in their toxic release levels because they do not materially change their pollution abatement processes.

TABLE 5 ABOUT HERE

Our evidence so far indicates that, on average, buyers of pollutive plants maintain toxic release levels similar to the pre-divestment levels. Thus, divested plants do not become "cleaner" under the new parent company. These results do not support the hypothesis that divestitures serve to transfer pollutive assets to new owners with higher capacity and better technology to abate emissions. Instead, they are consistent with the view that the market for divestitures allows firms to shed dirty assets and reshape their image as low-environmental-impact companies.

4.2 Alternative Explanations

As noted above, it is possible that firms choose to keep plants whose pollution they can treat and divest assets whose pollution they cannot treat. Alternatively, it is also possible for buyers to adjust existing plants' pollution, even though they do not change the pollution at the newly acquired plants. Therefore, the observed no change in the divested plants is insufficient to demonstrate that the overall amount of pollution of buyers and sellers do not respond to the divestitures. To further evaluate this possibility, we trace the pollution levels of sellers and buyers' peer outstanding plants around divestitures. Specifically, for all seller and buyers' outstanding plants (excluding sold plants), we define an indicator variable *Peer* that equals one if their parent company has divested or acquired at least one plant in a given year. We then estimate the changes in toxic release of these peer plants around the divestment transactions.

Table 6 reports the results of these analyses. As before, we report estimates from both generalized DID regressions (Panel A) and stacked regressions (Panel B), in which the unit of analysis is a chemical-plant-year triplet. In this analysis, we construct a stacked sample for each divested peer plant based on the year of the deal. In particular, for each peer plant, we choose never-divested plants in the same industry and state as the control group.

Table 6 About Here

The estimates in Table 6 indicate that total toxic release and toxic release intensity do not decline at the remaining peer plants for buyers and sellers. The coefficients on the interaction term *Peer* $\times$ *Post* are mostly statistically insignificant at conventional levels and switch signs across specifications. These results are inconsistent with the hypothesis that sellers choose to keep plants whose toxic release they can reduce, or buyers adjust pollution at other outstanding plants while acquiring new plants.

Another possible interpretation of our findings is that firms divest pollutive assets to retire obsolete plants. Under this view, divestitures can efficiently reallocate capital towards newer technology through creative destruction, with the divested plants gradually becoming obsolete. Our findings that pollution levels do not decline post-divestiture are consistent with the obsolescence view – firms will unlikely invest in pollution abatement efforts at plants that are being retired.

To test this view, we construct both an ex-ante measure and 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 non-divested plants.

In difference-in-differences and stacked regressions presented in Panel C of Table 6, we do not find significant differences in pre-divestiture sales growth rates between divested and non-divested plants. In particular, sales growth rates are indistinguishable across divested and non-divested plants over each of the five years prior to being divested. In Figure 2, we compare post-divestiture Kaplan-Meier survival rates across divested and matched never-divested plants (within the same NAICS3 industry and state). We find that divested plants do not have lower survival rates than never-divested plants. Combined, these findings are less consistent with the view that sellers choose to divest obsolete plants.

Lastly, in Appendix G we also investigate whether divestitures of pollutive plants coincide with the acquisition of new plants. The estimates in Table G.1 suggest that firms are less likely to acquire new plants after divesting pollutive plants. This result, however, only holds for divestitures of pollutive assets. As such, our findings are less consistent with the view that the divesitures of pollutive assets reflect creative destruction, whereby firms divest pollutive assets to reallocate capital to new plants.

5 Sellers and Buyers of Pollutive Assets

Our results so far suggest that divestitures are not associated with reductions in pollution. If not to reduce pollution, what are the motives behind the divestment of pollutive plants, and who are the sellers and buyers of pollutive assets? We seek to shed light on these questions by examining the determinants of divestitures and the attributes of buyers and sellers. We start by investigating whether highly pollutive plants are more likely to be divested, and whether public attention to a firm's ESG risks triggers selling pollutive plants. We then compare between the attributes of sellers and buyers to examine the comparative advantage of buyers in owning and operating pollutive assets.

5.1 Plant Emission Levels

We start by providing regression estimates of the relation between pollution levels and the likelihood of divestitures. We estimate the regressions in a plant-year panel that keeps observations for a plant only up to the year of its divestiture. We retain all observations related to plants that are never divested in our sample years. The key outcome variable in this analysis is $Divested_{i,t}$, an indicator for whether plant i is divested in year t. We multiply this indicator by 100 so the coefficients directly correspond to the percentage likelihood of a divestiture. A plant's emission level is measured in two ways. First, we compute the total volume of toxic release from the plant during the current and the previous year ($[t-1,t]$). Second, we calculate pollution intensity, which is the ratio of total release volume to the number of employees in the firm over $[t-1,t]$. Due to skewness in the distribution of toxic release, and for ease of interpretation, we group both total toxic release and per-employee toxic release into a quartile index, where 1 represents the lowest pollution level, and 4 represents the highest.

Panel A of Table 7 reports results from this analysis. Columns (1) through (4) present results related to total pollution; columns (5) through (8) present results related to pollution on a per-employee basis. We start by presenting the univariate association between plant pollution and divestment likelihood (columns (1) and (5)). We then add controls in stages. In columns (2) and (6), we include industry and year fixed effects. Industry fixed effects help us compare plants with similar production technologies and year fixed effects help remove macroeconomic dynamics. In columns (3) and (7), we include industry-by-year interactive effects, which allow us to narrow down the comparison to industry-peer plants at the same point in time. Finally, we add state-by-year interactive effects, which help remove effects from state policy or regulatory changes.

Across all measures and specifications, the coefficient estimates on past pollution are positive and statistically significant, suggesting that more pollutive plants are more likely to be sold to another firm. The economic magnitude of the effects is nontrivial. For example, the coefficient estimate in column (4) implies that an inter-quartile increase in pollution volume (moving from quartile 1 to quartile 4) increases the likelihood of the plant being sold by about 0.13 percentage point ($= 0.043 \times 3$). This represents a 45% increase relative to the average likelihood of plant divestitures (0.29 percentage points). Asset pollution intensity generates a similar magnitude, with an inter-quartile increase in pollution intensity associated with about 28% increase in its divestiture likelihood ($= 0.027 \times 3/0.29$).

<u>TABLE 7 ABOUT HERE</u>

5.2 Sellers' ESG Risk Exposures

Next, we examine whether firms are more likely to divest pollutive plants when they face negative ESG media exposure. As an initial proxy, we use the incidence of any negative ESG event as indication of media ESG exposure. In subsequent analyses, we zoom in on events specifically related to environmental risks, and test whether these events motivate firms to divest plants that produce toxic emissions.

Given that ESG exposure is measured at the firm level, we perform this analysis using a firm-year panel. The sample includes all public firms covered by RepRisk, who own at least one TRI plant in our sample period. In other words, we exclude firms that do not have a choice to sell pollutive assets. Again, we track each firm up to the year of its divestiture. We regress *Sell (Pollutive)*, an indicator variable for whether a firm sells a pollutive plant in a year, on indicators for negative ESG exposure in the current or the previous year. As a reminder, *Sell (Pollutive)* is multiplied by 100 so that the coefficients can be interpreted as the percentage likelihood of divestment.

The results are presented in Panel B of Table 7. Columns (1) through (3) report results related to any ESG incidents, and columns (4) through (6) present results related only to environmental risk events. In columns (7) through (9), we include environmental events and non-environmental events (social and governance events) side by side, to compare their influence on firms' propensity to divest assets.

The estimates in columns (1)–(3) suggest that firms facing negative ESG events are more likely to divest pollutive plants. Having an ESG risk event leads to a 0.7 percentage point increase in the likelihood that the firm sells a pollutive plant. Columns (4)-(6) show that the subset of ESG risk incidents tied to environmental risks has a considerably stronger effect on the likelihood of divesting pollutive plants. Column (6) suggests that an environmental risk event increases the likelihood of divestment by 1.3 percentage points. These are nontrivial magnitudes compared to the sample average of having a divestiture of 1.3 percentage points. Importantly, when we simultaneously include environment-related events and non-environment-related events in columns (7)-(9), we find that the effects are concentrated in environmental risk incidents. The coefficient on social and governance issues is small and indistinguishable from zero.

A possible concern is that negative ESG incidents represent inefficient operations or financial difficulties unrelated to pollution levels. Such incidents may push firms to sell assets irrespective of their pollution levels. We test this view by investigating the link between ESG risk incidents and divestitures of non-pollutive assets. The results in Panel C indicate that neither general ESG risk incidents nor environmental risk incidents are associated with an increase in the propensity to divest non-pollutive assets. In fact, the coefficient estimates across all 9 columns in Panel C are negative, albeit statistically insignificant at conventional levels. Lastly, in untabulated tests, we repeat the analyses in the full sample of public firms (and not just owners of TRI plants). We do not find any association between ESG events and the likelihood of divesting non-pollutive assets.

5.3 Buyers of Pollutive Assets

The previous subsections focused on the sellers of pollutive assets, and showed that public ESG pressures often trigger divestitures. A natural question that arises is who the buyers of these assets are, and whether they have a comparative advantage in operating and owning pollutive assets. To answer this question, we investigate whether acquiring firms face weaker environmental pressures. We conjecture that private firms, non-ESG-rated firms, firms that did not experience negative ESG incidents, and firms located in Republican-leaning regions, likely face weaker environmental pressures, and hence may be better situated to acquire and operate pollutive assets.

In particular, compared to publicly listed firms, private firms tend to be subject to less scrutiny and disclosure requirements regarding their environmental impact. For example, in 2010, the Securities and Exchange Commission (SEC) provided guidance regarding public firms' disclosure related to climate change. And, in 2022, the SEC enforced ESG disclosure requirements for investment funds and other investment companies, whose portfolios largely comprise publicly traded firms. In contrast, no regulations impose such disclosure requirements on private firms.

Similarly, firms not rated by any of the ESG rating agencies should also face weaker ESG pressures. Prior studies show that ESG ratings provide signals about firms' sustainability practices, and generate value-relevant responses from investors (see Hartzmark and Sussman 2019; Zaccone and Pedrini 2020; Krueger et al. 2020, among others). As such, unrated firms' cost of capital is less affected by their environmental policies. In addition, media coverage of ESG risk incidents likely also exposes firms to environmental pressures. Indeed, in Section 5.2 we provide evidence that negative ESG incidents push firms to divest pollutive assets. Lastly, political ideology has been shown to exert strong influence on local firms' environmental performance (Bisetti et al. 2021), which we include as another factor capturing the ESG pressure that firms face.

