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

Ran Duchin† — *Boston College*

Janet Gao‡ — *Georgetown University*

Qiping Xu§ — *University of Illinois*

September 2022

Abstract

This paper studies the asset market for pollutive plants. Firms divest pollutive plants following environmental risk incidents. Following these divestitures, however, total and per-employee pollution levels at the sold plants do not decline. The buyers tend to be private, non-ESG-rated, and have supply chain relationships or joint ventures with the sellers. The sellers earn higher environmental, social, and governance (ESG) ratings and face lower regulatory compliance costs after divesting. Overall, the evidence suggests that 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

JEL Classification: G32, G34, H57, K42, Q50

*We are grateful to Todd Gormley, Jonathan Karpoff, Paul Malatesta, Sohpie Shive, and conference participants at the University of Washington 2022 Conference, Wabash River Finance Conference 2022 for their thoughtful comments.

†Carroll School of Management, Boston College. Email: duchinr@bc.edu.

‡McDonough School of Business, Georgetown University. Email: janet.gao@georgetown.edu.

§Gies College of Business, University of Illinois. Email: qipingxu@illinois.edu.

1 Introduction

A growing trend in corporate finance, a result of pressure 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, Figure 1, Panel A 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 divestments are. 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 by James Mackintosh 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] This view further raises 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.

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

[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?" The Wall Street Journal, January 23rd, 2022.

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 issues, we compile a novel dataset of 719 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 how pollution levels change at the sold plants around divestitures. We measure plant-level pollution using both the total amount of toxic release and emission intensity, defined as the ratio of toxic release to the number of workers employed in the plant. 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, hold in different test windows, and remain largely unchanged after the inclusion of plant, industry-by-year, and state-by-year fixed effects. They continue to hold after weighing toxic release levels by the toxicity of each chemical, in plant-by-chemical panel regressions, and in stacked regressions that consider potential biases due to heterogeneous dynamic treatment effects (e.g., 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 firms choose to keep plants whose pollution they can treat and divest assets whose pollution they cannot treat. To evaluate this possibility, we separately trace the pollution levels of sellers' remaining plants ("peer" plants). We find that following divestitures, there is no reduction in the pollution levels of peer plants.

Taken together, the findings suggest that the allocation of assets resulting from divestitures does entail reductions in pollution levels. Following divestitures, pollution levels do not decline either at the sold plants or at the remaining unsold 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? To answer these questions, we investigate the exposure of sellers and buyers to environmental pressures from investors, regulators, and the media. We begin by analyzing the sellers. These analyses 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 incidents related to ESG risks, and particularly incidents related to environmental risks. ESG risk exopsure is measured based on publicly known, negative incidences related to a firm's business conduct, gathered by RepRisk. We also separately measure environmental risk events.[3] Our estimates indicate that the occurrence of environmental risk incidents 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 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.

Next, we investigate the buyers of pollutive plants. We find that, compared to the sellers, the buyers of pollutive plants are 6 percentage points more likely to be private and 5 percentage points less likely to be covered by ESG ratings (Becker 2005; Hartzmark

[3]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 Reprisk events put pressure on management and influence corporate policies.

and Sussman 2019; Zaccone and Pedrini 2020; Krueger et al. 2020).

Combined, these results give rise to a separating equilibrium in the real asset market whereby public firms that face strong ESG pressures sell their most pollutive assets to privately-owned, unrated firms that face weaker ESG pressures. These findings are consistent with recent evidence on a similar investment equilibrium that matches between investors' ESG preferences and green vs. brown assets (e.g., Pástor et al. 2021, Piccolo et al. 2022, Heinkel et al. 2001, among others).

In the final set of analyses, we investigate the gains from trading pollutive assets. We start by investigating the changes experienced by sellers following divestitures. 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 divestments, 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. These newly formed connections suggest that the sellers begin transacting with the buyers following the divestitures.

Importantly, we show that the changes in ESG ratings, EPA enforcement actions, and buyer-seller business ties are only present follow 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 of 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 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 achieve around $400 million higher value gain relative to the sellers. This finding is consistent with the buyers' comparative advantage in operating pollutive assets without being exposed to strong 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 are ineffective conduits to reduce industrial pollution. These findings are consistent with Broccardo et al. (2020), who show that exit is less efficient than voice when firms generate externalities.

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 regulatory and ESG-rating arbitrage through asset transfers along a firm's value chain.[4]

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

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

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. 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 plant-level toxic emissions 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.[5] 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. We first extract the total toxic emissions (*Total Release*) from a plant in a given year (Xu and Kim, 2022) to capture the aggregate impact of a plant's production activities on the environment and public health. In addition, we examine a plant's toxic emissions intensity (Copeland and Taylor, 2003; Shapiro

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

and Walker, 2018), defined as the amount of toxic release per employee (*Release/Emp*).

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.

In additional analysis, we also use data on toxicity of each chemical (RSEI) to construct alternative measures of toxic release. In particular, we use *RSEI hazard*, a toxicity weighted pound measure of toxic release, and *RSEI Score*, which is the modeled surrogate dose multiplied by toxicity weight and by population. Finally, we extract data on production ratio, which is a quantity-based measure of output growth at the chemical level.[6]

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.[7]

[6] 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)).

[7] 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-

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 719 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 period 2000–2020. 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

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.

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 the buyer and the seller of a deal. This measure helps us evaluate how much more rent buyer extract from the transaction relative to the seller. It is computed as the change in the buyer's market value of equity subtracting the change of the sellers' market value of equity during the $[-1, +1]$-day window around deal announcement. The change in market value is defined as the product of $CAR[-1, +1]$ around deal announcement date and the firm's total market capitalization, measured in the most recent calendar year end prior to that date.

3 Empirical Strategy

We perform two types of analyses, one at the plant level and one at the parent firm level. In the plant-level analysis, we examine whether a plant generates less pollutants after being sold to another firm. In the firm-level analysis, we investigate whether the sellers and buyers experience various changes, including ESG ratings, EPA enforcement costs, and business relationship.

Throughout our main analyses examining the changes in pollution and firm conditions around divestitures, we perform the tests using two types of samples. The first sample is a plant-by-year or a firm-by-year panel, where we perform generalized difference-in-difference (DID) regressions using two-way fixed effects, such as firm fixed effects and year (or industry-year) fixed effects. Next, we address concerns related to the heterogeneous treatment timing effects in generalized DID regressions by constructing a stacked event sample.[8] To construct that sample, we match each treated unit (plant 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 around each event is labeled as a "cohort." We then stack all such cohort groups together to form our testing sample. We show that our results remain robust to both testing approaches.

3.1 Plant-level Analysis

We compile a plant-year panel that contains all plants reported in the TRI database. The key variable of interest is *Divested* $\times$ *Post*, which equals one if a plant has been sold through a divestiture, and zero for observations related to the sold plant prior to the transaction as well as for plants that are never sold.

[8] The following papers provide a detailed discussion about the econometric theory: 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.

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 and t represents a year. $Y_{i,t}$ includes total release and toxic emissions 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 introduced by Cohn and Wardlaw (2016). Our regressions include plant fixed effects (α_i) and year fixed effects (τ_t). In more rigorous 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 perform these regressions both using the generalized difference-in-difference approach and using the stacked regression approach. To construct the stacked sample, we match each sold plant to never-sold plants in the same industry (NAICS3) and located in the same state. We then estimate Equation (1) on the stacked sample composed of all such cohorts. Given that the control groups are sampled with replacement, we interact all our fixed effects with cohort fixed effects, augmenting the regression with cohort-plant, cohort-year, cohort-state-year, and cohort-industry-year interactive fixed effects. These fixed effects allow us to make within-cohort comparisons, contrasting each treated plant to its matched control group, and examine how their emission levels deviate from each other around the divestiture.

