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

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**Abstract**

We study the asset market for pollutive plants. Firms divest pollutive plants following environmental risk incidents. However, pollution levels do not decline after divesting. The buyers are firms facing weaker environmental pressures, with supply chain relationships or joint ventures with the sellers. The sellers highlight their sustainable policies in subsequent conference calls, earn higher returns as they sell more pollutive plants, and benefit from higher ESG ratings and lower compliance costs. Overall, the asset market allows firms to redraw their boundaries in a manner perceived as environmentally friendly without real consequences for pollution levels and with substantial gains from trade.

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# 1 Introduction

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

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

In this paper, we aim to shed new light on this question by studying the reallocation of industrial pollution through acquisitions and sales of divested pollutive 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 that are more likely to treat pollution. This hypothesis is rooted in the theories of Magill et al. (2015) and Broccardo et al. (2020), which provide equilibrium models of investment and divestment, respectively, assuming stakeholders care about the

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

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

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

social impact of their decisions. Under this view, the divested assets will generate less pollution after the transfer of ownership. The second possibility is that divestitures of pollutive assets respond to external environmental pressures by transferring ownership from firms that face stronger pressures to firms that face weaker pressures (or are better at addressing those pressures). This hypothesis is consistent with a Fisherian (1930) equilibrium, where a firm's investment decisions are independent of investor preferences. It is also consistent with the predictions of more recent work by Heinkel et al. (2001), Davies and Van Wesep (2018), and Edmans et al. (2022), which shows that the effects of divestment can be undone by non-socially-conscious investors' increased purchases of pollutive assets or by agency conflicts. Under this view, divestitures allow sellers to gain from offloading pollutive assets to less scrutinized firms without having a real impact on pollution levels.

To evaluate these possibilities, we compile a novel dataset of 888 divestitures of pollutive industrial plants from 2000 to 2020, and investigate their determinants and implications for buyers and sellers. We hand-collect and merge data from several databases, including divestiture data from the Securities Data Company (SDC) database, plants' toxic release levels from the Environmental Protection Agency's (EPA) Toxic Release Inventory (TRI) database, plant-level employment data from the National Establishment Time-Series (NETS) database, ESG ratings from Kinder, Lydenberg, and Domini (KLD), Refinitive, and MSCI, conference call data from Thomson Reuters' Street Events Database, ESG-related incidents from Factset's RepRisk ESG Business Intelligence database, and supply-chain and joint ventures information from the Compustat Segment, Factset, and SDC databases.

We begin the empirical analyses by examining changes in pollution levels around divestitures. We measure plant-by-chemical pollution using both the total amount of toxic release and pollution intensity, defined as the ratio of toxic release to cumulative chemical production. In difference-in-difference Poisson regressions, we find no difference between the change in pollution at divested plants and the change in pollution at plants that were not divested. The estimates are statistically indistinguishable from zero, and remain largely unchanged after the inclusion of chemical-by-plant, chemical-by-year, industry-by-year, and state-by-year fixed effects. These findings continue to hold after weighing toxic release levels by the toxicity of each chemical, in collapsed plant-by-year panel regressions, in regressions estimated separately for divested and never-divested plants, and in stacked regressions that consider potential biases due to heterogeneous dynamic treatment effects (e.g., Gormley and Matsa

2011, Baker et al. 2022). In similar plant-by-chemical difference-in-differences specifications, we also find no difference between pollution abatement efforts at sold and unsold plants.

Since divestitures are clearly nonrandom, it is possible that sellers choose to keep plants whose pollution they can treat and divest assets whose pollution they cannot treat. It is also possible that buyers adjust production and pollution levels at their other plants upon acquiring new pollutive plants. To evaluate these possibilities, we trace the combined pollution levels of sellers' and buyers' plants around divestitures. We find that following divestitures, there is no reduction in the pollution levels of sellers' or buyers' other plants. As such, total pollution levels across buyers and sellers remain stable post-divestitures. It is also possible that firms reallocate capital, possibly to greener establishments, by divesting pollutive assets that become obsolete. However, we do not find empirical support for obsolescence or capital reallocation: productivity growth rates and survival rates are similar across sold and unsold plants, and divestitures are not accompanied by the introduction of new plants.

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

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

Second, we show that firms are more likely to divest pollutive assets following ESG risk exposure, particularly exposure to environmental risks. ESG risk exposure is measured based on publicly known, negative incidents related to a firm's business conduct, gathered by RepRisk.[4] Our estimates indicate that the occurrence of environmental risk incidents increases the likelihood of divesting a pollutive asset by 1.3 percentage points, or 92% relative to the sample mean.

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

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

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

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

We provide two additional analyses that aim to shed light on the strategic mechanisms underlying the divestment of pollutive plants. First, we use a BERT language model to analyze the text of firms' conference calls with investors. We find that following divestitures of pollutive plants, sellers are considerably more likely to mention and emphasize improvements in their environmental policies. This evidence suggests that sellers advertise their commitment to sustainability and the environment following divestitures, despite their muted effect on pollution levels.

Second, we find that the divested assets are sold to firms that have business ties with the sellers. Specifically, the buyers of divested plants 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 at a lower cost. Furthermore, the sellers are also likely to develop additional business relationships with the buyers after the sale, suggesting that the sellers begin transacting with the buyers of their pollutive plants. These findings provide suggestive evidence that the divestment of pollutive plants merely reflects a cosmetic redrawing of firm boundaries.

In the final set of analyses, we investigate the gains from trading pollutive assets. These analyses provide several key results. First, following the divestment of pollutive assets, the ESG ratings of sellers increase by roughly 22% (relative to the sample standard deviation), and the improvement is particularly strong for environmental ratings (27% relative to the sample standard deviation). Second, following divestitures, the likelihood of being hit with an EPA enforcement action drops by about 4-8 percentage points (a large magnitude compared to a sample mean of 7.4 percentage points). Moreover, the costs of regulatory enforcement, including fines and cleanup costs, also decline considerably.

Importantly, we show that the changes in ESG ratings, EPA enforcement actions, conference calls discussions of environmental performance, and buyer-seller business ties are only present following the divestment of pollutive assets, but are nonexistent following the divestment of non-pollutive assets. These results indicate that the benefits from divestitures are unique to the transfer of pollutive assets, and are not a general feature of asset sales.

Do shareholders recognize the above benefits from offloading pollutive assets? To answer this question, we estimate sellers' cumulative abnormal returns (CAR) around the announcement of divestitures of pollutive assets. We find that the average CAR is significantly higher when the divested plant is more pollutive. Our estimates suggest that an inter-quartile increase in pollution is associated with a 3–4 percentage-point increase in the average CAR.

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

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

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

Overall, our findings extend prior research on (1) industrial pollution, (2) ESG, and (3) divestitures. The literature on industrial pollution studies its determinants, which range from legal liability (e.g., Alberini and Austin 2002, Stafford 2002, Shapira and Zingales 2017, Akey and Appel 2021) to third-party auditors (Duflo et al. 2013), reputational penalties (Karpoff et al. 2005), supply chains (Schiller 2018), financial attributes (Chang et al. 2021, Xu and Kim 2022), imports and exports (Holladay 2016, Li and Zhou 2017), competition (Simon and Prince 2016), ownership structure (Shive and Forster 2020), and political ideologies (Bisetti et al. 2021), among others. We add to this literature by showing that industrial firms react to scrutinized environmental risks by divesting their pollutive assets in a concerted effort to improve their ESG ratings and lower their regulatory compliance costs.

We also add to the growing literature on ESG (see Hong et al. 2020 and Gillan et al. 2021 for a review). One strand of this literature studies the benefits of ESG, showing, for example, that better ESG performance helps firms mitigate downside risks (e.g., Lins 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; Hartzmark and Sussman 2019; Zaccone and Pedrini 2020; Krueger et al. 2020; Barber et al. 2021; Pástor et al. 2021; Bolton and Kacperczyk 2021; Hong et al. 2021). We contribute

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

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. These studies show that ratings from different agencies do not agree with one another, and do not reflect firms' actual ESG policies (Chatterji et al. 2016, Gibson 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 role of pollution in the divestiture market.