We start the analyses by constructing a deal-by-firm sample that pools together all sellers and buyers involved in divestitures of pollutive assets, and examine whether buyers are more likely than sellers to face weaker ESG pressures. In particular, we create four indicator variables: *Private*, an indicator variable that equals 1 if the firm is private, and 0 if it is public; *Unrated*, an indicator variable that equals 1 if a firm does not have an ESG rating, and 0 otherwise; *No Env. Event*, an indicator variable that equals 1 if the firm does not experience any negative environmental incidents in the year of the transaction or the year before, and 0 otherwise; and *Republican County*, an indicator variable that equals 1 a firm is headquartered in a county where the majority vote share went to a Republican candidate in the most recent general presidential election, and 0 otherwise. We regress each of these variables on the indicator variable *Buyer* in each deal:

$$Y_{k,i} = \beta_0 + \beta_1 \times Buyer_{k,i} + \epsilon_{k,i}, \tag{4}$$

where k indicates a divestiture deal, and i indicates either the buyer or the seller in the deal. Y includes $Buyer_{k,t}$ equals one if firm i is a buyer (instead of a seller) in deal k. In this test, we are interested in β_1. If $\beta_1 > 0$ ($\beta_1 < 0$), buyers likely face stronger (weaker) environmental pressures compared to the sellers.

Table 8 Panel A reports the results for pollutive asset divestitures. We find that relative to the sellers, buyers of pollutive plants are 7.9 percentage points more likely to be private firms (column (1)), 5.1 percentage points less likely to be covered by ESG ratings (column (2)), 4.8 percentage points less likely to experience any negative environmental incident before the transaction (column (3)), and 5.9 percentage points more likely to be headquartered in Republican-leaning counties.[10] These effects are economically large, representing increases of 5-19% relative to the sample averages shown in Table 2. The average across the four indicator variables, *Low Pressure*, delivers a similar estimate at 7.1 percentage points in column (5), corresponding to 11.5% of the sample average. These estimates collectively suggest that high-pressure firms tend to sell their pollutive assets to firms that face weaker environmental pressures.

TABLE 8 ABOUT HERE

In Panel B of Table 8, we repeat the analyses for non-pollutive asset divestitures. Across all five measures of ESG pressures, we do not find any evidence that non-pollutive assets are sold to less scrutinized firms. The contrast between panels A and B suggests that transferring assets into the "dark" domain is a unique feature of pollutive asset divestitures that does not apply universally to divestitures.

6 Gains from Trade

We investigate the potential gains from selling pollutive assets along two dimensions: (1) ESG ratings, and (2) Environmental regulatory compliance costs. We also investigate the existence of business ties between the sellers of the assets and their buyers, which would allow the sellers to maintain access to these assets even after their divestment. These analyses utilize the framework laid out in Equation (2). As a placebo test, we also examine these outcomes for the sellers of non-pollutive assets.

[10]Republican is set to missing for deals with parent headquarter location out of the United States or unavailable in the SDC MA database.

6.1 Sellers' ESG Ratings

Table 9 presents results on the changes in sellers' ESG ratings around the divestitures of pollutive assets. As discussed in Section 3, we provide estimates from two approaches, a generalized difference-in-difference specification and a stacked regression specification.

Table 9 About Here

Our analysis includes all firms with available ESG scores from the KLD database. Panel A reports effects for sellers of pollutive assets, and Panel B examines effects for firms that sell non-pollutive assets. Within each panel, the dependent variable is a firm's overall ESG score in columns (1) through (3), and environment-specific ratings in columns (4) through (6). We find that sellers of pollutive plants experience a significant improvement in their ESG ratings following divestitures. Based on the estimates in column (3) of Panel A, sellers' overall ESG scores increase by around 0.5 relative to non-sellers, a substantial change compared to the sample mean of 0.32 and the sample standard deviation of 2.31. Furthermore, columns (4)–(6) show that divestment of pollutive plants is associated with significant improvement in sellers' environmental scores. The estimates in column (6) of Panel A suggest that sellers' environmental scores increase by around 0.22, or 27% of the sample standard deviation. We obtain similar estimates in stacked regressions. In Appendix F, we compare between the coverage of the different ESG ratings, such as those provided by Refinitive and MSCI, and show that our results are robust to the inclusion of alternative ESG ratings.

Overall, these findings indicate that firms gain higher ESG ratings from divesting pollutive assets. In particular, ESG rating agencies respond to divestitures of pollutive plants by increasing the ESG scores of the sellers.

6.2 Sellers' EPA Enforcement Costs

Next, we investigate potential regulatory gains from divesting pollutive assets. Specifically, We analyze changes in the likelihood of EPA violations and compliance costs following the divestitures of pollutive plants. We estimate Equation (2) with the following two dependent variables: (1) An indicator variable that equals one if the company receives an enforcement action and zero otherwise (*Enforcement Action*), and (2) The dollar value of EPA enforcement costs (*Enforcement Cost*). In this analysis, we focus on publicly traded firms that own TRI plants since non-owners are not subject to EPA regulation.

Table 10 reports the results. As before, Panel A provides the results from generalized DID regressions while Panel B presents results from stacked regressions. In each panel, the first (last) three columns provide estimates of the incidence (cost) of an enforcement action.

TABLE 10 ABOUT HERE

We find that pollutive asset divestitures are associated with significant reductions in sellers' regulatory compliance costs. The effects are economically large. Based on column (3) of Panels A and B, following the divestment of pollutive plants, sellers are roughly 4 to 7 percentage points less likely to receive an EPA enforcement action. This decline is on par with the sample standard deviation of 8 percentage points. Moreover, the estimates in Panel A also show that conditional on an EPA enforcement action, enforcement costs decrease by around \$3–5 million following the divestment of pollutive assets, or roughly 10–15% of the sample standard deviation (30 million). 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.

6.3 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, US Premium Beef acquired 71% of the shares in Farmland National Beef Packing Co (FN) from its joint venture partner Farmland Industries Inc (FI) in 2003. Other deals lead to the start of cooperative relations between the buyer and the seller. For example, Outokumpu Oyj (OO) acquired the heat transfer business of

Lennox International Inc (LI) in 2002, and subsequently formed a joint venture with LI.

Motivated by such real-world examples, we next 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 after the divestiture. Specifically, we test whether firms that have pre-existing business ties with the sellers are more likely to purchase pollutive plants from the sellers. We consider two types of relationships: (1) customer-supplier relations; and (2) joint venture partnerships. We conjecture that the existence of such relationships facilitates the access of the seller to the plant's output even when it is operated by a different parent company, allowing the seller to maintain its current operation 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 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 code *Buyer of Pollutive Plants* to be 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 has started a joint venture prior to the deal. If so, we set the indicator variable *Operationally Related* to be 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 transaction by examining whether the seller is more likely to start a new business relationship with the actual buyer than with pseudo buyers after the year of the deal. This analysis sheds light on whether the divestiture indeed represents a material operational or production change for the seller, or simply reflects a change in the boundary of the firm without material operational shifts.

Panel A of Table 11 reports the results from this analysis. In column (1), we regress the indicator variable *Buyer of Pollutive Plants* on the indicator for shared business relations, *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 34 percent 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.

Table 11 About Here

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

All in all, our findings suggest that following the divestment of pollutive assets, firms enjoy benefits such as an increase in their ESG ratings and a reduction in environmental disciplinary actions and compliance costs. Nevertheless, the assets are reallocated to other industrial firms that maintain customer-supplier relations with the seller or remain connected through joint ventures. As such, our findings indicate that divestitures of pollutive assets convey various benefits to the sellers without giving up their access to those assets.

6.4 Placebo Tests: Sellers of Non-Pollutive Assets

We perform a placebo test examining outcomes for firms selling non-pollutive assets. This comparison helps alleviate concerns that our findings capture firm-level mechanical changes following asset divestitures, such as a reduction in operation scale, an influx of financial resources, or a change in production input. If the results are driven by forces common to all divestitures rather than those of pollutive assets, the effects should show up for both divestitures of pollutive and non-pollutive assets. On the other hand, if our findings capture the unique consequences of divesting pollutive assets, we expect the effects to not be present for divestitures of non-pollutive assets.

Table 12 provides results from the analyses of sellers of non-pollutive assets. Panel A presents the results on sellers' ESG ratings, Panel B reports the results on sellers' enforcement actions and costs, and Panel C provides results on the business ties between buyers and seller. Across the board, We do not find similar effects around divestitures of non-pollutive assets. The sellers of non-pollutive assets do not experience significant changes in their ESG scores or EPA enforcement. In particular, the coefficient estimates on the interaction term *Sell (NonPollutive)* × *Post* are generally small and statistically insignificant. We also do not find that buyers of non-pollutive assets have pre-existing business ties, or develop new ties with the sellers.

TABLE 12 ABOUT HERE

Overall, these estimates suggest that the benefits we documented are specific to divesting pollutive assets and are unlikely driven by mechanical changes common across all divestitures.

6.5 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 the pollution levels into quartiles, and regress sellers' CARs on the pollution quartile for each deal, controlling for sellers' industry fixed effects and year fixed effects.

Table 13 reports the results. Across all definitions of abnormal returns and pollution measures, we observe a significant, positive relation between the level of pollution of the sold plants and the announcement returns. The estimates suggest that an inter-quartile increase in pollution is associated with a 3- to 4-percentage-point higher CAR. These magnitudes are economically large compared to the sample average returns of 2 to 3 percent. These results are consistent with investors rewarding firms for divesting pollutive assets.

TABLE 13 ABOUT HERE

In the last set of analyses, we examine the relative gains from trade between buyers and sellers. If firms that have a comparative advantage in operating and owning pollutive plants are scarce, we expect them to have more bargaining power and consequently capture a higher share of the gains when they purchase more pollutive assets. On the other hand, sellers may capture a greater share of the gains for selling pollutive assets if they operate in an oligopolistic market segment because, for instance, their plants possess the technology or production capacity that is in high demand.

We measure the relative gains of asset buyers and sellers using the differential changes in their market value of equity during the three-day window 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 over the same deal. Market value gain is computed following the procedure outlined in Section 2.7. We partition all the divestiture deals into quartiles based on the pollution levels of the sold plants, both in terms of total emission quantity and emission intensity. We then compute the differential gains from trade for buyers relative to sellers for deals in each pollution quartile. Note that this analysis requires both the buyers and sellers to be public firms, reducing the sample size to 110 deals.

Figure 3 reports the results. Panels A and B plot the differential gains from trade measured using the market benchmark, and Panels C and D plot the differential gains measured using the Fama-French 3 factor benchmark. Within each measure, we present sample partitions based on the total quantities of emission as well as the intensity of emission (i.e., scaled by employment) from the sold plants. First, we notice that the differential gains (buyer − seller) are generally negative, suggesting that sellers tend to achieve a higher market value growth upon deal announcement compared to buyers. This is consistent with the findings in the broad M&A literature. Moreover, across the different measures of market value gains and pollution, we find that buyers' market values grow more than those of the sellers as the divestitures involve more pollutive assets.