In robustness analyses, we separately track the emission of each type of chemical from a plant over time. This helps account for the concern that the same weight of different types of chemicals may generate different environmental externalities. Accordingly, we construct a plant-by-chemical panel, where the unit of observation is a chemical-plant-year. In this chemical-level analysis, we continue to estimate Equation 1, but replacing "plant" with "plant-by-chemical" as i.

3.2 Firm-level Analysis

The firm-level analysis primarily centers 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:

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

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 rigorous specifications also include industry-year fixed effects. Standard errors are clustered by firm.

Similar to the plant-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 cohort and firm as well as industry-year dummies.

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 this analysis, we utilize a firm-year panel that includes all observations for publicly traded firms, except for ones that sold TRI plants.

This filter helps remove from our control group firms experiencing the treatment effect of selling 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 provides statistics for the plant-level sample. This sample consists of 37,564 unique plants with 352,938 plant-year observations. At the plant level, the distribution of pollution emission is skewed. The average toxic emission of our sample plant-year is around 58,528 pounds with the median being 1,687 pounds. On average, each plant-year is associated with 258 employees and generates $74 million dollars in sales revenue. On pollution abatement, an average plant-year adopts 9.3 source reduction practices, and the percentage of total generated toxic chemicals reduced through recycling, recovery, and treatment is 31.2%, 5.4%, and 21.4%, respectively.

Table 1 About Here

Panel B provides information for the firm-level sample. In this sample, the average firm in our sample emit 625,496 pounds of toxic chemicals, with the median being 22,479 pounds. The average firm also has an employment count of around 2,364 with the median being around 600. 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 C 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 various characteristics of buyers and sellers of the divestiture deals in our sample. To start, we look at the public trading status as well as ESG rating coverage for all buyers and sellers involved in our sample deals. Relative to sellers, buyers are 6% less likely to be publicly traded and 5% less likely to be covered by ESG ratings, suggesting pollutive assets are more likely to be transferred to firms facing less ESG pressure. Next, we restrict the comparison among publicly traded buyers and sellers, for whom more detailed information on firm characteristics is available. Interestingly, buyers are significantly smaller than sellers, either in terms of asset size and employment count, or sales and market share. These statistics suggest that the divestiture deals in our sample represent smaller firms purchasing assets from larger ones. Buyers also generate lower quantities of toxic releases than sellers and have higher environmental pillar ratings based on the KLD database. However, buyers' plants have similar toxic emissions intensity as sellers.

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). Table 3 presents the results. In Panel A we examine changes in 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, all results are estimated using 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 and year fixed effects, then augmenting them with state-year and industry-year interactive fixed effects. In stacked regressions, we interact these fixed effects with cohort dummies.

TABLE 3 ABOUT HERE

Across all specifications, we do not find sold plants to emit less pollutant after divestitures compared to the control group. *Divested* $\times$ *Post* even generates positive coefficients in all specifications. The coefficient turns statistically significant in one specification, suggesting that sold plants increase their emissions marginally more than the unsold ones.

In Figure 2, we separately trace the emissions generated by sold plants and their never-sold control group in the same state and industry around the year of divestiture. We estimate individual time indicators for each year during the $[-5, +5]$-year window around the event. Years after the fifth year post divestiture are grouped together. Panels A and B present the dynamic patterns for the changes in emission quantity and intensity for divested plants, respectively. Panels C and D depict the corresponding patterns for their matched control plants. Our estimation includes cohort-plant, state-year, and industry-year fixed effects. Year of the divestiture (Year 0) is absorbed as the benchmark.

From these patterns, we do not find divestitures to decelerate the emission activities at the sold plants. Instead, those plants seem to have increased their total toxic releases prior to their divestitures, and continue to do so after the deals. The emission intensity of sold plants does not exhibit a clear trend around divestitures, although it appears to increase in the long run.

In contrast, pollution levels of never-sold plants are highly stable. There is no significant changes in the average release quantity of those plants around the divestiture of the focal plant. Emission intensity exhibits a small downward trend.

In Appendix E, we perform several robustness checks to address the concern that, as toxicity varies across chemicals, the same weight of different types of chemicals may generate drastically different environmental impact. We perform two analyses. First, we employ two measures of pollution levels that assign weights to each type of toxic release based on its toxicity. *RSEI Hazard*, also referred to as toxicity-weighted pounds, accounts for the size of the release and the chemical's toxicity. *RSEI score* further adjusts for environmental fate and transport modeling or adjustments for population exposure. Panels A and B Table E.1 report results for these alternative measures using the generalized DID approach and stacked regression approach, respectively. Second, we construct a plant-by-chemical panel, tracking the emission volume of each chemical separately within the plant.

When measuring the emission intensity of chemical-level releases, we no longer use the total employment counts at the plant level because there is no information on the assignment of employees to each chemical class. Instead, we scale emission volume by production ratio, a quantity-based measure of output growth at the chemical level. Panels C and D report the results for this panel. Across both robustness checks, we continue to find no evidence that divested plants generate lower emissions or toxicity after the transaction.

We next turn to examine pollution abatement efforts at sold plants. In Table 4, we examine pollution abatement efforts implemented at the plant level, including source reduction (*#Source Reduction*) and post-production waste management (*%Recycling, %Recovery, and %Treatment*). Similar to Table 3, we first report results from the generalized DID framework in Panel A and results from stacked regressions in Panel B. Estimates across both panels consistently indicate barely any differential change in pollution abatement activities between divested and non-divested plants following divestitures. These results provide more context for the findings in Table 3 — plants do not experience meaningful changes in their toxic release levels as they do not materially change their pollution abatement processes.

TABLE 4 ABOUT HERE

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

4.2 Pollution at Remaining Plants

An explanation for our previous result is that firms may sell the plants that they fail to improve, but focus their resources to cut emissions from other, remaining plants. We evaluate this argument by examining concurrent changes in the pollution levels of the remaining plants of the seller around divestitures. Specifically, for all plants that did not go through a divestiture, we define an indicator variable *Peer Divestiture* $\times$ *Post*, which equals one if its parent company has divested at least one other plant in a given year, and that the plant has not been divested itself. Table 5 reports the results. Again, we report results from generalized (stacked) DID regressions in Panel A (B). For this analysis, a stacked sample is constructed for each peer plant of the divested plant based on the year of divestiture. For each peer plant, never-divested plants in the same industry and state are chosen as the control group.

<u>TABLE 5 ABOUT HERE</u>

Our estimates indicate that the quantities of toxic releases do not decline at remaining, non-divested plants. The coefficients on the interaction term *Peer Divestiture* $\times$ *Post* for total toxic releases are relatively small, statistically insignificant at conventional levels, and switch signs across specifications. Moreover, in some specifications, toxic release intensity significantly increases at remaining plants. These results are inconsistent with the argument that sellers seek to reduce emission at remaining plants.