# 2 Data and Variables

## 2.1 Toxic Release Inventory (TRI) Data

We obtain data on chemical-by-chemical toxic emissions for each plant from the EPA's Toxic Release Inventory (TRI) Program over the period 2000-2020. Section 313 of the Emergency Planning and Community Right-to-Know Act (EPCRA), which created the TRI program, requires industrial facilities to disclose the release of toxic chemicals. Toxic chemicals are defined as ones that cause one or more of the following: (a) cancer or other chronic human health effects, (b) significant adverse acute human health effects, and (c) significant adverse environmental effects.[6] The resultant list contains over 600 individual 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 detailed information on the level of each type of chemical

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

released by a plant during a given year. It also provides plants' addresses and NAICS industry classification codes. 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 measures of production such as the number of employees and the dollar amount of sales.

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

We construct the variable *Total Pollution* as the total toxic emission of each chemical for each plant in a given year. We also calculate a measure of a chemical's *Pollution Intensity* by dividing each chemical's total toxic emission by its production ratio.

In additional analyses, we consider two sets of alternative measures of pollution. First, we aggregate toxic release levels across all chemicals for a given plant in a given year (Xu and Kim, 2022). This measure captures the aggregate impact of a plant's production activities on the environment and public health. We compute a plant's pollution intensity (Copeland and Taylor, 2003; Shapiro and Walker, 2018) in an analogous way to the computation of a plant-chemical's pollution intensity. However, given that production ratios cannot be aggregated across chemicals, we instead scale a plant's total toxic release by the number of plant employees.

Second, we use data on the toxicity of each chemical (RSEI) to construct toxicity-weighted measures of toxic release. In particular, we use *RSEI hazard*, a toxicity-weighted pound mea-

[7]For chemicals directly used in the production process, the production ratio captures the ratio of $output_t$ relative to $output_{t-1}$. For chemicals that are used as support activities for production, this measure indicates the change in 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).

sure of toxic release, and *RSEI Score*, which incorporates both toxicity weight and modeled population exposure, to gauge the impact of each chemical on public health.

In addition to monitoring toxic releases, the EPA also records pollution abatement activities. Internet Appendix Section IA.1.1 provides an overview of the abatement process. We measure abatement in two ways. The first measure considers source reduction activities, 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 activities (*#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 (Li et al., 2021). To assess plants' engagement in post-production activities, we trace the percentage of total generated toxic waste that is reduced through recycling (*%Recycling*), energy recovery (*%Recovery*), and treatment (*%Treatment*), respectively.

We use a string-matching algorithm to link TRI establishments operated by public parent companies to the Compustat database to extract accounting information. The TRI database records the ultimate parent company name for each establishment every year. These can change over time following incidents such as ownership changes and parent company name changes. To map TRI plants to their owners at every point in time, we obtain historical names of publicly listed companies from CRSP and match those names to the names of plant owners.[8]

## 2.2 Divestitures

We collect data on divestitures completed between 2000 and 2020 from the SDC M&A database. For each deal, SDC provides the effective date, the names of the buyer and the seller, and the percentage of ownership 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 name and CUSIP identifier. We only retain deals classified as "divestiture" or "spin-off" by SDC. We also require the deal to represent a significant transfer of ownership, that is, the buyer must own more than 50% after the deal. Next, we remove deals involving

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

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, and funds. We also exclude deals in which the buyer or the seller is majority-owned by a financial firm.

We identify divested TRI plants by matching plants' parent names to acquirer and target names in SDC. Internet Appendix Section IA.1.2 describes the matching procedure in detail. Our final sample contains 888 deals involving 1,105 unique plants. Internet Appendix Table IA.1 presents the industry composition of divested plants. The vast majority of divested plants are located in a few manufacturing sectors known to be heavy polluters, such as chemical manufacturing and fabricated metal product manufacturing, among others.

In addition, we collect data on 41,001 divestitures of non-pollutive assets over the period 2000–2020. Non-pollutive assets include assets not linked to the TRI database. We follow the same approach and remove all transactions between financial buyers and sellers. Using these data, we compare between the effects of divesting pollutive plants and the effects of divesting non-pollutive assets. We also show in robustness tests that our results do not change if we also include financial buyers in our sample.

## 2.3 ESG Risk Incidents

The RepRisk database provides data on business-conduct risk by combining machine-learning tools and human intelligence. It collects and screens data from over 100,000 public sources and various stakeholders to identify whether a firm has had an ESG risk incident. RepRisk classifies these events into 28 categories such as pollution, waste management, human rights, occupational health, child labor, and discrimination. It also assigns each event into one of three broad categories: "Environmental", "Social", or "Governance."

Using these data, we define an indicator variable *RepRisk 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 define *RepRisk Environmental Event* as an indicator that equals one if RepRisk reports an environmental risk event and *RepRisk Social or Governance Event* as an indicator variable that equals one if RepRisk reports a social or governance-related risk event.

## 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' 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. 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-based measure of ESG events, we also separately compute the net strength in the environment category and create the variable *Environmental Score* to track firms' environmental ratings. We later augment the ESG ratings from KLD with ESG ratings from the Refinitive and MSCI databases and find our results to be robust.

## 2.5 EPA Enforcement Actions and Compliance Costs

In addition to the toxic release 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 costs (in dollars) of federal and local penalties, compliance, recovery, and supplemental environmental projects. We aggregate these items to evaluate the total regulatory compliance costs for each case. Using these estimates, we analyze the changes in enforcement actions and compliance costs for sellers of pollutive plants.

## 2.6 Supply-Chain and Joint Venture Relationships

We examine whether buyers and sellers of pollutive plants tend to have pre-existing business ties or are likely to develop new business ties following divestitures. We measure business ties based on supply-chain relations and joint venture partnerships. We obtain data on supply-chain relations from the Factset and Compustat Segment databases. We obtain

Information on joint ventures from SDC (see also Allen and Phillips 2000 and Schilling 2009). As we discuss in Section 6.2, we compile a matched sample of acquirer-target pairs and define a pair to have business ties if the acquirer and the target share either a supply-chain or a joint venture connection.

## 2.7 Announcement CARs

We compute sellers' cumulative abnormal returns (CARs) in the 3-day window centered around the divestiture announcement date (i.e., $CAR[-1, +1]$). We define abnormal returns both relative to the market model benchmark (*CAR, Market*) and relative to the Fama-French 3-factor model benchmark (*CAR, FF*). Stock return data come from CRSP.

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

## 2.8 Other Data Sources

We augment the analyses with data from several other sources. First, we use county-level vote share data compiled by the MIT Election Data and Science Lab to compute the share of a county's votes in support of Republican candidates during general presidential elections. We conjecture that firms face weaker environmental pressures in Republican-leaning counties compared to Democratic counties.

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

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

# 3 Empirical Strategy and Summary Statistics

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

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

## 3.1 Plant-by-Chemical Analyses

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

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

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

We estimate the following regression:

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

where $i$ represents a plant-chemical pair and $t$ represents a year. The dependent variables, $Y_{i,t}$, include total pollution, pollution intensity, and pollution abatement activities such as source reduction and the percentage of waste being recycled, recovered, or treated. When estimating the regressions for skewed dependent variables, such as total pollution, we use a Poisson regression specification (Cohn et al. 2021). The regressions include plant-by-chemical fixed effects ($\alpha_i$) and chemical-by-year fixed effects ($\tau_t$). In more stringent specifications, we control for industry-year interactive fixed effects and state-year interactive fixed effects. These controls mitigate concerns about confounding explanations related to industry dynamics, local economic conditions, or state-level policies. The standard errors are clustered by plant.

As mentioned above, we estimate these regressions in generalized difference-in-differences specifications and in stacked regressions. To construct the stacked sample, we match each sold plant to never-sold plants in the same industry (NAICS3) and state. We then estimate Equation (1) on the stacked sample composed of all such cohorts. In the stacked regression specification, the control plants are sampled with replacement. We interact all the fixed effects with cohort fixed effects, thus saturating the regressions with cohort-plant-chemical, cohort-chemical-year, cohort-state-year, and cohort-industry-year interactive fixed effects. These fixed effects allow us to make within-cohort comparisons, contrasting each treated unit with its matched control group.