These effects are economically nontrivial. Based on the market model, buyers capture roughly $400 higher value gains compared to the sellers in divestitures that involve plants in the highest pollution quartile. In contrast, buyers capture nearly $800 million lower gains than sellers for deals involving plants in the lowest pollution quartile. These results suggest that buyers of the most pollutive plants likely possess unique advantages in operating and owning those assets. As shown in Table 8, these advantages include exposure to weaker environmental pressures resulting, for example, from being headquartered in Republican counties and not having ESG ratings or past ESG risk incidents. We note, however, that our 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 could be underestimating the relative gains from trading pollutive assets.

Overall, the evidence suggests that while divested plants continue to emit similar levels of pollutants, the new owners face weaker environmental pressures, leading to gains from trading pollutive assets. As such, our findings provide a plausible mechanism through which firms respond to investors' ESG preferences. The reallocation of pollutive assets through the real asset market leads to pollution segmentation that caters both to investors with stronger ESG preferences, who gravitate towards green assets, and to those with weaker ESG preferences, who are more likely to hold brown assets (e.g., Pástor et al. 2021, Piccolo et al. 2022, Heinkel et al. 2001).

7 Conclusion

We study the real asset market for industrial pollution. In a sample of roughly 900 divestitures of pollutive plants over the period 2000-2020, we find that total or scaled emissions, as well as pollution abatement efforts, do not materially change at the sold plants. The estimates of pollution and abatement changes are statistically indistinguishable from zero, hold in 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-by-year panel regressions, in regressions estimated separately for divested and never-divested plants, 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 tend to divest their most pollutive plants, and the likelihood of divestment increases considerably following environmental risk incidents and negative media exposure. Second, the buyers of pollutive plants tend to be private, non-ESG-rated firms, which are headquartered in Republican-leaning districts and have not experienced environmental risk incidents. Moreover, the buyers tend to have pre-existing supply chain or joint venture relationships with the sellers, or develop new ones following the divestment of pollutive plants. Third, the sellers of pollutive plants gain higher ESG and environmental ratings, and lower environmental regulatory compliance costs. Lastly, sellers' announcement returns and the relative value gains captured by buyers are higher for divestitures of more pollutive assets.

Collectively, these findings suggest that regulators and rating agencies reward the divestment of pollutive assets, even though these divestitures only reflect a cosmetic redrawing of the boundaries of the firm without any real effects on abatement efforts or overall pollution levels. This evidence seems more consistent with the view that the divestment of pollutive assets supports a "greenwashing" strategy through which firms convey a false impression that they are more environmentally sound to obtain the benefits associated with a stronger environmental image. As such, our findings provide novel evidence on the role of the real asset market in firms' greenwashing strategies.

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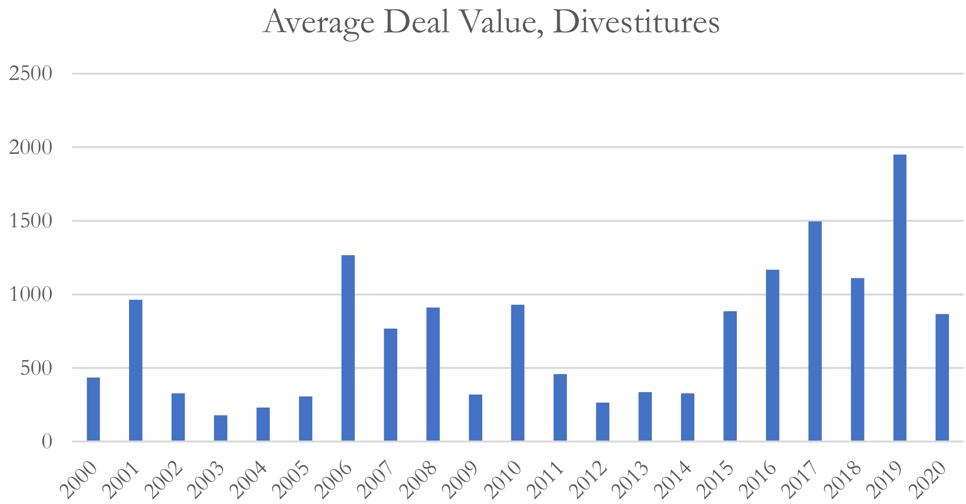
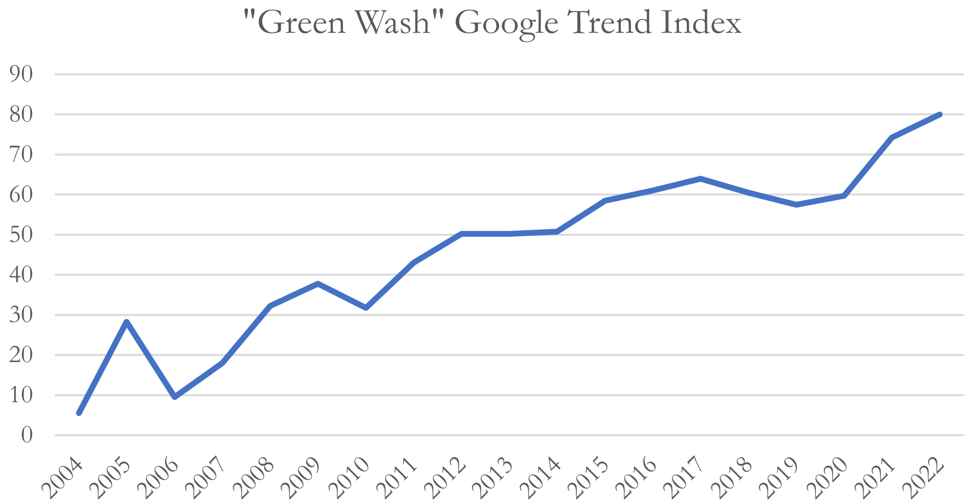
Figure 1. Trends in Divestitures and Attention to "Greenwashing"
Panel A reports the average deal value (in $millions) of divestitures involving TRI plants in each year. Panel B reports the average google search volume of the phrase "green wash" in each year.



Panel A. Trends in Average Divestiture Volume



Panel B. Trends in Google Search Volume of "Green Wash"

Figure 2. Plant Survival Rates
This figure presents the Kaplan-Meier survival estimates of divested plants and never-divested plants in our sample.

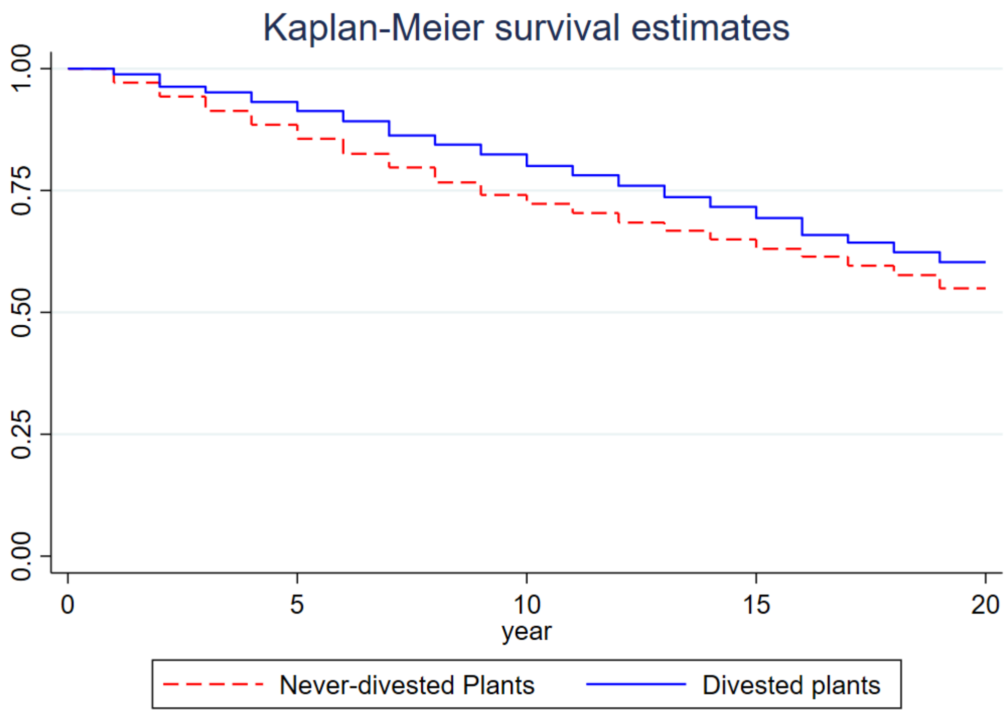
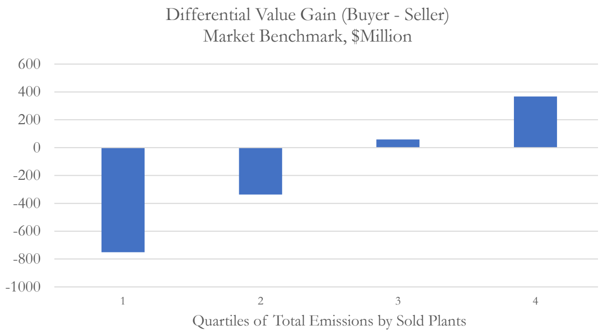
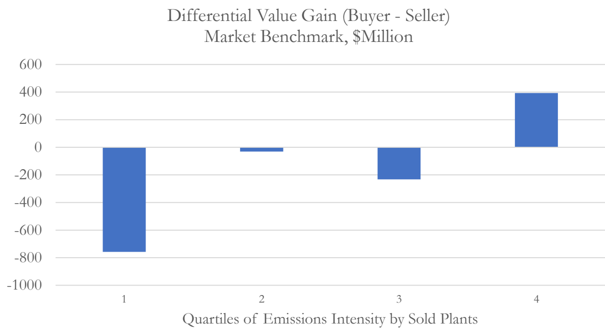


Figure 3. Relative Gains from Divesting Pollutive Plants

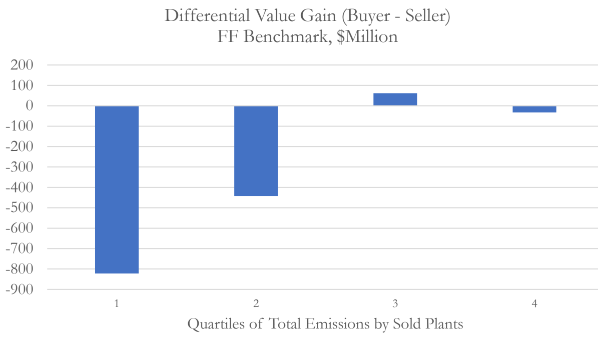
This figure presents the differential gain between buyers and sellers in divestiture deals. Differential gain refers to the difference between the market value gain for buyers relative to sellers around the deal announcement date ($Buyer - Seller$). Market value gains are measured by the the product of a firm's market capitalization and its $CAR[-1, +1]$ around deal announcement. Market capitalization is measured by the product between shares outstanding and share price of a firm, measured at the end of the year prior to the deal announcement. $CAR[-1, +1]$ represents the cumulative abnormal equity returns during the 3 days centered around deal announcement date. We use two benchmarks to measure abnormal return (Panels A and B), market benchmark and the Fama-French 3 factor benchmark (Panels C and D). For each measure of CAR, we measure differential gains for each quartiles of pollution from sold plants. Pollution is measured both in terms of total quantity of emission as well as emission intensity, which is emission quantity scaled by employment at the plant level.