5 Determinants of Pollutive Asset Divestitures

Our results so far suggest that divestitures are not associated with reductions in pollution. If not to reduce pollution, what motivates firms to transact these plants? We seek to shed light on this question by examining the determinants of divestitures, focusing in particular on the exposure of sellers and buyers to environmental pressures.

5.1 Plant Emission and The Likelihood of Being Sold

We start by examining whether more pollutive plants are more likely to be divested. To do so, we relate the pollution levels generated by a plant to the likelihood of its divestiture using a plant-year panel. A plant is included in the sample up to the year of its divestiture. All observations related to never-sold plants that retained. 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.

Consistent with Section 4, a plant's pollution level is measured both using total release and emission intensity. For each metric, we take its average value during the current and the previous year ($[t-1,t]$) so as to mitigate concerns that pollution during the year of the transaction could be volatile. Due to skewness in the distribution of toxic release, and for ease of interpretation, we group both release measures into quartile indices, where 1 represents the lowest pollution level, and 4 represents the highest.

Panel A of Table 6 reports results from this analysis. Columns (1) through (4) present results related to total pollution; Columns (5) through (8) present results related to pollution intensity. We start by presenting the univariate association between plant pollution and divestment likelihood, and then add control in stages, including industry-year fixed effects and state-year fixed effects. Across all measures and specifications, past pollution yields significant, positive coefficients for the likelihood of divestiture, suggesting that more pollutive plants are more likely to be divested. The estimate in Column (3) implies that an inter-quartile increase in pollution volume (quartile number from 1 to 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 divestiture (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 ($= 0.027 \times 3/0.29$).

TABLE 6 ABOUT HERE

5.2 ESG Risk Exposure and Asset Divestiture

We next examine whether firms are more likely to divest pollutive plants when they face public exposures of ESG risk. As an initial proxy, we use the incidence of any negative

ESG event as indication of public ESG exposure. Next, we focus on events specifically related to environmental risk, and test whether these events motivate firms to dissociate from 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. *Sell (Pollutive)* is multiplied by 100 so that the coefficients can be intepreted as the percentage likelihood of divestment.

Results are presented in Panel B of Table 6. Columns (1) through (3) report results related to any ESG incidences, 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' tendency to divest assets. We first document 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 greater likelihood that the firm sells a pollutive plant. Column (6) suggests that having an environmental risk event generates a much larger effect, reaching 1.3 percentage points. These are substantial magnitudes compared to the sample average of having a divestiture of 1.3 percentage points. Importantly, as we include environment-related events and non-environment-related events, we find that the effect on divestiture is concentrated on environmental issues. The coefficient on social and governance issues is small and indistinguishable from zero.

For context, we examine whether selling assets is a common response of all firms facing negative press exposure. It is possible that the negative ESG incidences simply represent inefficient operations or financial difficulties, which also force firms to sell productive assets. Under this explanation, we should expect ESG risk exposure to also be followed by divestitures of other, non-pollutive assets. However, results in Panel C suggest this is unlikely to be the case. In Columns (1) through (3), we do not find any positive association between ESG risk events and the divestment likelihood non-pollutive assets. Results in Columns (4) through (9) indicate that having an environmental exposure event is negatively associated with future divestitures of non-pollutive assets, although the effects are not statistically significant. This might be due to such exposure revealing risks embedded in firms' operations and increasing the difficulty for firms to attract buyers. In untabulated analysis, we repeat the analysis on a full sample of public firms (and not just owners of TRI plants). In that sample, we still do not find any association between ESG events and the likelihood of divesting non-pollutive assets.

Our results so far indicate that sold plants do not emit less toxic waste under the new owner. If pollution levels remain unchanged, why do firms purchase these plants, and how do they gain from such trade? We discuss the possibility that buyers of pollutive plants may have a comparative advantage at handling ESG pressures from various stakeholders, such as investors and regulators. We further substantiate this argument by investigating the relative market value gains from trade between buyers and sellers.

5.3 Who Buys Pollutive Assets?

As sellers face public pressure to offload pollutive assets, do buyers have comparative advantage in operating and owning pollutive assets? To answer this question, we look into whether buyers are more likely to be private firms or non-ESG-rated firms compared to the sellers. 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). Without such ratings, firms' cost of capital should be less sensitive to their ESG practices.

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 be private or ESG-unrated firms. In particular, we regress each of the two indicator variables, *Private Firm* and *Unrated Firm*, 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 *1(Private Firm)*, an indicator that equals 1 if the firm is private, and 0 if it is public, and *1(Unrated Firm)*, an indicator that equals 1 if a firm is not covered by the KLD, Refinitive, or MSCI ESG ratings, and 0 otherwise. $Buyer_{k,t}$ 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 are more (less) likely to be private and unrated firms than sellers.

Columns (1) and (2) in Table 7 report the results. We find that relative to sellers, buyers of pollutive plants are 6 percentage points more likely to be private firms and 5 percentage points less likely to be covered by any of the ESG rating agencies. These findings suggest that more scrutinized firms tend to offload their pollutive assets to less scrutinized firms.

<u>Table 7 About Here</u>

In Columns (3) through (6), we examine whether plants generating more pollution are more likely to be sold to a private or an ESG-unrated buyer. The results suggest that plants with greater pollution intensity are significantly more likely to be sold to private or unrated firms. The estimate in Column (4) implies that an inter-quartile increase in pollution intensity (from the lowest quartile to the highest quartile) increases the likelihood of being sold to private buyers by 15% (= 0.049 × 3), which represents a 28% increase relative to the sample average of 54%. Column (6) implies that a similar inter-quartile increase in pollution intensity increases the likelihood of being sold to unrated buyers by 12.6% ($= 0.042 \times 3$), which represents a 19% increase relative to the sample average of 66%. We find positive coefficients for total pollution levels, indicating an increasing relation between plant emission and the likelihood of being sold to private, unrated firms, although these coefficients are not statistically significant at conventional levels.

6 Gains from Trade

We explore firms' motives to sell pollutive assets by investigating the changes they experience following such divestitures. We provide three main analyses regarding changes around divestitures: (1) The ESG ratings of the sellers, (2) The environmental regulatory compliance costs of the sellers, and (3) 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). We also examine outcomes for sellers of non-pollutive assets as a placebo test.

6.1 Changes in Sellers' ESG Ratings

Table 8 presents results on the changes in ESG ratings around divestitures for the sellers. As discussed in Section 3, we rely on two methods to perform the difference-in-difference estimation. First, we conduct a generalized difference-in-difference estimation with firm and time fixed effects. Second, we use a stacked matched sample, comparing the outcomes of sellers to those of non-sellers following the divestiture event in the same industry at the same point in time.

Table 8 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 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 of sellers. Estimates from Column (6), Panel A suggest that sellers' environmental scores increase by around 0.22, or 27% of the sample standard deviation. We obtain similar estimates from the stacked regression approach, suggesting that these effects are unlikely driven by biases in a staggered DID design. In Appendix F, we consider alternative ESG ratings from Refinitive and MSCI. We compare between the coverage of the different ESG ratings, and show that our results are robust to the inclusion of alternative ESG ratings.