## 3.2 Firm-Level Analyses

The firm-level analyses primarily center on the sellers, and the sample includes all ultimate parent firms of TRI plants. If the dependent variable is available only for public firms, we restrict the sample to publicly traded parents. We estimate the following regression specification:

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

where $f$ represents a parent firm and $t$ represents a year. The dependent variables, $Y_{f,t}$, include conference call disclosures, ESG scores, enforcement actions, enforcement costs, and so forth. As before, we use a Poisson regression specification when the dependent variable is highly skewed (e.g., the amount of enforcement costs). The variable $Seller\,(Pollutive)_f$ 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 divestiture. $\mathbf{X}_{f,t}$ represents an array of firm characteristics, including firm size, leverage, profitability, and tangibility. Our estimation includes firm fixed effects ($\theta_f$) and year fixed effects ($\tau_t$). More stringent specifications also include industry-by-year fixed effects. The standard errors are clustered by firm.

Similar to the plant-chemical-level analyses, we estimate these effects using the generalized difference-in-difference regression method and the stacked regression method. The stacked regression sample is constructed by matching each seller firm to other publicly listed firms who never sold a plant during the sample period and that operate in the same industry (NAICS3) when the divestiture takes place. We again control for interactive fixed effects between cohorts and firms as well as industry-by-year fixed effects.

Finally, we use the divestitures of non-pollutive assets as comparison benchmarks, by estimating the following regression specification:

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

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

### 3.3 Summary Statistics

Table 1 presents summary statistics for all the variables used in the paper. Appendix A provides detailed definitions of the variables. Panel A and B provide statistics for the plant-chemical-level sample and plant-level sample. The sample includes 37,564 unique plants with 352,938 plant-year observations, and 1,056,361 plant-chemical-year observations. At the plant-chemical level, the distribution of toxic release is skewed. The average toxic release in the plant-chemical-year panel is roughly 16,893 pounds, and the median is 483 pounds. For pollution abatement, the plant-chemical-year average number of source reduction activities is roughly 2, and the percentage of total generated toxic chemicals reduced through recycling, recovery, and treatment is 24.4%, 8.4%, and 26%, respectively.

TABLE 1 ABOUT HERE

Panel C provides information for the firm-level sample. The average CSR score of the firms included in the KLD database is 0.32, and the average environmental score is 0.15. The probability of an ESG risk incident is roughly 7%, whereas that of an environmental risk incident is approximately 4%. The likelihood of an EPA regulatory enforcement action is 1%. The average enforcement cost across all sample firms is roughly $3 million, and, conditional on having positive enforcement costs, it is approximately $45 million.

Panel D provides summary statistics for divestiture announcement returns (CARs). The average seller's CAR is roughly 3%. The CARs are skewed: the median CAR is lower than 1%. The buyers earn lower announcement returns compared to the sellers, with an average CAR of roughly 2%.

# 4 Changes in Pollution Around Divestitures

## 4.1 Pollution at Sold Plants

We examine the changes in plant-level pollution following divestitures by estimating Equation (1) in an annual chemical-by-plant panel. Table 2 presents the results. In Panel A we examine changes in the pollution of sold plants compared to unsold plants in a generalized DID framework, and in Panel B, we compare the changes in pollution generated by sold plants relative to those by never-sold plants using stacked regressions. Given the skewness of the pollution variables, we estimate all the analyses in Poisson regressions. In each panel, columns (1) through (3) report results for total pollution and columns (4) through (6) report results for pollution intensity. For each regression specification and pollution measure, we impose progressively stringent fixed effects, starting with plant-by-chemical and year-by-chemical fixed effects, and then augmenting them with state-by-year and industry-by-year interactive fixed effects. In the stacked regression specifications, we interact these fixed effects with cohort indicators.

Table 2 About Here

The estimates across all the specifications in Table 2 suggest that, following divestitures, sold plants do not emit less toxic release compared to the control group. In particular, the coefficient estimates on the interaction term *Divested* $\times$ *Post* are positive and statistically insignificant across all the specifications.

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

We find similar results in alternative regression specifications. Panels A and B of Internet Appendix Table IA.3 provide estimates from OLS regressions instead of Poisson regressions. Panels C and D provide estimates from regressions that aggregate annual toxic releases across all the chemicals in each plant. Panels E and F provide estimates from toxicity-weighted measures of chemical emissions. Lastly, we extend the sample in Internet Appendix Table IA.4 to include deals that involve financial buyers such as private equity firms.

Across all these additional analyses, estimated in both generalized DID and stacked regressions, the coefficient estimates on the interaction term *Divested* $\times$ *Post* are never negative and statistically significant, suggesting that pollution levels do not decline following the divestment of pollutive plants.

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

To investigate this possibility, in Internet Appendix Table IA.5, we separately estimate the changes in emissions at divested plants and at their never-sold matched counterparts in the same state and industry around the divestiture year. Panel A corresponds to divested plants whereas Panel B corresponds to never-divested plants. The estimates in Panels A and

B suggest that toxic release levels and intensity do not meaningfully change either at divested plants or at undivested plants following divestitures. As such, these findings suggest that the difference-in-differences results are not driven by parallel declining trends in pollution.

Next, we turn to examine pollution abatement efforts at sold plants. In Table 3, we examine annual pollution abatement efforts at the plant-chemical level, including source reduction (*#Source Reduction*) and post-production waste management (*%Recycling, %Recovery, and %Treatment*). Similar to Table 2, we report results from both generalized DID regressions (Panel A) and stacked regressions (Panel B). The estimates in both panels consistently show insignificant differences between changes in pollution abatement activities across divested and undivested plants following divestitures. The coefficient estimates on the interaction term *Divested* × *Post* are statistically insignificant at conventional levels and change signs across specifications.

TABLE 3 ABOUT HERE

These results shed more light on the findings in Table 2. They imply that plants do not experience meaningful changes in their toxic release levels partly because they do not materially change their pollution abatement activities.

To summarize, the evidence so far indicates that, on average, buyers of pollutive plants maintain toxic release levels similar to the pre-divestment levels. Thus, divested plants do not become "cleaner" under the new parent company. These results do not support the hypothesis that divestitures transfer pollutive assets to new owners with higher capacity and better technology to abate emissions. Instead, they are consistent with the view that the market for divestitures allows firms to shed dirty assets and reshape their image as low-environmental-impact companies without any real impact on pollution levels.

## 4.2 Alternative Explanations

As noted above, it is possible that firms choose to keep plants whose pollution they can treat and divest assets whose pollution they cannot treat. Buyers may also adjust the overall pollution levels at their existing plants when they acquire new ones. To evaluate these possibilities, we trace the pollution levels of sellers' and buyers' peer plants around divestitures. Specifically, for all sellers' and buyers' existing plants (excluding the divested plants), we define an indicator variable *Peer* that equals one if their parent company has divested or acquired at least one plant in a given year, respectively. We then estimate the changes in toxic release of these peer plants around divestitures.

Table 4 reports the results of these analyses. As before, we report estimates from both generalized DID regressions (Panel A) and stacked regressions (Panel B), in which the unit of analysis is a plant-chemical-year triplet. In this analysis, we construct a stacked sample for each divested peer plant based on the year of the deal. In particular, for each peer plant, we choose never-divested plants in the same industry and state as controls.

TABLE 4 ABOUT HERE

The estimates in Table 4 indicate that total toxic release and toxic release intensity do not decline at peer plants of buyers and sellers. The coefficients on the interaction term *Peer* $\times$ *Post* are mostly statistically insignificant at conventional levels and switch signs across specifications. These results are inconsistent with the hypothesis that sellers choose to keep plants whose toxic release they can reduce, or that buyers reduce pollution at their other plants when acquiring new pollutive plants.

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

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

In generalized DID regressions and stacked regressions presented in Panel C of Table 4, we do not find significant differences in pre-divestiture sales growth rates between divested and non-divested plants. In particular, sales growth rates are indistinguishable across divested and non-divested plants over each of the five years prior to being divested. In Figure 2, we compare post-divestiture Kaplan-Meier survival rates across divested and matched never-divested plants (within the same NAICS3 industry and state). We find that divested plants do not have lower survival rates than never-divested plants. Combined, these findings are less consistent with the view that sellers choose to divest obsolete plants.

Lastly, in Internet Appendix Table IA.6 we also investigate whether divestitures of pollutive plants coincide with the acquisition of new plants. The estimates suggest that firms are less likely to acquire new plants after divesting pollutive plants. This result only holds for divestitures of pollutive assets, and is not a general feature of divesting non-pollutive plants. As such, our findings are less consistent with the view that divestitures of pollutive assets reflect creative destruction, whereby firms divest pollutive assets to reallocate capital to new, potentially greener, plants.