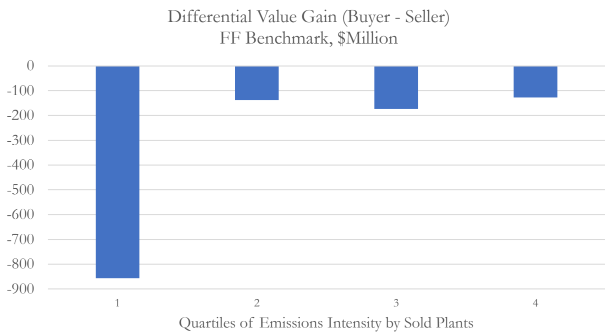
(A) Differential Gains based on Total Emission Market Benchmark



(B) Differential Gains based on Emission Intensity Market Benchmark



(C) Differential Gains based on Total Emission FF Benchmark



(D) Differential Gains based on Emission Intensity FF Benchmark

Table 1. Summary Statistics
This table presents summary statistics for the variables used in the analyses. Panel A presents summary statistics for the TRI plant-chemical-year panel, Panel B presents summary statistics for the TRI plant-year panel, and Panel C presents summary statistic for the firm-year panel. Panel D reports statistics for buyers' and sellers' announcement cumulative returns.

Panel A. Plant-chemical-Level Sample

	N	Mean	Median	SD	P25	P75
Total Release	1,056,361	16,893	483.00	60,761	14.45	5,300
Release/Prod Ratio	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

Panel B. Plant-Level Sample

	N	Mean	Median	SD	P25	P75
Total Release	352,938	58,529	1,687.19	215,345	24.00	17,705
Release/Emp	285,242	1,159	18.42	5,191	0.28	221
RSEI Hazard(000s)	320,261	497,438	646.57	2,239,238	33.00	26,218
RSEI Score	320,261	15,858	26.29	75,157	1.03	981

Panel C. Firm-Level Sample

	N	Mean	Median	SD	P25	P75
Total Release (000s)	14,328	626.16	22.48	2,039.89	1.10	220.64
Release/Emp	13,468	882.68	33.37	3,614.33	2.52	280.08
CSR Score (KLD)	38,203	0.32	0.00	2.31	-1.00	1.00
Environment Score (KLD)	38,203	0.15	0.00	0.83	0.00	0.00
Have ESG Event	180,203	0.07	0	0.26	0	0
Have Env. Event	180,203	0.04	0	0.19	0	0
Have Social, Governance Event	180,203	0.07	0	0.25	0	0
Enforcement Action	182,184	0.01	0	0.08	0	0
Enforcement Cost	182,184	302,184	0	30,287,516	0	0
Size	184,691	5.32	5.55	2.95	3.43	7.37
M/B	168,278	3.17	1.36	6.38	1.02	2.36
Leverage	180,965	0.39	0.34	0.34	0.04	0.64
Cash Holding	184,650	0.21	0.10	0.26	0.03	0.30
Tangibility	180,154	0.25	0.12	0.28	0.02	0.40
Distance to Default	93,635	5.88	4.94	4.73	2.58	8.11
Default Probability	93,635	0.06	0.00	0.17	0.00	0.00

Panel D. Announcement CARs

	N	Mean	Median	SD	P25	P75
Seller CAR, Market	290	2.91%	0.72%	12.80%	-1.19%	3.26%
Seller CAR, FF	287	2.85%	0.47%	12.76%	-1.41%	3.22%
Buyer CAR, Market	272	2.02%	1.08%	5.86%	-0.63%	3.92%
Buyer CAR, FF	270	1.69%	0.78%	5.65%	-0.82%	3.49%

Table 2. Buyer and Seller Characteristics

This table presents univariate evidence on buyer and seller characteristics. *Private Firm* is an indicator variable that equals 1 if the company is private. *Unrated Firm* is an indicator variable that equals 1 if the company is non-ESG rated. *No Env. Event* is an indicator variable that equals 1 if the company has not faced an ESG exposure incidence in the past or current year. *Republican County* is an indicator variable that equals 1 if the company is headquartered is in a Republican-leaning county. Republican-leaning counties are those where the majority of the votes went to a Republican presidential candidate in the most recent presidential election. The variables *Private Firm* and *Unrated Firm* are measured at a deal-by-firm level. All other variables are tabulated for publicly traded buyers and sellers in the year preceding the divestiture ($[t-1, t]$).

	Buyer		Seller		Difference	
	Obs	Mean	Obs	Mean	(Buyer−Seller)	
Private Firm	888	0.54	888	0.46	0.08	***
Unrated Firm	888	0.71	888	0.66	0.05	**
No Env. Event	888	0.94	888	0.89	0.05	**
Republican County	548	0.36	607	0.30	0.05	**
No Pressure	888	0.68	888	0.62	0.07	***
Total Release (000 lbs)	348	910.11	373	2205.82	-1,295.71	***
Release/Emp	332	522.47	369	584.82	-62.35	
CSR Score (KLD)	278	0.16	351	0.21	-0.05	
Environment Score (KLD)	278	0.09	351	-0.07	0.16	
Total Assets	498	10395.06	524	18659.45	-8,264.39	***
M/B	492	1.61	516	1.53	0.09	**
Leverage	498	0.42	523	0.45	-0.03	**
Cash Holding	498	0.09	524	0.09	-0.00	
Tangibility	498	0.30	522	0.30	0.01	
Distance to Default	436	6.94	473	6.52	0.42	
Default Probability	436	0.03	473	0.05	-0.02	*

Table 3. Difference-in-Differences Estimates of Pollution Following Divestitures This table presents results for the pollution level and intensity of divested plants around the divestiture. The sample includes all plants in the TRI database. Panel A reports generalized DID regression estimates and Panel B reports regression estimates with stacked panels of divested plants and matched never-divested plants within the same NAICS3 industry and state. *Divested* is an indicator of whether a plant has been divested by its parent over our sample period. *Post* is an indicator for years after the transaction. We use a plant-chemical-year panel, and *Total release* is the total amount released for a plant-chemical-year, while a chemical's toxic release intensity (*Toxic Release/Prod Ratio*) is the ratio of total toxic release over the chemical-level cumulative production ratio obtained from the TRI. All regressions are Poisson regressions described in Cohn et al. (2021). A cohort includes all divested plants and matched never-divested control plants sharing the same event year. Standard errors are presented in parentheses and clustered by plant. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A. Generalized DID Regressions

Dep. Var.:	*Total Release*			*Release/Prod Ratio*		
	(1)	(2)	(3)	(4)	(5)	(6)
Divested × *Post*	0.030	0.022	0.024	0.046	0.027	0.044
	(0.035)	(0.037)	(0.035)	(0.046)	(0.046)	(0.048)
Plant-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE		Yes	Yes		Yes	Yes
Industry-Year FE			Yes			Yes
Observations	992,424	992,418	992,313	992,424	992,418	992,313
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson

Panel B. Stacked Regressions

Dep. Var.:	*Total Release*			*Release/Prod Ratio*		
	(1)	(2)	(3)	(4)	(5)	(6)
Divested × *Post*	0.037	0.054	0.038	0.028	0.066	0.071
	(0.041)	(0.040)	(0.040)	(0.051)	(0.050)	(0.049)
Cohort-Plant-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort-Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort-State-Year FE		Yes	Yes		Yes	Yes
Cohort-Industry-Year FE			Yes			Yes
Observations	3,406,359	3,406,296	3,405,723	3,406,359	3,406,296	3,405,723
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson

Table 4. Divested vs. Never-Divested Plants

This table presents results for the pollution level and intensity around the divestiture for divested plants in Panel A and never-divested plants in Panel B. The sample comes from the stacked panels of divested plants and matched never-divested plants within the same NAICS3 industry and state. *Post* is an indicator for years after the transaction. We use a plant-chemical-year panel. *Total Release* is the total amount released for a plant-chemical-year, and a chemical's toxic release intensity (*Toxic Release/Prod Ratio*) is the ratio of total toxic release over the chemical-level cumulative production ratio obtained from the TRI. All regressions are Poisson regressions described in Cohn et al. (2021). A cohort includes all divested plants and matched never-divested control plants sharing the same event year. Standard errors are presented in parentheses and clustered by plant. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A. Divested Plants

Dep. Var.:	*Total Release*			*Release/Prod Ratio*		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.094**	0.052	0.025	0.036	0.030	0.014
	(0.040)	(0.039)	(0.037)	(0.053)	(0.051)	(0.049)
Cohort-Plant-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE		Yes	Yes		Yes	Yes
Industry-Year FE			Yes			Yes
Observations	58,936	58,925	58,904	58,936	58,925	58,904
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson

Panel B. Never-divested Plants

Dep. Var.:	*Total Release*			*Release/Prod Ratio*		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.011	-0.010*	-0.006	0.000	0.007	0.012*
	(0.007)	(0.006)	(0.005)	(0.007)	(0.007)	(0.007)
Cohort-Plant-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE		Yes	Yes		Yes	Yes
Industry-Year FE			Yes			Yes
Observations	3,365,777	3,365,773	3,365,571	3,365,777	3,365,773	3,365,571
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson

Table 5. Abatement Activities

This table presents results for the abatement activities of divested plants around the divestiture. The sample includes all TRI plants. Panel A reports generalized DID regression estimates and Panel B reports regression estimates with stacked panels of divested plants and never-divested plants within the same NAICS3 industry and state. *Divested* is an indicator of whether a plant has been divested by its parent over our sample period. *Post* is an indicator variable that equals 1 in all the years following the transaction. We examine various pollution abatement efforts, including the total number of source reduction practices (*#Source Reduction*), and the percentage of generated toxic chemicals reduced through recycling (*%Recycling*), energy recovery (*%Recovery*), and treatment (*%Treatment*). A cohort includes all divested plants and matched never-divested control plants sharing the same event year. Standard errors are presented in parentheses and clustered by plant. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A. Generalized DID Regressions