6.2 Changes in Sellers' EPA Enforcement Costs

We next analyze changes in the likelihood of EPA violations and in sellers' compliance costs surrounding the divestitures of pollutive assets. We estimate Equation 2 using as dependent variables the indicator for receiving an enforcement action (*Enforcement Action*) and the dollar value of cost from EPA enforcement (*Enforcement Cost*). In this analysis, we focus on a set of publicly traded firms who own TRI plants, because non-owners do not have EPA violations by design. Table 9 reports the results. Again, Panel A provides the results from generalized DID regressions while Panel B presents results from stacked regressions. Within each panel, the first three columns provide results for the incidence of an enforcement action for a firm-year, and the last three columns contain results for costs associated with enforcement. Such costs equal zero in cases of no enforcement actions.

Table 9 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 divestiture of a pollutive plant, the seller is 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 further show that conditional on an EPA enforcement action, enforcement costs decrease by around \$3–5 million following the divestment of pollutive assets, around 10–15% of the its sample standard deviation (30 million). These results provide evidence that selling pollutive plants enables sellers to increase their compliance with environmental regulations and to reduce the costs associated with enforcement actions.

6.3 Business Ties Between Buyers and Sellers

Anecdotal evidence suggests that the divestitures of pollutive assets tend to 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. 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. Others deals signal the start of cooperative relations between the buyer and the seller. For example, Outokumpu Oyj (OO) acquired the majority interest in the heat transfer business of Lennox International Inc (LI) in 2002 to form a joint venture.

Motivated by the above 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. These relationships may facilitate the transfer of pollutive assets for several reasons. First, both types of relationships imply operational and technological complementarities between the seller and the buyer. Hence, related buyers are better positioned to utilize the divested asset, and are therefore likely to offer a higher price.

Second, existing business relationships help firms navigate the negotiation process and increase the likelihood of firms reaching a divestment agreement. Third, the existence of a business relationship 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," who 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 five pseudo buyers and one actual buyer for the seller. Accordingly, 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 buyers are more likely to start a new business relationship with the actual buyer than with pseudo buyers after the year of the deal. This investigation helps reveal 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 10 reports the results from this analysis. In Column (1), we regress the indicator for the real buyer, *Buyer of Pollutive Plants* on the indicator for shared business relations, *Operationally Related*. The regression controls for match group fixed effects, which is an indicator for each individual divestiture transaction. This stringent set of fixed effects allows us to compare each buyer-seller pair to its matched pseudo buyer-seller pairs. These fixed effects also absorb any variation at the deal level, or broader than the deal level, including macroeconomic trends, seller characteristics, and industry dynamics. Our 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 10 ABOUT HERE

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 polluting 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 and remain connected through joint ventures. As such, our findings indicate that divestitures of pollutive assets convey various benefits to the sellers without having to give 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 the concern that our findings could capture mechanical changes to firms after asset divestitures, such as a reduction in operation scale, an influx of financial resources, or a change in production input. If our results are driven by these forces associated with any divestiture and does not uniquely relate to the incentive to dissociate with pollutive assets, our effects should show up for both divestitures of pollutive and non-pollutive assets. If our findings capture firms' intention to offload dirty assets, we expect effects not to be present for divestitures of pollutive assets.

Table 11 provides results from the analyses of sellers of non-pollutive assets. Panel A presents results regarding sellers' ESG ratings, Panel B reports results for sellers' enforcement actions and costs, and Panel C provides results on the business ties between buyers and seller. We do not find sellers of non-pollutive assets to experience a major change in their ESG scores or a reduction in EPA enforcement. The coefficient estimates on the interaction term *Sell(NonPollutive)* $\times$ *Post* are generally small and statistically insignificant. We also do not find buyers of non-pollutive assets to have pre-existing business ties, or to develop new relations with the sellers.

Table 11 About Here

Analysis of the sellers of non-pollutive assets reveals little changes to their ESG scores, EPA enforcement, or relationship-transactions around asset divestitures. These results are in stark contrast with the ones from pollutive divestitures, suggesting that the benefits we documented are specific to divesting pollutive assets and are unlikely driven by generic changes in firm characteristics around all asset sales.

6.5 Analysis of Divestiture Announcement Returns

As sellers obtain various benefits from offloading pollution, it is natural to ask whether shareholders recognize these benefits and adjust their valuation of the divesting firms. We study 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 12 reports the results. Across both definitions of abnormal returns and both pollution measures, we observe a significant, positive relation between the level of pollution of the sold plants and 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 comparing to the sample average returns of 2 to 3 percent. These results are consistent with investors rewarding firms for divesting pollutive assets.

Table 12 About Here

In the last set of analysis, we examine the relative gains from trade between buyers and sellers. If buyers are among the limited group of entities that have comparative advantage in operating and owning pollutive plants, we expect them to capture more gains when purchasing dirtier assets. On the other hand, sellers may capture a greater share of the gains for selling brown 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 gain between 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 metric indicate that the buyer experiences 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 pollutiveness 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 buyers and sellers to both be public entities, leading to a smaller sample of 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 both measures of market value gains and pollution, we find that buyers' market values grow more than those of sellers as the divestitures involve dirtier assets. When measured using the market benchmark, buyers achieve higher market value gains from the deals than sellers in the highest quartile of plant pollution by around $400 million. In contrast, buyers capture nearly $800 million less gain than sellers for deals involving plants with the lowest pollution. These results suggest that buyers of the most pollutive plants likely possess unique advantages in operating and owning those assets.

Taken together, our buyer-side analysis shows that pollutive assets are often transferred from publicly listed firms to private firms, and from firms with ESG ratings to firms not covered by any of the ESG rating agencies. This evidence sheds light on the motivation behind the divestiture of pollutive assets. While the divested plants continue to emit similar levels of pollutants, the new owners face lower ESG compliance costs, leading to gains from trading pollutive assets with the publicly listed, rated owners. In this regard, our findings are related to the argument from the existing literature that investors with stronger ESG preferences gravitate towards green assets, and those with weaker ESG preferences are more likely to hold brown assets (e.g., Pástor et al. 2021, Piccolo et al. 2022, Heinkel et al. 2001).

7 Conclusion

In this paper, we investigate the motivations behind, and implications of, divestitures of pollutive assets. We find that sellers of pollutive assets benefit from divestitures in several ways. They receive higher ESG ratings and face lower environmental compliance costs and enforcement risks.

At the same time, pollution levels do not decline. Divested plants generate similar amounts of toxic release under the new owners, and even higher levels of toxic release per employee. Furthermore, plants that remain under the ownership of sellers do not experience a reduction in pollution either.

Moreover, we find suggestive evidence that sellers maintain access to the sold plants as they are more likely to sell their pollutive assets to joint-venture or supply-chain partners. After the sale, the seller and the buyer are also more likely to develop new business relations.

Combined, 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 polluting assets allows the possibility of 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 that the real asset market plays in firms' greenwashing strategies.

References

Akey, Pat, and Ian Appel, 2019, Environmental externalities of activism, *Available at SSRN 3508808* .

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

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

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

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

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

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

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

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

Barko, Tamas, Martijn Cremers, and Luc Renneboog, 2021, Shareholder engagement on environmental, social, and governance performance, *Journal of Business Ethics* 1–36.

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

Becker, Randy A, 2005, Air pollution abatement costs under the clean air act: evidence from the pace survey, *Journal of environmental economics and management* 50, 144–169.

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

Berg, Florian, Julian F Koelbel, and Roberto Rigobon, 2020, Aggregate confusion: the divergence of ESG ratings, *Available at SSRN 3438533* .

Bisetti, Emilio, Stefan Lewellen, and Arkodipta Sarkar, 2021, Smokestacks and the swamp, *Available at SSRN 3947936* .