We note, however, that it is possible that pressuring firms to divest pollutive plants will lead them to build new productive capacity that is greener. Further, pushing for the sale of pollutive plants may drive down the price of such assets, ultimately reducing their supply in the market through equilibrium effects. The evidence that divestitures are uncorrelated with the introduction of new plants nor with shorter survival rates of pollutive plants does not support this possibility. Nevertheless, the growing trend to divest pollutive assets in more recent years can generate long-term effects that we cannot yet observe in our sample.

# 5 Sellers and Buyers of Pollutive Assets

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

## 5.1 Divestment and High Pollution levels

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

Panel A of Table 5 reports the 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 (columns (1) and (5)). We then add controls in stages. In columns (2) and (6), we include industry and year fixed effects. Industry fixed effects help us compare plants with similar production technologies, and year fixed effects help remove macroeconomic time trends. In columns (3) and (7), we include industry-by-year interactive effects, which allow us to narrow down the comparison to industry-peer plants at the same year. Finally, we add state-by-year interactive fixed effects, which help remove temporal effects from state policies and regulatory changes.

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

TABLE 5 ABOUT HERE

## 5.2 Divestment and ESG Risk Exposures

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

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

The results are presented in Panel B of Table 5. Columns (1) through (3) report results related to any ESG incidents, and columns (4) through (6) present results related only to environmental risk events. In columns (7) through (9), we include environmental events and non-environmental events (social and governance events) side by side, to compare their influence on firms' propensity to divest pollutive assets.

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

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

## 5.3 Buyers of Pollutive Assets

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

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

Similarly, firms not covered by any of the ESG rating agencies also face weaker ESG pressures. Prior studies show that ESG ratings provide signals about firms' sustainability practices, and generate value-relevant responses from investors (see Hartzmark and Sussman 2019; Zaccone and Pedrini 2020; Krueger et al. 2020, among others). As such, unrated firms' cost of capital is less affected by their environmental policies. In addition, media coverage of ESG risk incidents likely also exposes firms to environmental pressures. Indeed, in Section 5.2

we provide evidence that negative ESG incidents push firms to divest pollutive assets. Lastly, political ideology has been shown to exert strong influence on local firms' environmental performance (Bisetti et al. 2021). We therefore include local political leanings as another measure of the ESG pressures that firms face.

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

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

where $k$ indicates a divestiture deal, and $i$ indicates either the buyer or the seller in the deal. $Y$ is the indicator variable $Buyer_{k,i}$, which equals 1 if firm $i$ is the buyer (rather than the seller) in deal $k$. In this test, we are interested in $\beta_1$. If $\beta_1 > 0$ ($\beta_1 < 0$), buyers likely face stronger (weaker) environmental pressures compared to the sellers.

Panel A of Table 6 reports the results for pollutive asset divestitures. We find that relative to the sellers, buyers of pollutive plants are 7.9 percentage points more likely to be private firms (column (1)), 5.1 percentage points less likely to be covered by ESG ratings (column (2)), 4.8 percentage points less likely to experience any negative environmental incident before the deal takes place (column (3)), and 5.9 percentage points more likely to be headquartered in Republican-leaning counties.[10] These effects are economically large, representing increases of 5-19% relative to sample average values. The average across the four indicator variables, *Low Pressure*, delivers a similar estimate at 7.1 percentage points

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

in column (5), corresponding to 11.5% of the sample average. These estimates collectively suggest that firms facing stronger environmental pressures tend to sell their pollutive assets to firms that face weaker environmental pressures.

<u>Table 6 About Here</u>

In Panel B of Table 6, we repeat the analyses for non-pollutive asset divestitures. Across all five measures of environmental pressures, we do not find clear evidence that non-pollutive assets are sold to less scrutinized firms. The contrast between panels A and B suggests that transferring assets into the "dark" domain is a unique feature of pollutive asset divestitures that does not apply universally to divestitures.

# 6 Strategic Mechanisms

In this section, we investigate the strategic mechanisms behind the divestment of pollutive assets. First, we investigate how firms exploit the divestment of pollutive plants to advertise their environmental policies by analyzing the text of earnings conference calls. Second, we study 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.

## 6.1 Earnings Conference Calls

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

After identifying these sentence groups, we manually read through 1000 randomly selected examples to classify whether the text indicates a positive or a negative environmental impact. For example, we consider the following statements to be positive: "We continued our strong safety and environmental performance"; "The application of our rigorous environmental management systems and practices resulted in improvements in spill performance and in emission reductions." Next, we deployed the Bidirectional Encoder Representations from Transformers (BERT) natural language processing model (Devlin et al. 2018), using the above manually classified sample as the training set.[11] We use the resulting classifications to define two indicator variables. *Positive Env. Disclosure* is an indicator variable that equals one if the firm discloses an improvement in its environmental performance. The indicator variable *Negative Env. Disclosure* is defined analogously with respect to a decline in environmental performance.

We regress the above indicator variables on *Sell (Pollutive)* $\times$ *Post*. Table 7 reports the results. Panel A presents results from generalized DID regressions, whereas Panel B presents results from stacked regressions. We find that sellers of pollutive assets are significantly more likely to highlight improvement and less likely to mention deterioration in their environmental performance. Column (6) of both panels suggests that after selling a pollutive plant, firms are roughly 12 percentage points more likely to highlight improved environmental performance during conference calls. This represents an 18% increase compared to the average likelihood of providing positive environmental disclosures (66 percent). In contrast, sellers are around 2–3 percentage points less likely to provide negative environmental disclosures. Yet, this effect is statistically insignificant at conventional levels.

<u>TABLE 7 ABOUT HERE</u>

Overall, the evidence from earnings conference calls suggests that sellers of pollutive assets emphasize their environmental policies in subsequent conference calls. Doing so allows them

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

to strengthen their public image as being environmentally friendly, despite that muted impact of divestitures on pollution levels and abatement efforts.

## 6.2 Business Ties Between Buyers and Sellers

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

Motivated by such real-world examples, we investigate the nature of the relationship between sellers and buyers of pollutive assets to shed light on the incentives of the buyers and on the ability of the sellers to access the divested plants and their products after the divestiture. Specifically, we test whether firms that have pre-existing business ties with the sellers are more likely to purchase pollutive plants from the sellers. We consider two types of relationships: (1) customer-supplier relations; and (2) joint venture partnerships. We argue that the existence of such relationships reduces the frictions and costs associated with accessing the plant's output even when it is operated by a different parent company, allowing the seller to maintain its current operations and production processes.

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

We also consider the possibility that sellers maintain their access to products or services of divested plants after the deal by examining whether the seller is more likely to start a new business relationship with the actual buyer than with pseudo buyers after the deal takes place. This analysis sheds light on whether the divestiture 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 8 reports the results from this analysis. In column (1), we regress the indicator variable *Buyer (Pollutive)* on the indicator variable for business ties, *Operationally Related*. The regression model includes match group fixed effects, which allow us to compare each buyer-seller pair to its matched pseudo buyer-seller pairs, and absorb deal-level variation, as well as macroeconomic trends, seller characteristics, and industry dynamics.

The results suggest that operationally related firms are 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.

<u>TABLE 8 ABOUT HERE</u>

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

Overall, the results in this section provide evidence on the strategic implications of divesting pollutive plants. The sellers tend to advertise their environmental progress in subsequent conference calls with analysts and investors despite the muted effects of divestment on pollution levels. Moreover, the sold plants end up in the hands of firms connected to the sellers through pre-existing and newly formed supply chain relations and joint ventures. This suggests that pollution remains part of the sellers' value chain, and could thus merely represent a cosmetic redrawing of the boundaries of the firm.

# 7 Gains from Trade

We investigate the potential gains from selling pollutive assets along two dimensions: (1) ESG ratings, and (2) Environmental regulatory compliance costs. These analyses utilize the framework laid out in Equation (2). As a placebo test, we also examine these outcomes for the sellers of non-pollutive assets.