	(1)	(2)	(3)	(4)
Dep. Var.:	*#Source Reduction*	*%Recycling*	*%Recovery*	*%Treatment*
Divested $\times$ *Post*	-0.005	0.477	-0.551	0.438
	(0.079)	(0.560)	(0.615)	(0.755)
Plant-Chemical FE	Yes	Yes	Yes	Yes
Chemical-Year FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Observations	1,218,156	1,035,311	1,035,311	1,035,311
R^2	0.933	0.870	0.749	0.821
Model	OLS	OLS	OLS	OLS

Panel B. Stacked Regressions

	(1)	(2)	(3)	(4)
Dep. Var.:	*#Source Reduction*	*%Recycling*	*%Recovery*	*%Treatment*
Divested $\times$ *Post*	-0.070	-0.226	-0.098	1.116
	(0.102)	(0.656)	(0.738)	(0.913)
Cohort-Plant-Chemical FE	Yes	Yes	Yes	Yes
Cohort-Chemical-Year FE	Yes	Yes	Yes	Yes
Cohort-State-Year FE	Yes	Yes	Yes	Yes
Cohort-Industry-Year FE	Yes	Yes	Yes	Yes
Observations	3,912,048	3,449,343	3,449,343	3,449,343
R^2	0.943	0.827	0.714	0.765
Model	OLS	OLS	OLS	OLS

Table 6. Alternative Explanations

This table presents results for the emissions of remaining (non-divested) plants of firms that have divested or acquired divested plants in our sample (Panels A and B), and compares sales growth of divested and never-divested plants five years before divestitures (Panel C). Panel A reports generalized DID regression estimates, and Panel B reports stacked regression estimates, where the sample is a stacked event panel consisting of peer plants and their own matched control plants within the same NAICS3 industry and state. Control plants are never divested in our sample. *Peer* is an indicator for whether a plant is owned by a parent firm that divests other plants or acquires divested plants over our sample period. *Post* indicates years during and after the divestiture. We use a plant-chemical-year panel, and *Total Release* is the total amount released for a plant-chemical-year, while a chemical's toxic release intensity (*Toxic Release/Prod Ratio*) is the ratio of total toxic release over the chemical-level cumulative production ratio obtained from the TRI. A cohort includes all divested plants and matched never-divested control plants sharing the same event year. In Panel C, The omitted benchmark is the transaction year of the divestitures. Column (1) presents estimates from the GDID sample, and column (2) presents estimates from the stacked regression sample. All fixed effects in column (2) are interacted with cohort fixed effects. Standard errors are presented in parentheses and clustered by plant. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A. Remaining Plants: Generalized DID Regressions

Dep. Var.:	*Total Release*			*Release/Prod Ratio*		
	(1)	(2)	(3)	(4)	(5)	(6)
Peer × *Post*	0.003	0.008	-0.003	-0.021	-0.024	-0.026
	(0.021)	(0.020)	(0.021)	(0.027)	(0.026)	(0.026)
Plant-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE		Yes	Yes		Yes	Yes
Industry-Year FE			Yes			Yes
Observations	849,798	849,792	849,696	849,798	849,792	849,696

Panel B. Remaining Plants: Stacked Regressions

Dep. Var.:	*Total Release*			*Release/Prod Ratio*		
	(1)	(2)	(3)	(4)	(5)	(6)
Peer × *Post*	0.080	0.080	0.080	0.064	0.064	0.064
	(0.070)	(0.070)	(0.070)	(0.069)	(0.069)	(0.069)
Cohort-Plant-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort-Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort-State-Year FE		Yes	Yes		Yes	Yes
Cohort-Industry-Year FE			Yes			Yes
Observations	11,275,719	11,275,719	11,275,719	11,275,719	11,275,719	11,275,719
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson

Panel C. Sales Growth before Divestitures

Dep. Var.: *Sales Growth*	(1)	(2)
Seller(Pollutive) × *D(year=-5)*	0.001	-0.008
	(0.033)	(0.037)
Seller(Pollutive) × *D(year=-4)*	-0.004	-0.013
	(0.030)	(0.031)
Seller(Pollutive) × *D(year=-3)*	0.030	0.033
	(0.031)	(0.032)
Seller(Pollutive) × *D(year=-2)*	0.011	0.036
	(0.030)	(0.033)
Seller(Pollutive) × *D(year=-1)*	-0.035	-0.027
	(0.025)	(0.026)
Plant FE	Yes	Yes
Year FE	Yes	Yes
State-Year FE	Yes	Yes
Industry-Year FE	Yes	Yes
Cohort-Interacted FEs		Yes
Observations	265,446	147,692
Adjusted R^2	0.021	0.114
Method	GDID	Stacked Regression
Model	OLS	OLS

Table 7. The Determinants of Divestitures

In this table, we examine what determines pollutive plant divestitures. In particular, we focus on two aspects: pollution levels and exposure to ESG risk incidents. Panel A studies the link between plant-level pollution and the likelihood of being sold. The dependent variable is *Divested*, an indicator variable that equals 1 if a plant is divested in a given year. *Past Release (Quartile)* is the quartile partition of the total toxic release generated by a plant, averaged over the past two years ($[t-1, t]$). *Past Release/Emp (Quartile)* is the quartile partition of the toxic emission intensity by a plant (emission per employee), averaged over the past two years($[t-1, t]$). Both measures take the value of 1 to 4, with 4 being the highest pollution level. Data on the number of employees in a plant come from NETS. The sample is a plant-year panel, including all TRI plant observations up to the year it is sold. Panel B studies the link between firms' ESG risk exposure and the likelihood of selling a plant. Information on ESG risk events comes from RepRisk. The dependent variable is *Sell (Pollutive)*, an indicator variable that equals 1 if a firm divests at least one TRI plant in a given year. *Have ESG Risk Event* is a dummy variable that equals one if a firm incurs an ESG risk event in the current or the past year. *Have Env. Risk Event* is an indicator variable that equals one if a firm incurs an environment-related risk event in the current or the past year. Similarly, *Have Social, Governance Event* indicates whether a firm incurs a social or an environmental risk event in the current or the past year. We use a parent firm-year panel that comprises all parents of TRI plants that have appeared at least once in the RepRisk database. In Panel C, we examine whether the same set of parent firms are more likely to divest other, non-TRI assets when facing ESG risk exposures. The dependent variable is *Sell (Non-Pollutive)*, defined as an indicator variable that equals 1 if a firm divests other assets in a given year. All dependent variables in this table are multiplied by 100. *Firm Char* includes *Size*, *M/B*, *Leverage*, *Cash*, and *Tangibility*. Standard errors are clustered by plant in Panel A and by firm in Panel B. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A. Pollution Levels

Dep. Var.: *Divested*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Past Release (Quartile)	0.058***	0.044***	0.046***	0.043***				
	(0.009)	(0.010)	(0.010)	(0.010)				
Past Release/Emp (Quartile)					0.040***	0.026**	0.029***	0.027**
					(0.010)	(0.011)	(0.011)	(0.011)
Year FE		Yes				Yes		
Industry FE		Yes				Yes		
Industry-Year FE			Yes	Yes			Yes	Yes
State-Year FE				Yes				Yes
Observations	301,172	301,166	301,044	301,032	242,258	242,254	242,125	242,102
R^2	0.000	0.002	0.010	0.015	0.000	0.001	0.006	0.012
Model	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS

Panel B. ESG Risk Incidents: Pollutive Plants

Dep. Var.: *Sell (Pollutive)*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Have RepRisk Event	0.669**	0.685**	0.729**						
	(0.310)	(0.312)	(0.321)						
Have Environment Event				1.012**	1.242***	1.300***	0.887**	1.198**	1.231**
				(0.397)	(0.462)	(0.487)	(0.419)	(0.488)	(0.515)
Have Social, Governance Event							0.245	0.090	0.142
							(0.321)	(0.313)	(0.329)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes			Yes			Yes		
Industry-Year FE		Yes	Yes		Yes	Yes		Yes	Yes
Firm Char			Yes			Yes			Yes
Observations	9,172	8,733	8,336	9,172	8,733	8,336	9,172	8,733	8,336
R^2	0.198	0.258	0.263	0.198	0.259	0.263	0.198	0.259	0.263
Model	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	

Panel C. ESG Risk Incidents: Non-Pollutive Plants

Dep. Var.: *Sell (Non-Pollutive)*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Have RepRisk Event	-1.361	-1.574	-2.117						
	(1.275)	(1.306)	(1.291)						
Have Environment Event				-1.574	-2.097	-2.339	-1.164	-1.502	-1.577
				(1.516)	(1.490)	(1.485)	(1.481)	(1.483)	(1.464)
Have Social, Governance Event							-0.817	-1.224	-1.570
							(1.207)	(1.306)	(1.284)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes			Yes			Yes		
Industry-Year FE		Yes	Yes		Yes	Yes		Yes	Yes
Firm Char			Yes			Yes			Yes
Observations	10,179	9,767	9,373	10,179	9,767	9,373	10,179	9,767	9,373
R^2	0.741	0.761	0.768	0.741	0.761	0.768	0.741	0.761	0.768
Model	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	

Table 8. Buyers of Pollutive Plants

This table examines whether buyers of TRI plants are more likely to face weaker environmental pressures. We compare buyers and sellers in divestitures of pollutive plants in Panel A, and non-pollutive divestitures in Panel B. The unit of observation is a deal-firm pair, where each deal includes two firm observations, one for the buyer and one for the seller. The variables of interest include *Private Firm*, an indicator variable that equals 1 if the firm is privately owned and 0 otherwise, *Unrated Firm*, an indicator variable that equals 1 if the firm does not have an ESG rating and 0 otherwise, *No Env. Event*, an indicator variable that equals 1 if the firm did not experience an environmental risk incident in the Reprisk database and 0 otherwise, *Republican County*, an indicator variable that equals 1 if the firm is headquartered in a county where the Republican party won the majority vote in the most recent presidential election and 0 otherwise, and *Low Pressure*, the average of the four indicator variables. Robust standard errors are included. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A. Pollutive Asset Divestitures

	(1)	(2)	(3)	(4)	(5)
Dep. Var.:	*Private*	*Unrated*	*No Env. Event*	*Republican County*	*Low Pressure*
Buyer	0.079***	0.051**	0.048***	0.058**	0.071***
	(0.024)	(0.022)	(0.013)	(0.028)	(0.014)
Observations	1,753	1,753	1,753	1,144	1,753
Adjusted R^2	0.006	0.002	0.007	0.003	0.013
Model	OLS	OLS	OLS	OLS	OLS