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

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess, 2021, Revisiting event study designs: Robust and efficient estimation, *arXiv preprint arXiv:2108.12419* .

Broccardo, Eleonora, Oliver Hart, and Luigi Zingales, 2020, Exit vs. voice .

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

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

Chang, Xin Simba, Kangkang Fu, Tao Li, Lewis Tam, and George Wong, 2021, Corporate environmental liabilities and capital structure, *Available at SSRN 3200991* .

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

Cohn, Jonathan B, and Malcolm I Wardlaw, 2016, Financing constraints and workplace safety, *The Journal of Finance* 71, 2017–2058.

Copeland, Brian, and Scott Taylor, 2003, *Trade and the environment: Theory and evidence* (Princeton University Press, Princeton, NJ).

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

De Chaisemartin, Clément, and Xavier d'Haultfoeuille, 2020, Two-way fixed effects estimators with heterogeneous treatment effects, *American Economic Review* 110, 2964–96.

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

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

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

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

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

Gantchev, Nickolay, Mariassunta Giannetti, and Rachel Li, 2019, Does money talk? market discipline through selloffs and boycotts, *Market Discipline through Selloffs and Boycotts (May 20, 2021). European Corporate Governance Institute–Finance Working Paper* 19–9.

Gibson, Rajna, Philipp Krueger, and Peter Steffen Schmidt, 2019, Esg rating disagreement and stock returns, *Swiss Finance Institute Research Paper* .

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

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

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

Heath, Davidson, Daniele Macciocchi, Roni Michaely, and Matthew C Ringgenberg, 2021, Does socially responsible investing change firm behavior?, *Available at SSRN 3837706* .

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

Hoepner, Andreas GF, Ioannis Oikonomou, Zacharias Sautner, Laura T Starks, and Xiaoyan Zhou, 2018, Esg shareholder engagement and downside risk .

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

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

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

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

Jovanovic, Boyan, and Peter L Rousseau, 2002, The q-theory of mergers, *American Economic Review* 92, 198–204.

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

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

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

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

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

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

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

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

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

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

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

Piccolo, Alessio, Jan Schneemeier, and Michele Bisceglia, 2022, Externalities of responsible investments, *Available at SSRN 4183855* .

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

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

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

Shapira, Roy, and Luigi Zingales, 2017, Is pollution value-maximizing? the dupont case Working Paper.

Shapiro, Joseph S, and Reed Walker, 2018, Why is pollution from us manufacturing declining? the roles of environmental regulation, productivity, and trade, *American Economic Review* 108, 3814–54.

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

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

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

Starks, Laura T, Parth Venkat, and Qifei Zhu, 2017, Corporate esg profiles and investor horizons Working Paper, University of Texas at Austin.

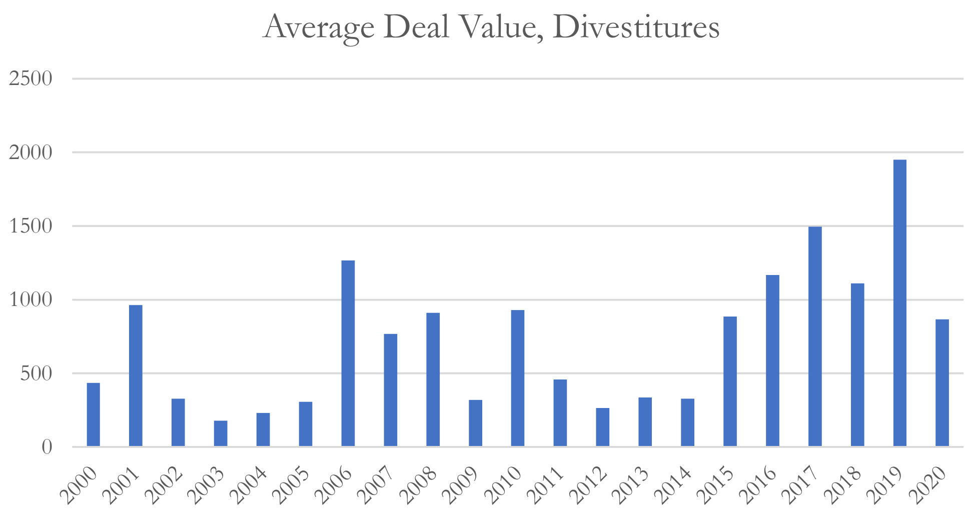
Sun, Liyang, and Sarah Abraham, 2021, Estimating dynamic treatment effects in event studies with heterogeneous treatment effects, *Journal of Econometrics* 225, 175–199.

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

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

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

Figure 1. Trends in Divestitures and Awareness of "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.

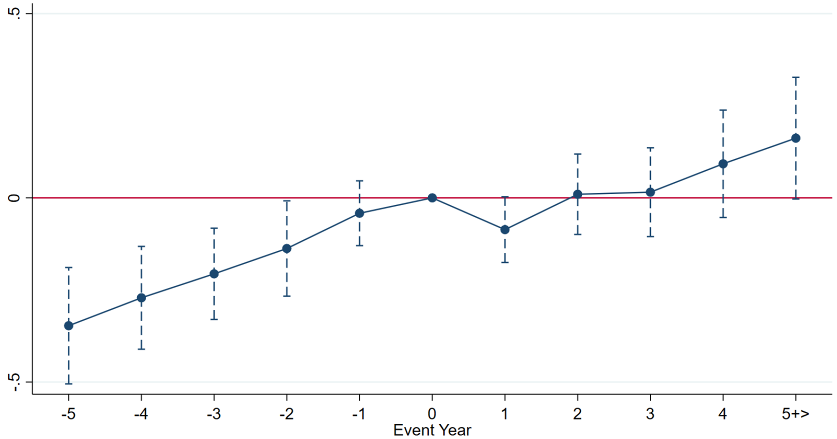


Panel A. Trends in Average Divestiture Volume

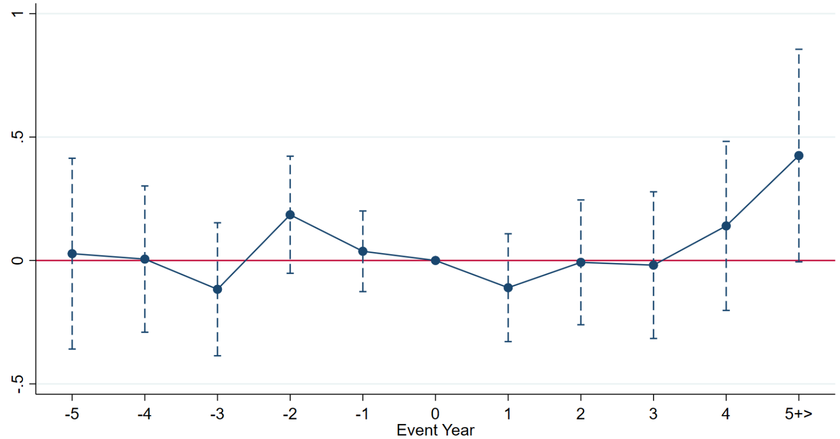
Panel B. Trends in Google Search Volume of "Green Wash"