## 7.1 Sellers' ESG Ratings

Table 9 presents results on the changes in sellers' ESG ratings following the divestitures of pollutive assets. As before, we provide estimates from two approaches, a generalized difference-in-difference specification and a stacked regression specification. The sample includes all firms with available ESG scores from the KLD database. Panel A studies sellers of pollutive assets, whereas Panel B focuses on sellers of non-pollutive assets. Within each panel, the dependent variable is a firm's overall ESG score in columns (1) through (3), and environmental ratings in columns (4) through (6).

TABLE 9 ABOUT HERE

We find that sellers of pollutive plants experience a significant improvement in their ESG ratings following divestitures. Based on the estimates in column (3) of Panel A, sellers' overall ESG scores increase by approximately 0.5 relative to non-sellers, a substantial change compared to the sample mean of 0.32 and the sample standard deviation of 2.31. Furthermore, columns (4)–(6) show that divestment of pollutive plants is associated with significant improvement in sellers' environmental scores. The estimates in column (6) of Panel A suggest that sellers' environmental scores increase by around 0.22, or 27% of the sample standard deviation. We obtain similar estimates in stacked regressions. In Internet Appendix Table IA.7, we consider alternative sources of ESG ratings, such as those provided by Refinitive and MSCI. We find that the results remain similar if we include those alternative ESG ratings.

Overall, these findings indicate that firms gain higher ESG ratings after divesting pollutive assets.

## 7.2 Sellers' EPA Enforcement Costs

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

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

Table 10 About Here

We find that pollutive asset divestitures are associated with significant reductions in sellers' regulatory enforcement costs. The effects are economically large. Based on column (3) of Panels A and B, following the divestment of pollutive plants, sellers are roughly 4 to 8 percentage points less likely to receive an EPA enforcement action. This decline is on par with the sample standard average of 7.4 percentage points. Moreover, the estimates also suggest that divestment eliminates the majority of sellers' enforcement costs. Based on column (6) of Panel A, following divestitures, the average enforcement costs of the sellers drop to roughly 5% of their original level ($e^{-3}$) – an average decline of $43 million in enforcement costs.

Overall, these results provide evidence that sellers of pollutive plants gain from increasing their compliance with environmental regulations and reducing the costs associated with enforcement actions.

## 7.3 Placebo Tests: Sellers of Non-Pollutive Assets

In this subsection, we provide estimates from placebo tests that focus on sellers of non-pollutive assets. These analyses aim to alleviate concerns that our estimates capture generic effects of divestitures, such as reductions in operation scale, an influx of capital, or changes in production inputs, rather than effects specific to the divestment of pollutive plants. Our logic is simple. If the results are driven by forces common to all divestitures rather than those of pollutive assets, the effects should show up for both divestitures of pollutive and non-pollutive assets. On the other hand, if our findings capture the unique consequences of divesting pollutive assets, we expect the effects not to be present for divestitures of non-pollutive assets.

Table 11 provides results from the analyses of sellers of non-pollutive assets. Panel A presents the results on sellers' ESG ratings. Panel B reports the results on sellers' enforcement actions and costs. Panel C reports the results on earnings conference calls. And Panel D provides results on business ties between buyers and seller. Across all these analyses, we do not find similar effects following divestitures of non-pollutive assets.

More specifically, the sellers of non-pollutive assets do not experience significant changes in their ESG scores or EPA enforcement costs compared to non-sellers. Furthermore, they are not any more likely to discuss their environmental progress in earnings conference calls compared to non-sellers. In particular, the coefficient estimates in Panels A, B, and C on the interaction term *Sell (NonPollutive)* $\times$ *Post* are generally small and statistically insignificant. Lastly, sellers and buyers of non-pollutive assets are also not more likely to have pre-exiting business ties or develop new ones compared to matched pairs of sellers and pseudo-buyers.

TABLE 11 ABOUT HERE

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

### 7.4 Divestiture Announcement Returns

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

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

Table 12 reports the results. Across all measures of abnormal returns and pollution, we observe a significant, positive relation between the level of pollution of the sold plants and the announcement returns. The estimates suggest that an inter-quartile increase in pollution is associated with a 3- to 4-percentage-point higher CAR. These magnitudes are economically large compared to the sample average CARs of 3 percentage points. These results are consistent with investors rewarding firms for divesting pollutive assets.

Table 12 About Here

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

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

Figure 3 reports the results. Panels A and B plot the relative gains from trade based on the market model, and Panels C and D plot the relative gains based on the Fama-French 3 factor model. The main takeaways are twofold. First, the relative gains (buyer − seller) are generally negative, suggesting that sellers earn a higher market value growth upon deal announcement compared to the buyers. This is broadly consistent with the findings in the M&A literature. Second, and more importantly, the relative gains tilt towards the buyers when the sold assets are more pollutive.

These effects are economically nontrivial. Based on the market model, buyers capture roughly $400 higher value gains compared to the sellers in divestitures that involve plants in the highest pollution quartile. In contrast, buyers capture nearly $800 million lower gains than sellers for deals involving plants in the lowest pollution quartile. These results suggest that buyers of the most pollutive plants likely possess unique advantages in operating and owning those assets. As shown in Table 6, these advantages include exposure to weaker environmental pressures. We note, however, that the evidence is based on the limited sample of public-to-public divestitures. To the extent that private firms' advantages cannot be gauged through market-based metrics, we may be underestimating buyers' relative gains from trading pollutive assets.

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

# 8 Conclusion

We study the real asset market for industrial pollution. In a sample of roughly 900 divestitures of pollutive plants over the period 2000-2020, we find that chemical-by-chemical total and scaled emissions, as well as pollution abatement efforts, do not materially change at divested plants. The estimates of pollution and abatement changes are statistically indistinguishable from zero, hold in different test windows, and remain largely unchanged after the inclusion of alternating sets of fixed effects. They also remain unchanged after weighing toxic release levels by the toxicity of each chemical, in collapsed plant-by-year panel regressions, in regressions estimated separately for divested and never-divested plants, and in stacked regressions that consider potential biases due to heterogeneous dynamic treatment effects.

We explore the determinants, attributes, and consequences of pollutive plant divestitures, and provide several key findings. First, firms tend to divest their most pollutive plants, and the likelihood of divestment increases considerably following environmental risk incidents. Second, the buyers of pollutive plants face weaker environmental pressures. They tend to be private, non-ESG-rated firms, which are headquartered in Republican-leaning districts and have not experienced environmental risk incidents.

Third, the divestment of pollutive plants appears to have strategic implications. After divesting pollutive plants, the sellers advertise their environmental progress in conference calls with investors and analysts. Moreover, the buyers tend to have pre-existing business ties with the sellers, or develop new ones following the divestment of pollutive plants.

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

Collectively, these findings suggest that regulators and rating agencies reward the divestment of pollutive assets, even though these divestitures only reflect a cosmetic redrawing of the boundaries of the firm without any real effects on abatement efforts or overall pollution levels. This evidence seems more consistent with a "greenwashing" strategy. As such, our findings provide novel evidence on the role of the real asset market in firms' greenwashing strategies.

We note, however, that pressuring firms to divest pollutive plants may have long-term effects on green productive capacity. For example, pushing for the sale of pollutive plants may drive down the price of such assets, ultimately reducing their supply in the market through equilibrium effects. While our evidence does not support this possibility, the growing trend to divest pollutive assets in more recent years can generate long-term effects that we cannot yet observe in our sample.

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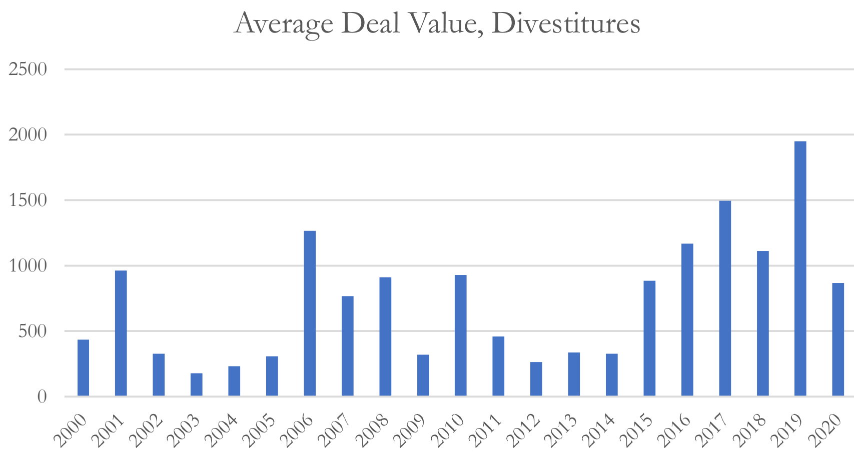
**Figure 1. Time Trends in Divestitures and Attention to "Greenwashing"**
Panel A reports the average deal value (in $millions) of divestitures involving TRI plants in each year. Panel B reports the average google search volume of the phrase "green wash" in each year.