Panel B. Non-pollutive Asset Divestitures

	(1)	(2)	(3)	(4)	(5)
Dep. Var.:	*Private*	*Unrated*	*No Env. Event*	*Republican County*	*Low Pressure*
Buyer	-0.007**	-0.014***	0.009***	-0.016***	-0.003*
	(0.003)	(0.003)	(0.001)	(0.004)	(0.002)
Observations	82,066	82,066	82,066	57,996	82,066
Adjusted R^2	0.000	0.000	0.001	0.000	0.000
Model	OLS	OLS	OLS	OLS	OLS

Table 9. Changes in ESG Ratings Following Divestitures

This table examines how ESG ratings of sellers change around divestitures. The sample includes all firms covered by the KLD-MSCI database. Panel A reports generalized DID regression estimates and Panel B reports regression estimates with stacked panels of sellers and control firms within the same NAICS3 industry who have not sold a plant in our sample period. *Seller (Pollutive)* is an indicator of whether a firm sells a plant in a divestiture transaction over our sample period. The dependent variable in columns (1)-(3) is *Overall CSR Score*, and the dependent variable in columns (4)-(6) is *Environmental Scores*. *Post* indicates years during or after the deals. Rating data come from the KLD database. *Firm Char* includes *Size*, *M/B*, *Leverage*, *Cash*, and *Tangibility*. A cohort includes all divested plants and matched never-divested control plants in the same event year. Standard errors are reported in parentheses and clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A. Generalized DID Regressions

Dep. Var.:	*Overall CSR Scores*			*Environment Scores*		
	(1)	(2)	(3)	(4)	(5)	(6)
Seller (Pollutive) × *Post*	0.701***	0.468**	0.483**	0.501***	0.249**	0.224**
	(0.226)	(0.220)	(0.223)	(0.111)	(0.108)	(0.109)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes			Yes		
Industry-Year FE		Yes	Yes		Yes	Yes
Firm Char			Yes			Yes
Observations	38,226	38,103	35,962	38,226	38,103	35,962
R^2	0.623	0.650	0.651	0.510	0.558	0.562
Model	OLS	OLS	OLS	OLS	OLS	OLS

Panel B. Stacked Regressions

Dep. Var.:	*Overall CSR Scores*			*Environment Scores*		
	(1)	(2)	(3)	(4)	(5)	(6)
Seller (Pollutive) × *Post*	0.502**	0.482**	0.557**	0.302**	0.252**	0.228*
	(0.241)	(0.233)	(0.235)	(0.124)	(0.117)	(0.119)
Cohort-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort-Year FE	Yes			Yes		
Cohort-Industry-Year FE		Yes	Yes		Yes	Yes
Firm Char			Yes			Yes
Observations	121,127	121,067	120,157	121,127	121,067	120,157
R^2	0.654	0.666	0.668	0.543	0.564	0.567
Model	OLS	OLS	OLS	OLS	OLS	OLS

Table 10. Changes in Environmental Compliance Costs Following Divestitures
This table presents changes in enforcement costs for sellers around the divestiture. Panel A reports generalized DID regression estimates and Panel B reports regression estimates with stacked panels of sellers and control firms within the same NAICS3 industry who have not sold a plant in our sample period. The dependent variable is *Enforcement Action*, an indicator is a firm faces an EPA enforcement action in a given year, and *Enforcement Cost*, the dollar amount of cost incurred by the firm due to the enforcement in millions, including fines and cleanup costs. *Seller (Pollutive)* is an indicator for whether a firm sells a plant in a divestiture transaction over our sample period. *Post* indicates years during or after the deals. *Firm Char* includes *Size*, *M/B*, *Leverage*, *Cash*, and *Tangibility*. A cohort includes all divested plants and matched never-divested control plants sharing the same event year. Standard errors are clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A. Generalized DID Regressions

	Enforcement Action			*Enforcement Cost*		
Dep. Var.:	(1)	(2)	(3)	(4)	(5)	(6)
Sell (Pollutive) × *Post*	-0.050***	-0.050***	-0.044***	-2.271***	-2.605***	-3.138***
	(0.014)	(0.014)	(0.014)	(0.662)	(0.726)	(0.994)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes			Yes		
Industry-Year FE		Yes	Yes		Yes	Yes
Firm Char			Yes			Yes
Observations	17,991	17,622	16,612	7,079	5,850	5,453
R^2	0.289	0.322	0.330			
Model	OLS	OLS	OLS	Poisson	Poisson	Poisson

Panel B. Stacked Regressions

	Enforcement Action			*Enforcement Cost*		
Dep. Var.:	(1)	(2)	(3)	(4)	(5)	(6)
Sell (Pollutive) × *Post*	-0.078***	-0.081***	-0.069***	-2.280***	-2.636***	-4.662***
	(0.022)	(0.020)	(0.020)	(0.749)	(0.736)	(1.159)
Cohort-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort-Year FE	Yes			Yes		
Cohort-Industry-Year FE		Yes	Yes		Yes	Yes
Firm Char			Yes			Yes
Observations	114,219	113,324	109,906	55,270	48,457	46,251
R^2	0.275	0.296	0.304			
Model	OLS	OLS	OLS	Poisson	Poisson	Poisson

Table 11. Business Ties between Buyers and Sellers of Pollutive Assets

This table examines whether the buyers and sellers of pollutive plants share operational relations, such as supply-chain relationships and joint-ventures. Column (1) examines whether pre-existing operational relationships predict future participation in pollutive asset divestitures. *Operationally Related* is an indicator that equals 1 if a firm has a pre-existing supply-chain relationship or joint ventures the seller. *Buyer of Pollutive Plants* (*Buyer of Non-Pollutive Plants*) is an indicator variable that equals 1 if a firm purchases a pollutive (non-pollutive) asset from the seller. In column (2), we examine whether firms are more likely to develop new supply-chain or joint venture relations after the divestiture. For each divestiture deal, we match the buyer with five randomly chosen acquirers in the SDC universe in the same industry. Each matched acquirer is considered a potential buyer. The analysis utilizes a matched-pair sample, wherein each observation is a seller-potential buyer pair. As such, each deal has six observations (a matched group), consisting of the actual buyer-seller pair and five potential buyer-seller pairs. Regressions include matched group fixed effects. Standard errors are double clustered by matched group and deal year. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dep. Var.:	(1) *Buyer of Pollutive Plants*	(2) *Develop New Relationship*
Operationally Related	0.342***	
	(0.067)	
Buyer of Pollutive Plants		0.071***
		(0.013)
Matched Group FE	Yes	Yes
Observations	2,814	2,814
R^2	0.027	0.206
Model	OLS	OLS

Table 12. Non-Pollutive Divestitures

This table provides estimates of ESG ratings, regulatory enforcement costs, and business ties between buyers and sellers in divestitures of non-pollutive assets. *Seller (Non-Pollutive)* is an indicator of whether a firm sells a non-pollutive (non-TRI) asset in a divestiture transaction over our sample period. *Post* indicates years during or after the deals. *Firm Char* includes *Size*, *M/B*, *Leverage*, *Cash*, and *Tangibility*. Standard errors are reported in parentheses and clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: ESG Ratings

Dep. Var.:	*Overall CSR Scores*			*Environment Scores*		
	(1)	(2)	(3)	(4)	(5)	(6)
Seller(Non-Pollutive) × *Post*	0.101*	0.032	0.043	0.038	-0.009	-0.019
	(0.060)	(0.061)	(0.064)	(0.027)	(0.028)	(0.030)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes			Yes		
Industry-Year FE		Yes	Yes		Yes	Yes
Firm Char			Yes			Yes
Observations	38,226	38,103	35,962	38,226	38,103	35,962
R^2	0.623	0.650	0.651	0.507	0.557	0.561
Model	OLS	OLS	OLS	OLS	OLS	OLS

Panel B. Enforcement

Dep. Var.:	*Enforcement Action*			*Enforcement Cost*		
Sample: Unmatched	(1)	(2)	(3)	(4)	(5)	(6)
Sell (NonPollutive) × *Post*	-0.012	-0.010	-0.012	-0.003	0.510	1.412
	(0.008)	(0.008)	(0.008)	(0.811)	(1.136)	(1.157)
Year FE	Yes			Yes		
Firm FE	Yes	Yes	Yes			
Industry-Year FE		Yes	Yes		Yes	Yes
Firm Char			Yes			Yes
Observations	16,968	16,646	15,677	6,583	5,531	5,181
R^2	0.286	0.323	0.332			
Model	OLS	OLS	OLS	Poisson	Poisson	Poisson

Panel C. Business Ties

Dep. Var.:	(1) *Buyer of Non-Pollutive Plants*	(2) *Develop New Relationship*
Operationally Related	-0.011	
	(0.014)	
Buyer of Non-Pollutive Plants		0.003
		(0.002)
Matched Group FE	Yes	Yes
Observations	271,101	271,101
R^2	0.004	0.207
Model	OLS	OLS

Table 13. Equity Returns to Deal Announcement

This table examines sellers' cumulative abnormal returns (CARs) around a three-day window of the divestiture announcement date in relation to the pollution level of plants being sold. Abnormal returns are computed in two ways. First, we subtract market returns from firms' equity returns and define the difference as abnormal returns ("Market" benchmark). Second, we take the residual from regressing total returns on the Fama-French 3-factor model ("FF" benchmark). We examine the relation between announcement CARs and past releases of sold plants in a deal. Past releases of a deal is measured as both the total quantity of toxic releases generated by all plants sold in the deal (*Quantity*), or the ratio of total release over total employment of the sold plants (*Intensity*). Similar to Table 7, we assign quartile values of these pollution metrics, ranging from 1 (least pollutive) to 4 (most pollutive). The unit of observation is a divestiture deal that includes a publicly traded seller. All regressions include industry fixed effects and year fixed effects. Standard errors are double clustered by year and industry. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dep. Var.: Seller $CAR[-1,+1]$	(1)	(2)	(3)	(4)
Benchmark	Market	Market	FF	FF
Past Release Measured By:	Quantity	Intensity	Quantity	Intensity
Past Release (Quartile)	0.011**	0.012**	0.012**	0.013**
	(0.004)	(0.005)	(0.004)	(0.006)
Seller Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	279	248	276	244
R^2	0.308	0.412	0.309	0.433
Model	OLS	OLS	OLS	OLS