Figure 2. Changes in Plant-level Pollution Following Divestitures

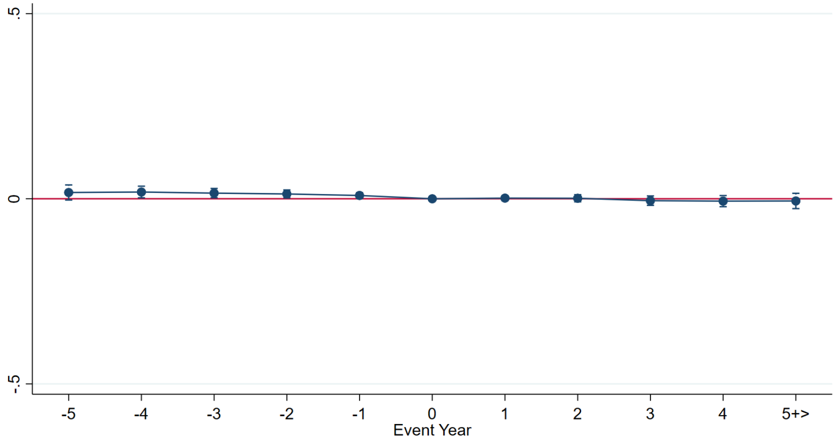
This figure presents the changes in of plant-level pollution around divestitures. Panels A and B present results for divested plants, and Panels C and D plot the pollution levels for matched never-divested plants within the same industry (3-digit NAICS) and state. The outcome variable in Panels A and C is the total toxic release, in Panels B and D is release intensity, as measured by total toxic releases scaled by employment count. All regressions include cohort-plant fixed effects, industry-year fixed effects, and state-year fixed effects. A cohort refers to the divested plant and its matched control group of never-divested plants. The solid dots indicate point estimates and the vertical intervals indicate 95% confidence intervals.



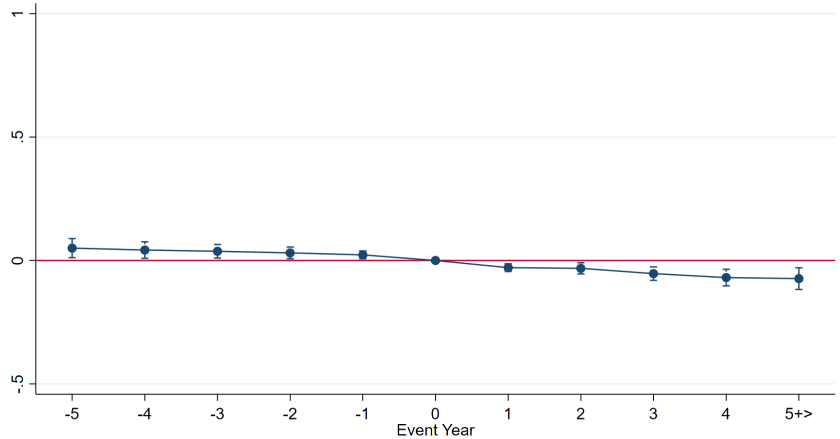
(A) Divested Plants: Total Release



(B) Divested Plants: Release/Emp



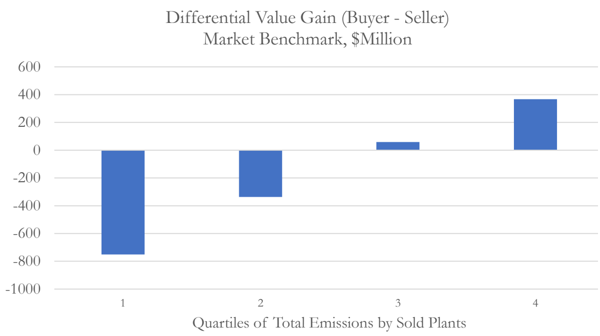
(C) Never-Divested Plants: Total Release



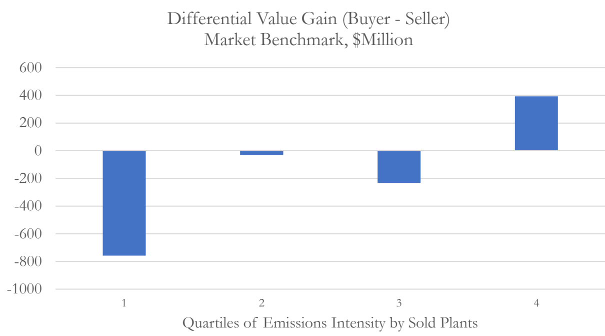
(D) Never-Divested Plants: Release/Emp

Figure 3. Differential Gain and Pollution by Sold Plants

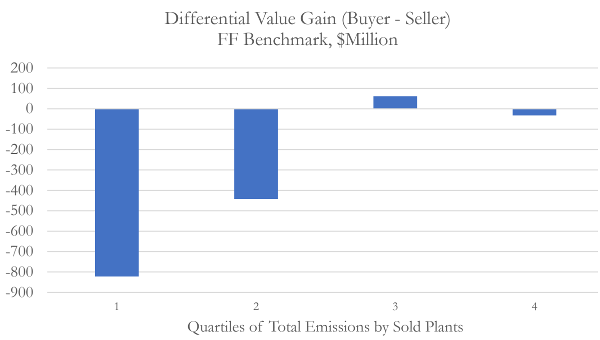
This figure presents the differential gain between buyers and sellers in divestiture deals. Differential gain refers to the difference between the market value gain for buyers relative to sellers around the deal announcement date ($Buyer - Seller$). Market value gains are measured by the the product of a firm's market capitalization and its $CAR[-1, +1]$ around deal announcement. Market capitalization is measured by the product between shares out standing 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. 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.



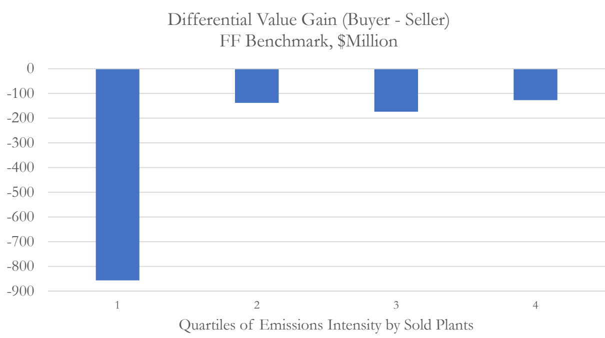
(A) Differential Gains based on Total Emission Market Benchmark



(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 variables used. Panel A presents summary statistics for the TRI plant-year panel, and Panel B presents the summary for the firm-year panel. Panel C reports statistics for buyers' and sellers' announcement cumulative returns.

Panel A: Plant-Level Sample

	N	Mean	Median	SD	P25	P75
Total Release	352,938	58,528.59	1,687.19	215,344.54	24	17,705
Release/Emp	285,242	1,158.93	18.42	5,190.52	0.28	220.51
Sales (in $M, NETS)	284,538	73.92	20	174.94	6.40	59.99
Employment (NETS)	285,242	258.02	100	449.79	39	277
#Source Reduction	352,938	9.30	1.00	21.21	0.00	8.00
%Recycling	352,938	31.18	0.00	43.34	0.00	90.11
%Recovery	352,938	5.35	0.00	18.17	0.00	0.00
%Treatment	352,938	21.42	0.00	36.38	0.00	30.78

Panel B: Firm-Level Sample

	N	Mean	Median	SD	P25	P75
Release	14,326	625,496.30	22,479	2,037,716	1,101	220,629.90
Release/Emp	13,466	898.05	33.33	3,721.17	2.52	280.69
Employment (NETS)	14,326	2,364.07	584	5,000.88	150	2,064
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

Panel C: 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 the univariate comparison of buyer and seller characteristics. *1(Private Firm)* (*1(Unrated Firm)*) is an indicator that the buyer or seller of a deal is a private company (not covered by KLD, Refinitive, or MSCI ratings). *1(Private Firm)* and *1(Unrated Firm)* are measured at a deal-by-firm panel. All other characteristics are tabulated for publicly traded buyers and sellers for the year before and in the year of the divestiture ($[t-1, t]$).