**Panel A. Trends in Average Divestiture Volume**


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

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

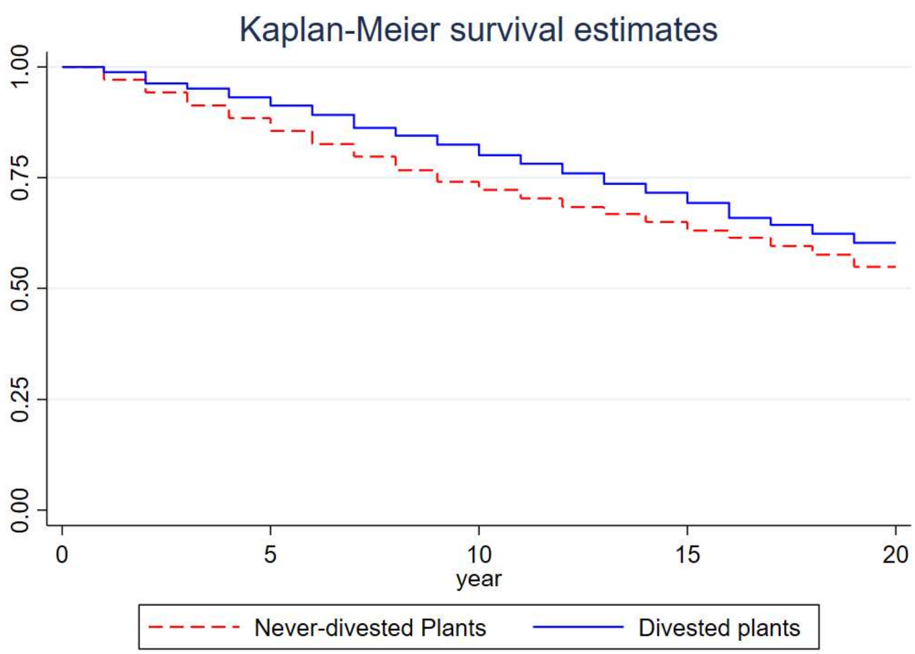
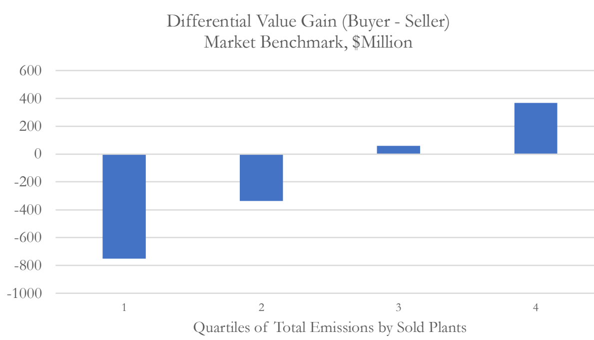
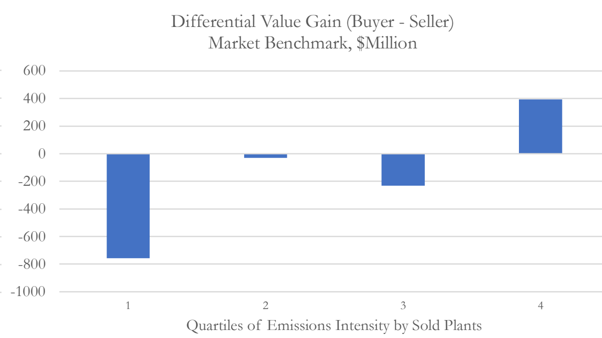


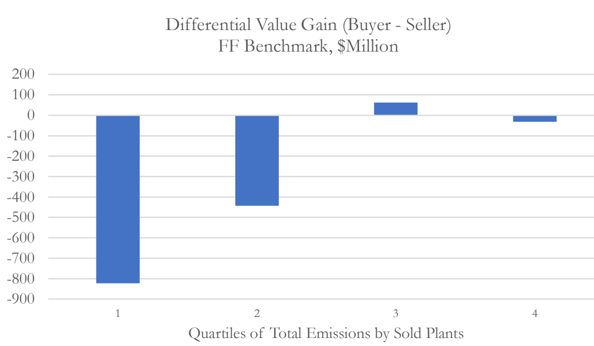
**Figure 3. Relative Gains from Divesting Pollutive Plants**
This figure presents the difference in market value gains between buyers and sellers of pollutive plants around deal announcement ($Buyer - Seller$). Market value gains are measured by the the product of a firm's market capitalization and its $CAR[-1, +1]$ around deal announcement. Market capitalization is measured by the product of shares outstanding and share price of a firm at the end of the year prior to deal announcement. $CAR[-1, +1]$ represents the cumulative abnormal equity returns during the 3 days surrounding the deal's announcement date. In Panels A and B, we calculate abnormal returns based on the market model. In Panels C and D we use the Fama-French 3 factor model. We consider two measures of pollution: the total quantity of emissions and emission intensity, which scales total emissions by employment at the plant level.



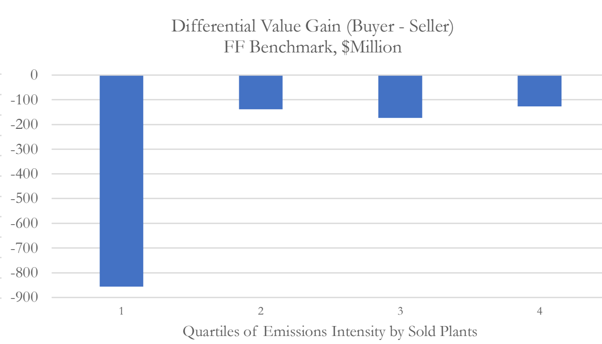

(A) Differential Gains based on Total Emission Market Benchmark




(B) Differential Gains based on Emission Intensity Market Benchmark




(C) Differential Gains based on Total Emission FF Benchmark




(D) Differential Gains based on Emission Intensity FF Benchmark

**Table 1. Summary Statistics**

This table presents summary statistics for the variables used in the analyses. Panel A presents summary statistics for the TRI plant-chemical-year panel, Panel B presents summary statistics for the TRI plant-year panel, and Panel C presents summary statistic for the firm-year panel. Panel D reports summary statistics for buyers' and sellers' announcement cumulative returns. All variable definitions appear in Appendix A.

**Panel A. Plant-Chemical-Level Sample**

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

**Panel B. Plant-Level Sample**

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

**Panel C. Firm-Level Sample**

| | N | Mean | Median | SD | P25 | P75 |
|---|---|---|---|---|---|---|
| *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 |
| *RepRisk ESG Event* | 180,203 | 0.07 | 0 | 0.26 | 0 | 0 |
| *RepRisk Env. Event* | 180,203 | 0.04 | 0 | 0.19 | 0 | 0 |
| *RepRisk Soc. or Gov. Event* | 180,203 | 0.07 | 0 | 0.25 | 0 | 0 |
| *Enforcement Action* | 18,045 | 0.074 | 0 | 0.26 | 0 | 0 |
| *Enforcement Cost ($Mil)* | 18,045 | 3.044 | 0 | 96.194 | 0 | 0 |
| *Positive Env Disclosure* | 8,250 | 0.14 | 0.00 | 0.34 | 0.00 | 0.00 |
| *Negative Env Disclosure* | 8,250 | 0.05 | 0.00 | 0.21 | 0.00 | 0.00 |
| | | | | | | |
| *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 Holdings* | 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 D. Announcement CARs**