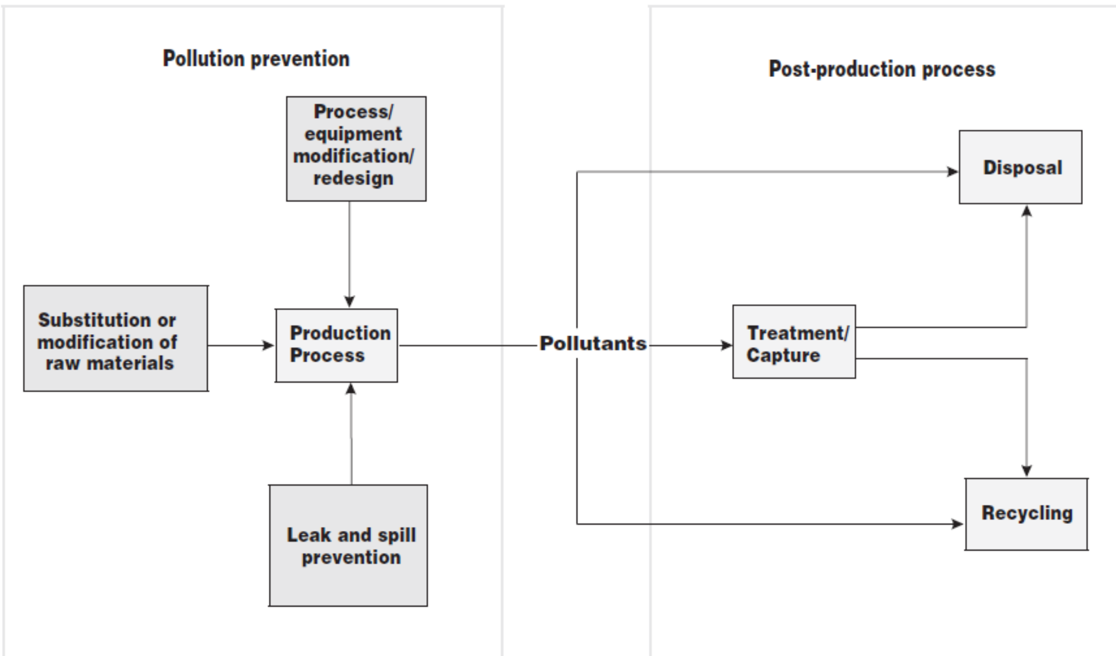
Appendix A Pollution Abatement Activities

The figure below provides an overview of plants' pollution abatement activities under two major categories: *pollution prevention* (also referred to as *source reduction*) and *post-production processes*.

Each year, facilities must report their newly implemented source reduction activities by selecting 47 codes that fall under eight broad categories (ranked according to reported frequency): (1) Good Operating Practices; (2) Process Modifications; (3) Spill and Leak Prevention; (4) Raw Material Modifications; (5) Inventory Control; (6) Surface Preparation and Finishing; (7) Cleaning and Degreasing; (8) Product Modifications.

Post-production waste management includes the following: (1) Recycling, which involves a series of activities through which discarded materials are collected, sorted, processed, and converted into raw materials and used in the production of new products; (2) Energy recovery (Capture), which is process of generating energy from the combustion of wastes, including at waste-to-energy combustion facilities and landfill-gas-to-energy facilities; (3) Treatment, which involves the use of various processes, such as incineration or oxidation, to alter the properties or composition of hazardous materials.

Figure A.1. Pollution Abatement Activities



Appendix B Detecting Ownership Changes of TRI Plants

We track the changes in ownership of TRI plants as follows.

First, we flag incidences where a plant experiences a change of parent names and label the parent name before the change as the seller and the name after the change as the buyer. Parent name changes are either directly reported by the TRI, or could be detected by changes in a plant's CUSIP number.

Next, we match the buyer and seller names to those of divestiture deals from the SDC database. The matching is performed both at the subsidiary firm level as well as the ultimate parent level. In this process, we account for the scenario that TRI data may capture inaccurately the timing of ownership changes, and require the SDC deal year to fall within a $[-3, 3]$ year window around the year of the parent name change in TRI. We use SDC's deal effective date as the official date for the ownership change.

We further consider the possibility that the TRI data may not update parent information correctly in all cases. To address this concern, for each plant in TRI, we track whether it has gone through a divestiture by matching its name or its parent's name to the target name in SDC. We also require the TRI plant to fit the target's geographical location and industry classification in SDC. For example, Westmoreland Coal acquired the Roanoke Valley Energy Facility from its joint venture partner, LG&E Energy Corp in 2006. While we do not see a change of parent name for the Roanoke valley Energy Facility in TRI, we still classify it as a divested plant.

Finally, we remove plants that have been sold multiple times during the sample period. We do so because the difference-in-differences tests struggle with the classification of repeat divestiture targets as treatment vs. control plants. Our final sample contains 719 deals.

Appendix C Industry Composition

Table C.1. Industry Composition
This table reports the three-digit NAICS3 code for our sample divested plants.

NAICS3	Industry	Observations
325	Chemical Manufacturing	258
332	Fabricated Metal Product Manufacturing	117
311	Food Manufacturing	89
336	Transportation Equipment Manufacturing	73
424	Merchant Wholesalers, Nondurable Goods	72
331	Primary Metal Manufacturing	66
334	Computer and Electronic Product Manufacturing	63
326	Plastics and Rubber Products Manufacturing	53
333	Machinery Manufacturing	47
322	Paper Manufacturing	45
321	Wood Product Manufacturing	39
324	Petroleum and Coal Products Manufacturing	31
335	Electrical Equipment, Appliance, and Component Manufacturing	30
221	Utilities	25
327	Nonmetallic Mineral Product Manufacturing	21
562	Waste Management and Remediation Services	12
339	Miscellaneous Manufacturing	12
312	Beverage and Tobacco Product Manufacturing	10
112	Animal Production and Aquaculture	9
323	Printing and Related Support Activities	7
212	Mining (except Oil and Gas)	7
316	Leather and Allied Product Manufacturing	5
337	Furniture and Related Product Manufacturing	4
313	Textile Mills	3
493	Warehousing and Storage	3
811	Repair and Maintenance	1
314	Textile Product Mills	1
315	Apparel Manufacturing	1
517	Telecommunications	1

Appendix D Variable Definitions

Panel A: Plant-chemical-level Variable

- *Release*: The amount of total toxic releases
- *Release/Prod Ratio*: The amount of total toxic releases divided by the cumulative producation ratio
- *#Source Reduction*: The total number of source reduction activities
- *%Recycling*: The percentage of total produced toxic chemicals reduced through recycling
- *%Recovery*: The percentage of total produced toxic chemicals reduced through energy recovery
- *%Treatment*: The percentage of total produced toxic chemicals reduced through treatment

Panel B: Plant-Level Variable

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

Panel C: Firm-Level Variable

- *Private*: An indicator of a firm being private
- *Unrated*: An indicator of a firm not rated by the KLD
- *No Env. Event*: an indicator variable that equals 1 if the company has not faced an ESG risk incidence in the past or current year.
- *Republican County*: an indicator variable that equals 1 if the company is headquartered in a Republican-leaning county. Republican-leaning counties are those where the majority of the county's votes went to a Republican presidential candidate in the most recent presidential elections.
- *Release*: The total amount of toxic releases
- *Release/Emp*: The total amount of toxic releases divided by the number of employees
- *Emp* (NETS): The number of employees based on NETS
- *CSR Score* (KLD): The aggregate net strength and concern counts across six dimensions in KLD
- *Env. Score* (KLD): The net strength and concern counts for the environmental dimension in KLD
- *Size*: The natural log of total assets
- *M/B* : $(at - ceq + csho * prcc_f)/at$
- *Leverage*: $(dlc + dltt)/(dlc + dltt + ceq)$
- *Cash Holding*: $Cash/at$
- *Tangibility*: $PPENT/at$
- *Log(Sales)*: The natural log of sales (Compustat)
- *Have ESG Event*: An indicator of a firm having an ESG risk event based on RepRisk
- *Have Env. Event*: An indicator of a firm having an environmental risk event based on RepRisk
- *Enforcement Action*: An indicator of a firm experiencing a regulatory enforcement event
- *Enforcement Cost* (in $M): The total dollar amount of regulatory enforcement costs
- *Operationally Related*: An indicator of a firm being a supply-chain or join venture partner with the seller in the past
- *Develop New Relationship*: An indicator of a firm developing new supply-chain or join venture relation with the seller

Appendix E Robustness Tests

Table E.1. Changes in Pollution Following Divestitures: Robustness
This table presents robustness tests for pollution of divested plants around the divestiture. The sample includes all TRI plants. Panels A, C, and E report GDID regression estimates , and Panels B, D, and F report regression estimates with stacked panels of divested plants and matched never-divested plants within the same NAICS3 industry and state. *Divested* is an indicator of whether a plant has been divested by its parent. *Post* is an indicator for years after the transaction. Panels A and B use a plant-chemical-year panel, and *Total release* is the total amount released for a plant-chemical-year, while a chemical's toxic release intensity (*Toxic Release/Prod Ratio*) is the ratio of total toxic release over the chemical-level cumulative production ratio obtained from the TRI. Panels C-F use a plant-year panel. *Total Release* is the sum across all toxic chemicals released within a plant-year. A plant's toxic release intensity (*Release/Emp*) is calculated as the ratio of total toxic release over the establishment's employment (based on information from NETS). *RSEI Hazard* is the toxicity weighted pollution amount, while *RSEI Score* incorporates both toxicity weight and modeled population exposure to gauge the impact on public health. Standard errors are presented in parentheses and clustered by plant. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A. Pollution, Stacked Regressions

Dep. Var.:	Total Release			Release/Prod Ratio		
	(1)	(2)	(3)	(4)	(5)	(6)
Divested × *Post*	1337.700*	951.780	868.654	1984.599	1767.528	1658.644
	(705.732)	(714.626)	(692.429)	(1401.805)	(1398.385)	(1429.657)
Plant-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE		Yes	Yes		Yes	Yes
Industry-Year FE			Yes			Yes
Observations	1,035,411	1,035,405	1,035,311	1,035,411	1,035,405	1,035,311
Adjusted R^2	0.804	0.805	0.810	0.793	0.793	0.796
Model	OLS	OLS	OLS	OLS	OLS	OLS

Panel B. Pollution, Stacked Regressions

Dep. Var.:	Total Release			Release/Prod Ratio		
	(1)	(2)	(3)	(4)	(5)	(6)
Divested × *Post*	92.493	838.863	972.886	383.618	1391.738	1435.055
	(885.020)	(829.007)	(863.006)	(1536.460)	(1487.513)	(1484.358)
Cohort-Plant-Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort-Chemical-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort-State-Year FE		Yes	Yes		Yes	Yes
Cohort-Industry-Year FE			Yes			Yes
Observations	3,449,868	3,449,809	3,449,343	3,449,868	3,449,809	3,449,343
Adjusted R^2	0.806	0.807	0.809	0.779	0.780	0.780
Model	OLS	OLS	OLS	OLS	OLS	OLS