	Buyer		Seller		Difference	
	Obs	Mean	Obs	Mean	(Buyer−Seller)	
1(Private Firm)	719	0.54	719	0.48	0.06	**
1(Unrated Firm)	719	0.66	719	0.62	0.05	**
Total Release (000 lbs)	352	919.05	373	2203.85	-1,284.80	***
Release/Emp	336	678.02	369	584.82	93.19	
Emp (NETS)	352	4,268.01	373	8,032.99	-3,764.98	***
Sales (NETS)	352	1,449.68	373	2,928.06	-1,478.38	***
CSR Score (KLD)	282	0.14	350	0.22	-0.08	
Environment Score (KLD)	282	0.09	350	-0.07	0.15	
Total Assets	506	10,616.60	522	18,709.55	-8,092.95	***
M/B	500	1.61	514	1.53	0.09	**
Leverage	506	0.42	521	0.45	-0.03	**
Cash Holding	506	0.09	522	0.09	-0.00	
Tangibility	506	0.30	520	0.30	0.00	

Table 3. Changes in Plant 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. Panels 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. *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). All regressions are Poisson regressions described in Cohn and Wardlaw (2016). A cohort refers to a group of plants that includes a divested plant and its matched never-divested control plants. Standard errors are presented in parentheses and clustered by plant. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A. 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 B. 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

Table 4. Changes in Plant Abatement Activities Following Divestitures:
This table presents results for the abatement activities of divested plants around the divestiture. The sample includes all TRI plants. Panels 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 for years after 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 refers to a group of plants that includes a divested plant and its matched never-divested control plants. Standard errors are presented in parentheses and clustered by plant. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A. Pollution Abatement Activities, Generalized DID Regressions

	(1)	(2)	(3)	(4)
Dep. Var.:	*#Source Reduction*	*%Recycling*	*%Recovery*	*%Treatment*
Divested × *Post*	0.140	0.289	-0.007	1.294
	(0.298)	(0.797)	(0.551)	(0.823)
Plant FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Observations	349,172	349,172	349,172	349,172
R^2	0.955	0.839	0.706	0.817
Model	OLS	OLS	OLS	OLS

Panel B. Pollution Abatement Activities, Stacked Regressions

	(1)	(2)	(3)	(4)
Dep. Var.:	*#Source Reduction*	*%Recycling*	*%Recovery*	*%Treatment*
Divested × *Post*	0.136	-0.206	0.193	1.859**
	(0.505)	(0.877)	(0.673)	(0.932)
Cohort-Plant FE	Yes	Yes	Yes	Yes
Cohort-State-Year FE	Yes	Yes	Yes	Yes
Cohort-Industry-Year FE	Yes	Yes	Yes	Yes
Observations	742,119	742,119	742,119	742,119
R^2	0.961	0.831	0.712	0.795
Model	OLS	OLS	OLS	OLS

Table 5. Pollution Levels at Remaining Plants Following Divestitures

This table presents results for the emissions of remaining (non-divested) plants of firms that have divested plants in our sample. Panels 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 Divestiture* is an indicator for whether a plant is owned by a parent firm that divests other plants over our sample period. *Post* indicates years during and after the divestiture of other plants. *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). All estimates are based on Poisson regressions described in Cohn and Wardlaw (2016). A cohort refers to a group of plants that includes a peer plant of a divested plant and the peer plant's matched control plants. Standard errors are presented in parentheses and clustered by plant. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A. Remaining Plants, Generalized DID Regressions

Dep. Var.:	*Total Release*			*Release/Emp*		
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Divestiture × *Post*	0.044	0.020	-0.012	0.230***	0.190**	0.161*
	(0.037)	(0.037)	(0.034)	(0.085)	(0.086)	(0.088)
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	292,242	292,236	292,095	234,825	234,804	234,644
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson

Panel B. Remaining Plants, Stacked Regressions

Dep. Var.:	*Total Release*			*Release/Emp*		
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Divestiture × *Post*	-0.030	-0.012	-0.017	0.078	0.088	0.071
	(0.050)	(0.044)	(0.043)	(0.107)	(0.100)	(0.108)
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	1,242,366	1,242,226	1,241,277	1,029,368	1,029,171	1,028,370
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson

Table 6. Determinants of Divestitures: Plant-Level Pollution and Exposure to ESG Risks

In this table, we examine what determines pollutive plant divestitures. In particular, we focus on two aspects: plant-level pollution and sellers' exposure to ESG risk incidences. Panel A relate plant-level pollution to the likelihood of being sold. The dependent variable is *Divested* an indicator for whether a plant is divested in a given year. *Past Release (Quartile)* is the quartile partitions 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 emissions 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 regarding 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 examines 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 is 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* 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 environmental-related risk event in the current or the past year. We use a parent firm-year panel, including 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 assets when facing ESG risk exposures. The dependent variable is *Sell (Non-Pollutive)*, an indicator for whether a firm divests other assets in a given year. All dependent variables in this table are multiplied by 100. 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. Plant Pollution and the Likelihood of Being Divested

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 A. RepRisk Events and Decisions to Sell 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 B. RepRisk Events and Decisions to Sell Non-Pollutive Assets

Dep. Var.: *Sell (Non-Pollutive)*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(8)
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 7. Buyers of Pollutive Plants: Ownership and ESG Ratings

This table examines whether buyers of TRI plants are more likely to be private and non-ESG-rated, and whether this pattern is most salient for highly pollutive plants. In Columns (1)-(2), we compare the firm types across buyers and sellers of divestiture deals. The sample is a deal-firm panel. The independent variables are *Private Firm*, an indicator of a private firm, and *Unrated Firm*, an indicator of a firm not covered by KLD, Refinitive, or MSCI. In Columns (3)-(6), we regress plant-level past pollution (sorted into quartiles) on their buyer types. The sample is a deal-plant panel. The dependent variables are *Private Buyer*, an indicator of a buyer being a private company, and *Unrated Buyer*, an indicator of a buyer not covered by KLD, Refinitive, or MSCI. Robust standard errors are included. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dep. Var:	*Private Firm*	*Unrated Firm*	*Private Buyer*		*Unrated Buyer*	
	(1)	(2)	(3)	(4)	(5)	(6)
Past Release Measured By:			Quantity	Intensity	Quantity	Intensity
Buyer	0.062**	0.052**				
	(0.027)	(0.025)				
Past Release (Quartile)			0.010	0.049**	0.009	0.042**
			(0.017)	(0.017)	(0.017)	(0.018)
Industry FE	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
Observations	1,419	1,419	855	708	855	708
R^2	0.003	0.002	0.105	0.121	0.113	0.134
Model	OLS	OLS	OLS	OLS	OLS	OLS