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

**Table 2. Difference-in-Differences Estimates of Pollution Following Divestitures**
This table presents estimates from difference-in-differences Poisson regressions explaining the pollution levels of divested plants around their divestitures. The unit of observation is a plant-chemical-year. The sample includes all plants in the TRI database. Panel A reports generalized DID regression estimates and Panel B reports regression estimates with stacked panels of divested plants and matched never-divested plants within the same NAICS3 industry and state. *Divested* is an indicator variable that equals 1 if a plant has been divested by its parent during the sample period. *Post* is an indicator variable that equals 1 in the years following the divestiture. *Total Pollution* is the total amount of toxic release for a plant-chemical-year. A chemical's pollution intensity (*Pollution Intensity*) is measured by the ratio of total toxic release over the chemical-level cumulative production ratio obtained from the TRI. A cohort includes all divested plants and matched never-divested control plants sharing the same event year. Standard errors are presented in parentheses and clustered by plant. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

**Panel A. Generalized DID Regressions**

| Dep. Var.: | *Total Pollution* | | | *Pollution Intensity* | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Divested* × *Post* | 0.035 | 0.030 | 0.038 | 0.044 | 0.035 | 0.050 |
| | (0.032) | (0.034) | (0.032) | (0.041) | (0.041) | (0.042) |
| Plant-Chemical FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Chemical-Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| State-Year FE | | Yes | Yes | | Yes | Yes |
| Industry-Year FE | | | Yes | | | Yes |
| Observations | 992,424 | 992,418 | 992,313 | 992,424 | 992,418 | 992,313 |
| Model | Poisson | Poisson | Poisson | Poisson | Poisson | Poisson |

**Panel B. Stacked Regressions**

| Dep. Var.: | *Total Pollution* | | | *Pollution Intensity* | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Divested* × *Post* | 0.031 | 0.050 | 0.037 | 0.034 | 0.078* | 0.069 |
| | (0.038) | (0.036) | (0.036) | (0.046) | (0.043) | (0.043) |
| 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 | 3,994,778 | 3,995,278 | 3,994,695 | 3,994,778 | 3,995,278 | 3,994,695 |
| Model | Poisson | Poisson | Poisson | Poisson | Poisson | Poisson |

**Table 3. Abatement Activities**

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

**Panel A. Generalized DID Regressions**

| Dep. Var.: | (1)<br>*#Source Reduction* | (2)<br>*%Recycling* | (3)<br>*%Recovery* | (4)<br>*%Treatment* |
|---|---|---|---|---|
| *Divested* × *Post* | -0.014 | 0.340 | -0.732 | 0.840 |
| | (0.070) | (0.510) | (0.523) | (0.689) |
| Plant-Chemical FE | Yes | Yes | Yes | Yes |
| Chemical-Year FE | Yes | Yes | Yes | Yes |
| State-Year FE | Yes | Yes | Yes | Yes |
| Industry-Year FE | Yes | Yes | Yes | Yes |
| Observations | 1,218,156 | 1,035,311 | 1,035,311 | 1,035,311 |
| $R^2$ | 0.933 | 0.870 | 0.749 | 0.821 |
| Model | OLS | OLS | OLS | OLS |

**Panel B. Stacked Regressions**

| Dep. Var.: | (1)<br>*#Source Reduction* | (2)<br>*%Recycling* | (3)<br>*%Recovery* | (4)<br>*%Treatment* |
|---|---|---|---|---|
| *Divested* × *Post* | -0.080 | 0.029 | -0.337 | 1.344 |
| | (0.089) | (0.628) | (0.630) | (0.828) |
| Cohort-Plant-Chemical FE | Yes | Yes | Yes | Yes |
| Cohort-Chemical-Year FE | Yes | Yes | Yes | Yes |
| Cohort-State-Year FE | Yes | Yes | Yes | Yes |
| Cohort-Industry-Year FE | Yes | Yes | Yes | Yes |
| Observations | 4,580,228 | 4,045,971 | 4,045,971 | 4,045,971 |
| $R^2$ | 0.943 | 0.828 | 0.717 | 0.767 |
| Model | OLS | OLS | OLS | OLS |

**Table 4. Alternative Explanations**

Panels A and B present estimates from difference-in-differences Poisson regressions explaining the pollution levels of remaining (non-divested) plants of firms that have divested or acquired divested plants. Panel C compares between the sales growth rates of divested and never-divested plants over the five years leading to the divestiture. In Panels A and B, the unit of observation is a plant-chemical-year. Panel A reports generalized DID regression estimates and Panel B reports regression estimates with stacked panels of divested plants and matched never-divested plants within the same NAICS3 industry and state. *Peer* is an indicator variable that equals 1 if a plant belongs to a parent company that divested a pollutive plant or acquired one. *Post* is an indicator variable that equals 1 in the years following the divestiture. *Total Pollution* is the total amount of toxic release for a plant-chemical-year. A chemical's pollution intensity (*Pollution Intensity*) is measured by the ratio of total toxic release over the chemical-level cumulative production ratio obtained from the TRI. In Panel C, the divestiture year is the omitted benchmark year. Column (1) presents generalized DID regression estimates and column (2) reports stacked regression estimates. All the fixed effects in column (2) are interacted with cohort fixed effects. A cohort includes all divested plants and matched never-divested control plants sharing the same event year. Standard errors are presented in parentheses and clustered by plant. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

**Panel A. Remaining Plants: Generalized DID Regressions**

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

**Panel B. Remaining Plants: Stacked Regressions**

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

**Panel C. Sales Growth before Divestitures**

| Dep. Var.: *Sales Growth* | (1) | (2) |
|---|---|---|
| *Sell (Pollutive)* × *D(year=-5)* | -0.001 | -0.011 |
| | (0.029) | (0.032) |
| *Sell (Pollutive)* × *D(year=-4)* | 0.002 | 0.000 |
| | (0.027) | (0.027) |
| *Sell (Pollutive)* × *D(year=-3)* | 0.040 | 0.041 |
| | (0.028) | (0.029) |
| *Sell (Pollutive)* × *D(year=-2)* | 0.020 | 0.042 |
| | (0.026) | (0.029) |
| *Sell (Pollutive)* × *D(year=-1)* | -0.017 | -0.010 |
| | (0.023) | (0.024) |
| Plant FE | Yes | Yes |
| Year FE | Yes | Yes |
| State-Year FE | Yes | Yes |
| Industry-Year FE | Yes | Yes |
| Cohort-Interacted FEs | | Yes |
| Observations | 263,230 | 176,159 |
| Adjusted $R^2$ | 0.022 | 0.111 |
| Method | Generalized DID | Stacked Regression |
| Model | OLS | OLS |

**Table 5. The Determinants of Divesting Pollutive Plants**

In this table, we examine what determines pollutive plant divestitures. We focus on two aspects: pollution levels and exposure to ESG risk incidents. Panel A studies the link between plant-level pollution and the likelihood of being sold. The dependent variable is *Divested*, an indicator variable that equals 1 if a plant is divested in a given year. *Past Total Pollution (Quartile)* is the quartile of the total toxic release generated by a plant, averaged over the past two years ($[t-1, t]$). *Past Pollution Intensity (Quartile)* is the quartile of the toxic emission scaled by employees of a plant, averaged over the past two years($[t-1, t]$). Both measures range between 1 and 4, with 4 being the highest pollution level. Data on the number of employees in a plant come from NETS. The unit of observation is a plant-year, and the sample includes all TRI plant observations up to the year they are sold. Panel B studies the link between firms' ESG risk exposure and the likelihood of selling a plant. Information on ESG risk events comes from RepRisk. The dependent variable is *Sell (Pollutive)*, an indicator variable that equals 1 if a firm divests at least one TRI plant in a given year. *RepRisk ESG Event* is an indicator variable that equals 1 if a firm experiences an ESG risk event in the current or past year. *RepRisk Environmental Event* is an indicator variable that equals one if a firm incurs an environmental risk event in the current or past year. Similarly, *RepRisk Social or Governance Event* indicates whether a firm incurs a social or an governance-related risk event in the current or past year. The unit of observation is a parent firm-year, and the sample includes all parents of TRI plants that have appeared at least once in the RepRisk database. In Panel C, we examine whether the same set of parent firms are more likely to divest other, non-TRI assets following ESG risk events. The dependent variable is *Sell (NonPollutive)*, defined as an indicator variable that equals 1 if a firm divests non-pollutive assets in a given year. All dependent variables in this table are multiplied by 100. *Firm Char* includes *Size*, *M/B*, *Leverage*, *Cash Holdings*, and *Tangibility*. All variable definitions appear in Appendix A. 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. Divestment and Pollution Levels**