Panel C. Plant Pollution, Generalized DID Regressions

Dep. Var.:	*Total Release*			*Release/Emp*		
	(1)	(2)	(3)	(4)	(5)	(6)
Divested × *Post*	0.094*	0.074	0.027	0.124	0.146	0.123
	(0.049)	(0.052)	(0.047)	(0.114)	(0.103)	(0.104)
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes			Yes		
State-Year FE		Yes	Yes		Yes	Yes
Industry-Year FE			Yes			Yes
Observations	334,852	334,838	334,683	269,656	269,635	269,474
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson

Panel D. Plant Pollution, Stacked Regressions

Dep. Var.:	*Total Release*			*Release/Emp*		
	(1)	(2)	(3)	(4)	(5)	(6)
Divested × *Post*	0.029	0.055	0.033	0.135	0.207	0.167
	(0.055)	(0.053)	(0.053)	(0.139)	(0.131)	(0.131)
Cohort-Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort-Year FE	Yes			Yes		
Cohort-State-Year FE		Yes	Yes		Yes	Yes
Cohort-Industry-Year FE			Yes			Yes
Observations	743,279	743,128	742,071	612,725	612,495	611,610
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson

Panel E. Plant RSEI, Generalized DID Regressions

Dep. Var.:	*RSEI Hazard*			*RSEI Score*		
	(1)	(2)	(3)	(4)	(5)	(6)
Divested × *Post*	0.065	0.038	0.028	0.029	0.042	0.017
	(0.103)	(0.111)	(0.102)	(0.110)	(0.107)	(0.101)
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes			Yes		
State-Year FE		Yes	Yes		Yes	Yes
Industry-Year FE			Yes			Yes
Observations	316,806	316,790	316,627	312,530	312,514	312,342
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson

Panel F. Plant RSEI, Stacked Regressions

Dep. Var.:	*RSEI Hazard*			*RSEI Score*		
	(1)	(2)	(3)	(4)	(5)	(6)
Divested × *Post*	-0.155	-0.125	-0.075	-0.116	-0.032	0.073
	(0.179)	(0.170)	(0.190)	(0.200)	(0.149)	(0.163)
Cohort-Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort-Year FE	Yes			Yes		
Cohort-State-Year FE		Yes	Yes		Yes	Yes
Cohort-Industry-Year FE			Yes			Yes
Observations	722,519	722,347	721,307	720,553	720,381	719,326
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson

Appendix F Alternative ESG Rating Measures

Our analysis on ESG ratings relies primarily on the KLD database, because this database provides ratings on firm business conducts in earlier years of our sample. Figure G.1 presents the number of unique firms covered by KLD, Refinitive, and MSCI ESG ratings during 1990-2020. KLD provides the most comprehensive coverage in the early sample period.

In Table G.1, we augment KLD rating data with the Refinitive and MSCI ratings. Specifically, we first standardize ratings within each dataset-year, and then fill in firm-years missing KLD ratings with Refinitive and MSCI ratings when available. If both Refinitive and MSCI ratings are available, we prioritize Refinitive ratings due to a higher correlation with KLD: in the overlapping sample across three datasets, the correlation of the Overall CSR (Environmental) scores is 0.50 (0.45) between the standardized Refinitive and KLD ratings, and 0.40(0.26) between the standardized MSCI and KLD ratings. Our results remain robust to the augmented ESG rating measures.

Figure G.1. KLD, Refinitive, and MSCI Coverage
This figure reports the number of U.S. non-financial firms included in the KLD, Refinitive, and MSCI ESG ratings between 1990-2020.

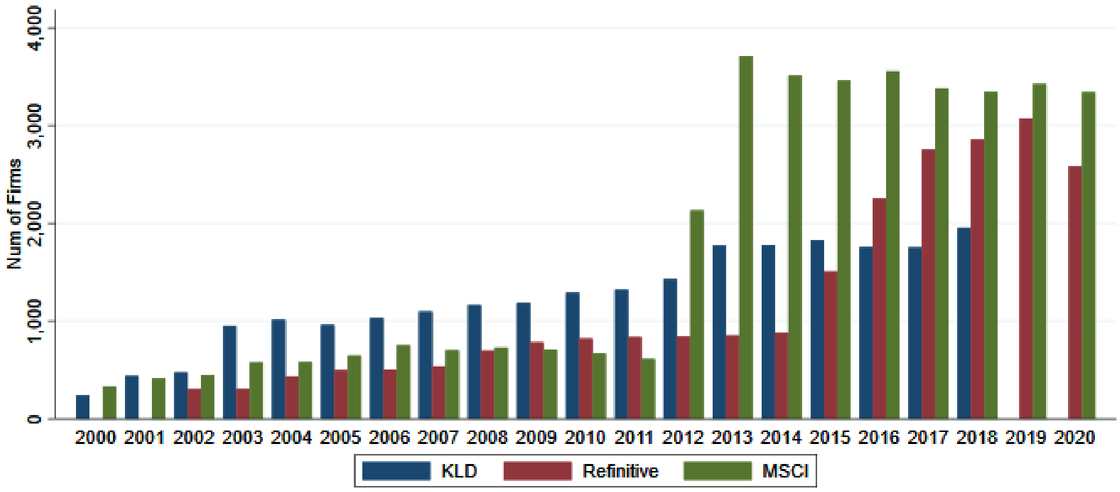


Table G.1. Robustness: Alternative ESG Ratings

This table presents ESG Rating changes post-divestitures for sellers, where we use Refinitive and MSCI data to augment KLD ratings. All rating observations are first standardized with each dataset-year, and then observations with missing KLD ratings are filled in with ratings from Refinitive and MSCI if available. Panels A reports generalized DID regression estimates , and Panel B reports regression estimates with stacked panels of divested firms and matched never-divested firms. *Seller (Pollutive)* is an indicator of whether a firm sells a plant in a divestiture transaction over our sample period. The dependent variable in columns (1)-(3) is *Overall CSR Score*, and the dependent variable in columns (4)-(6) is *Environmental Scores*. *Post* indicates years during or after the deals. *Firm Char* includes *Size*, *M/B*, *Leverage*, *Cash*, and *Tangibility*. Standard errors are reported in parentheses and clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A. ESG Ratings, Generalized DID Regressions

Dep. Var.:	*Overall CSR Scores*			*Environment Scores*		
	(1)	(2)	(3)	(4)	(5)	(6)
Seller(Pollutive) × *Post*	0.309***	0.218**	0.228**	0.644***	0.392***	0.369***
	(0.097)	(0.094)	(0.095)	(0.145)	(0.137)	(0.138)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes			Yes		
Industry-Year FE		Yes	Yes		Yes	Yes
Firm Char			Yes			Yes
Observations	53,250	53,111	49,880	53,242	53,103	49,871
R^2	0.518	0.545	0.547	0.410	0.456	0.459

Panel B. ESG Ratings, Stacked Regressions

Dep. Var.:	*Overall CSR Scores*			*Environment Scores*		
	(1)	(2)	(3)	(4)	(5)	(6)
Seller(Pollutive) × *Post*	0.219**	0.209**	0.246**	0.436***	0.375**	0.367**
	(0.104)	(0.101)	(0.100)	(0.158)	(0.150)	(0.150)
Cohort-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort-Year FE	Yes			Yes		
Cohort-Industry-Year FE		Yes	Yes		Yes	Yes
Firm Char			Yes			Yes
Observations	162,694	162,655	160,962	162,670	162,631	160,938
R^2	0.553	0.564	0.567	0.433	0.455	0.456

Appendix G Acquisition of New Plants

Table G.1. Acquisition of New Plants

This table examines new plant acquisition for seller firms post divestitures. Panels A reports generalized DID regression estimates , and Panel B reports regression estimates with stacked panels of divested plants and matched never-divested firms. *Seller (Pollutive)* is an indicator of whether a firm sells a plant in a divestiture transaction over our sample period. The dependent variable in columns (1)-(3) is *D(New Plant)*, an indicator for acquiring any new plants in a given year, and the dependent variable in columns (4)-(6) is *Num(New Plant)*, the total number of new plants acquired in a given year. *Post* indicates years during or after the deals. Panel C reports results related to divestitures of other, non-pollutive assets. *Seller (Non-Pollutive)* is an indicator of whether a firm sells a non-pollutive asset in a divestiture transaction over our sample period. *Firm Char* includes *Size*, *M/B*, *Leverage*, *Cash*, and *Tangibility*. Standard errors are reported in parentheses and clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A. New Plant Acquisition, Generalized DID Regressions

Dep. Var.:	*D(New Plant)*			*Num(New Plant)*		
	(1)	(2)	(3)	(4)	(5)	(6)
Seller(Pollutive) × *Post*	-0.107***	-0.113***	-0.091***	-0.456***	-0.478***	-0.422***
	(0.023)	(0.023)	(0.023)	(0.098)	(0.103)	(0.105)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes			Yes		
Industry-Year FE		Yes	Yes		Yes	Yes
Firm Char			Yes			Yes
Observations	14,210	13,884	13,110	14,210	13,884	13,110
R^2	0.185	0.183	0.193	0.147	0.175	0.187

Panel B. New Plant Acquisition, Stacked Regressions

Dep. Var.:	*D(New Plant)*			*Num(New Plant)*		
	(1)	(2)	(3)	(4)	(5)	(6)
Seller(Pollutive) × *Post*	-0.101***	-0.109***	-0.088***	-0.492***	-0.482***	-0.438***
	(0.026)	(0.025)	(0.025)	(0.104)	(0.099)	(0.100)
Cohort-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort-Year FE	Yes			Yes		
Cohort-Industry-Year FE		Yes	Yes		Yes	Yes
Firm Char			Yes			Yes
Observations Observations	83,512	83,410	80,379	83,512	83,410	80,379
R^2	0.168	0.171	0.176	0.131	0.148	0.152

Panel C. New Plant Acquisition, Non-pollutive Divestitures

Dep. Var.:	*D(New Plant)*			*Num(New Plant)*		
	(1)	(2)	(3)	(4)	(5)	(6)
Seller(Non-Pollutive) × *Post*	-0.010	-0.012	-0.008	-0.014	-0.042	-0.022
	(0.013)	(0.014)	(0.014)	(0.044)	(0.044)	(0.044)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes			Yes		
Industry-Year FE		Yes	Yes		Yes	Yes
Firm Char			Yes			Yes
Observations	14,210	13,884	13,110	14,210	13,884	13,110
R^2	0.185	0.183	0.193	0.147	0.174	0.187