Table 8. 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 refers to a group of firms that includes a seller firm and its matched non-seller firms. 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*	0.701***	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. ESG Ratings, 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 9. 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 refers to a group of firms that includes a seller firm and its matched non-seller firms. Standard errors are clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A. Enforcement, 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)
Year FE	Yes			Yes		
Firm FE	Yes	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. Enforcement, 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 10. Business Ties between Buyers and Sellers of Pollutive Assets
This table reports results regarding whether the buyer and seller of a divestiture share operational relations, such as supply-chain or joint-venture partners. Panel A reports the results for the relations between buyers and sellers of pollutive plants, while Panel B reports results for the relations between buyers and sellers of non-pollutive assets in divestiture deals. In each panel, column (1) examines whether firms that shared operational relationships with the seller in the past are more likely to become buy the divested assets from the seller. *Operationally Related* is an indicator for whether a firm is a supply-chain or joint venture partner with the seller in the past. *Buyer of Pollutive Plants* (*Buyer of Non-Pollutive Plants*) is an indicator for whether 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 11. Non-Pollutive Divestitures

This table presents results regarding outcomes of sellers 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) $\times$ *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) $\times$ *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 12. 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 6, 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

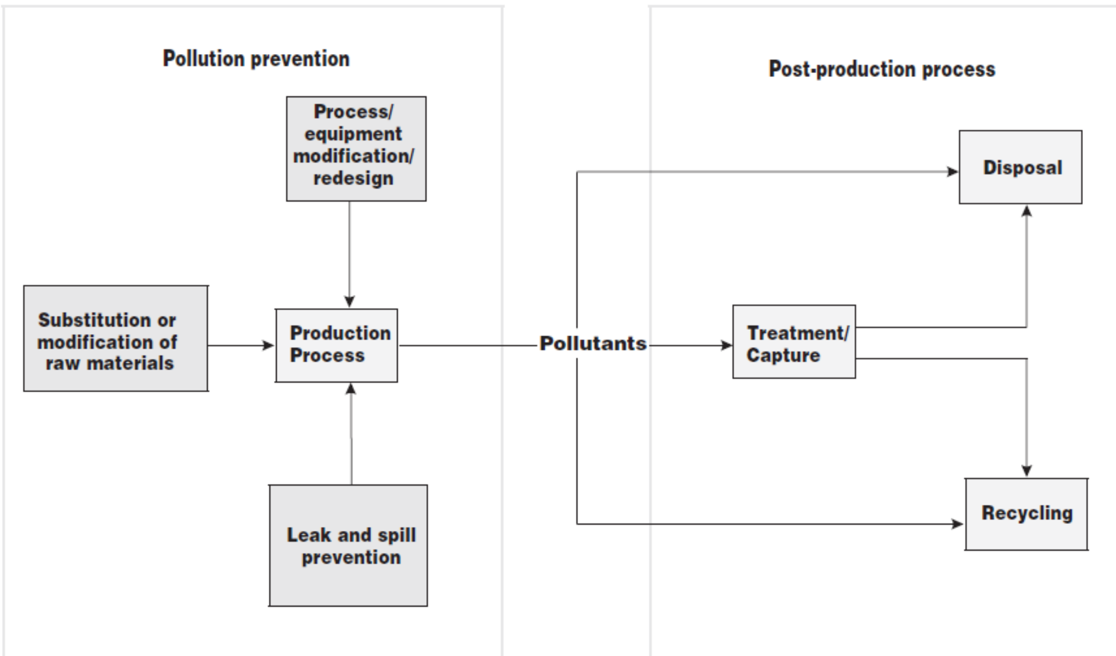
Appendix A Pollution Abatement Activities

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 Definition

Plant-Level Variable

- *Release*: The amount of total toxic releases
- *Release/Emp*: The amount of total toxic releases divided by the number of employees
- *Sales* (in $M, NETS): The total sales dollar amount based on NETS
- *Emp* (NETS): The number of employees based on NETS
- *#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: Firm-Level Variable

- *D(Public firms)*: An indicator of a firm being publicly traded
- *D(KLD rating)*: An indicator of a firm having KLD rating
- *Release*: The total amount of toxic releases
- *Release/Emp*: The total amount of toxic releases divided by the number of employees
- *Sales* (in $M, NETS): The total sales dollar amount based on NETS
- *Emp* (NETS): The number of employees based on NETS
- *CSR Score* (KLD): The aggregate net strength and concern counts across six dimensions in KLD
- *Environment 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*: $PPENT/at$
- *Market Share*: The percentage of sales (Compustat) within all public firms in the same NAICS3-year
- *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 Checks for Plant-level Pollution

Table E.1. Changes in Plant 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) and (C) report GDID regression estimates , and Panels (B) and (D) report regression estimates with 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-year panel, and *RSEI Hazard* is the toxicity weighted pollution amount, while *RSEI Score* is the modeled surrogate dose multiplied by toxicity weight and by population. Panels (C) and (D) 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. Standard errors are presented in parentheses and clustered by plant. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A. 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 B. 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

Panel C. Chemical-level Pollution, Generalized DID Regressions

Dep. Var.:	*Total Release*			*Toxic 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 D. Chemical-level Pollution, Stacked Regressions

Dep. Var.:	*Total Release*			*Toxic 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

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 F.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 F.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 F.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.

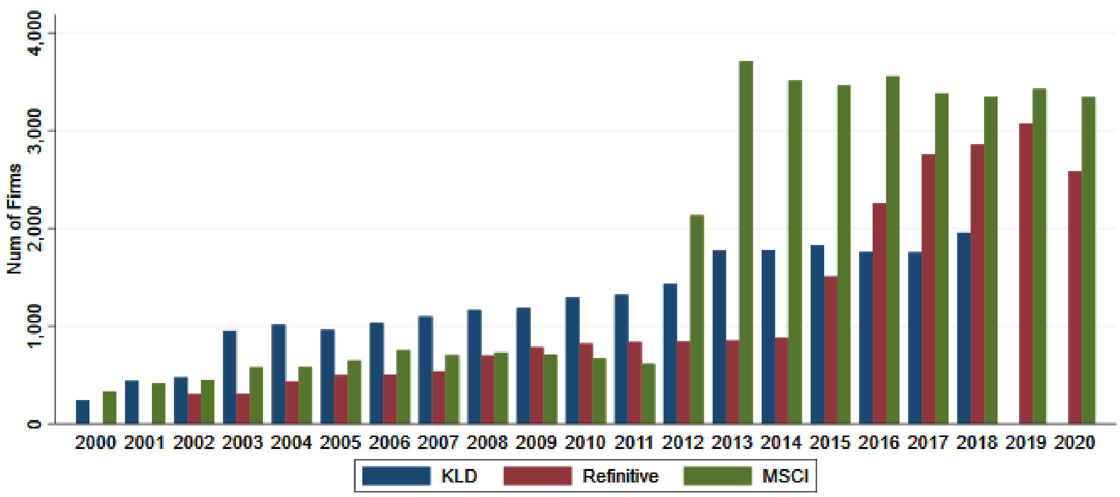


Table F.1. Robustness: Alternative ESG Ratings

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 plants and matched never-divested plants within the same NAICS3 industry. *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
R^2	0.518	0.545	0.547	0.410	0.456	0.459
Observations	53,250	53,111	49,880	53,242	53,103	49,871

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
R^2	0.553	0.564	0.567	0.433	0.455	0.456
Observations	162,694	162,655	160,962	162,670	162,631	160,938