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

**Panel B. Divestment and ESG Risk Events**

| Dep. Var.: *Sell (Pollutive)* | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| *RepRisk ESG Event* | 0.669** | 0.685** | 0.729** | | | | | | |
| | (0.310) | (0.312) | (0.321) | | | | | | |
| *RepRisk Env. 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) |
| *RepRisk Soc. or Gov. Event* | | | | | | | 0.245 | 0.090 | 0.142 |
| | | | | | | | (0.321) | (0.313) | (0.329) |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | | | Yes | | | Yes | | |
| Industry-Year FE | | Yes | Yes | | Yes | Yes | | Yes | Yes |
| Firm Char | | | Yes | | | Yes | | | Yes |
| Observations | 9,172 | 8,733 | 8,336 | 9,172 | 8,733 | 8,336 | 9,172 | 8,733 | 8,336 |
| $R^2$ | 0.198 | 0.258 | 0.263 | 0.198 | 0.259 | 0.263 | 0.198 | 0.259 | 0.263 |
| Model | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | |

**Panel C. Divestment and ESG Risk Events: Non-Pollutive Plants**

| Dep. Var.: *Sell (NonPollutive)* | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| *RepRisk ESG Event* | -1.361 | -1.574 | -2.117 | | | | | | |
| | (1.275) | (1.306) | (1.291) | | | | | | |
| *RepRisk Env. 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) |
| *RepRisk Soc. or Gov. 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 6. Environmental Pressures**
This table examines whether buyers of TRI plants are more likely to face weaker environmental pressures. We compare buyers and sellers in divestitures of pollutive plants in Panel A, and in non-pollutive divestitures in Panel B. The unit of observation is a deal-firm pair, where each deal includes two firm observations, one for the buyer and one for the seller. The variables of interest include *Private Firm*, an indicator variable that equals 1 if the firm is privately owned and 0 otherwise, *Unrated Firm*, an indicator variable that equals 1 if the firm does not have an ESG rating and 0 otherwise, *No Env. Event*, an indicator variable that equals 1 if the firm did not experience an environmental risk event in the Reprisk database and 0 otherwise, *Republican County*, an indicator variable that equals 1 if the firm is headquartered in a county where the Republican party won the majority vote in the most recent presidential election and 0 otherwise, and *Low Pressure*, the average of the four indicator variables. All variable definitions appear in Appendix A. Robust standard errors are included. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

**Panel A. Pollutive Asset Divestitures**

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

**Panel B. Non-pollutive Asset Divestitures**

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

**Table 7. Changes in Conference Call Environmental Disclosures Following Divestitures** This table presents estimates from difference-in-differences OLS regressions explaining sellers' environmental disclosures from earnings conference calls around divestitures of pollutive plants. The sample includes firm-years where we can identify environmental disclosures in firms' conference calls. 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 that have not sold a plant during the sample period. In columns (1)–(3), the dependent variable is *Positive Env. Disclosure*, an indicator variable that equals 1 if a firm discusses improvements in its environmental performance during its earnings conference calls in a given year. In columns (4)–(6), the dependent variable is *Negative Env. Disclosure*, which is defined analogously with respect to deterioration in the firm's environmental performance. *Seller (Pollutive)* is an indicator variable that equals 1 if a firm divests a pollutive plant during the sample period. *Post* is an indicator variable that equals 1 in the years following the divestiture. *Firm Char* includes *Size*, *M/B*, *Leverage*, *Cash Holdings*, and *Tangibility*. All variable definitions appear in Appendix A. A cohort includes all divested plants and matched never-divested control plants sharing the same event year. The standard errors are reported in parentheses and clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

**Panel A. Generalized DID Regressions**

| Dep. Var.: | *Positive Env Disclosure* | | | *Negative Env Disclosure* | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Seller (Pollutive)* × *Post* | 0.081* | 0.101* | 0.115** | -0.054 | -0.019 | -0.015 |
| | (0.047) | (0.056) | (0.057) | (0.040) | (0.042) | (0.041) |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | | | Yes | | |
| Ind-Year FE | | Yes | Yes | | Yes | Yes |
| Firm Char | | | Yes | | | Yes |
| Observations | 6,722 | 6,433 | 5,976 | 6,722 | 6,433 | 5,976 |
| $R^2$ | 0.539 | 0.588 | 0.596 | 0.672 | 0.718 | 0.721 |
| Model | OLS | OLS | OLS | OLS | OLS | OLS |

**Panel B. Stacked Regressions**

| Dep. Var.: | *Positive Env Disclosure* | | | *Negative Env Disclosure* | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Seller (Pollutive)* × *Post* | 0.064 | 0.109* | 0.122** | -0.065 | -0.035 | -0.024 |
| | (0.054) | (0.057) | (0.058) | (0.044) | (0.046) | (0.046) |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | | | Yes | | |
| Ind-Year FE | | Yes | Yes | | Yes | Yes |
| Firm Char | | | Yes | | | Yes |
| Observations | 37,097 | 36,283 | 35,355 | 37,097 | 36,283 | 35,355 |
| $R^2$ | 0.502 | 0.536 | 0.539 | 0.692 | 0.721 | 0.729 |
| Model | OLS | OLS | OLS | OLS | OLS | OLS |

**Table 8. Business Ties between Buyers and Sellers of Pollutive Assets**
This table examines whether the buyers and sellers of pollutive plants are operationally related through supply-chain relationships and joint-ventures. Column (1) examines whether pre-existing operational relations predict future participation in pollutive asset divestitures. The dependent variable, *Buyer (Pollutive)*, is an indicator variable that equals 1 if a firm purchases a pollutive asset from the seller. *Operationally Related* is an indicator variable that equals 1 if a firm has a pre-existing supply-chain relationship or a joint venture partnership with the seller. Column (2) examines whether buyers and sellers develop new supply-chain or joint venture relations following the divestiture. The tests are designed as follows. For each divestiture deal (or a buyer-seller pair), we generate five control pairs that match the buyer with randomly chosen pseudo-acquirers. These pseudo-acquirers are acquirers from the SDC universe that operate in the same industry as the actual acquirer. The analyses utilize a matched-pair sample, in which each observation is a seller-pseudo buyer pair. As such, each deal has six observations, consisting of the actual buyer-seller pair and five potential buyer-seller pairs. The regressions include matched group fixed effects. The standard errors are reported in parentheses and double clustered by matched group and deal year. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

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

**Table 9. Changes in ESG Ratings Following Divestitures**

This table presents estimates from difference-in-differences OLS regressions explaining sellers' ESG ratings around divestitures of pollutive plants. 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 that have not sold a plant during the sample period. The dependent variable in columns (1)–(3) is *Overall CSR Score*, and the dependent variable in columns (4)–(6) is *Environmental Scores*. *Seller (Pollutive)* is an indicator variable that equals 1 if a firm divests a pollutive plant during the sample period. *Post* is an indicator variable that equals 1 in the years following the divestiture. *Firm Char* includes *Size*, *M/B*, *Leverage*, *Cash Holdings*, and *Tangibility*. All variable definitions appear in Appendix A. A cohort includes all divested plants and matched never-divested control plants sharing the same event year. The standard errors are reported in parentheses and clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

**Panel A. Generalized DID Regressions**

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

**Panel B. Stacked Regressions**

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

**Table 10. Changes in Environmental Compliance Costs Following Divestitures**
This table presents estimates from difference-in-differences OLS regressions explaining sellers' environmental compliance costs around divestitures of pollutive plants. 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 that have not sold a plant during the sample period. In columns (1)–(3), the dependent variable is *Enforcement Action*, an indicator variable that equals 1 if a firm faces an EPA enforcement action in a given year. In columns (4)–(6), the dependent variable is *Enforcement Cost*, the dollar amount (in millions) of regulatory costs incurred by the firm due to EPA enforcement actions, including fines and cleanup costs. *Seller (Pollutive)* is an indicator variable that equals 1 if a firm divests a pollutive plant during the sample period. *Post* is an indicator variable that equals 1 in the years following the divestiture. *Firm Char* includes *Size*, *M/B*, *Leverage*, *Cash Holdings*, and *Tangibility*. All variable definitions appear in Appendix A. A cohort includes all divested plants and matched never-divested control plants sharing the same event year. The standard errors are reported in parentheses and clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

**Panel A. Generalized DID Regressions**

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

**Panel B. Stacked Regressions**

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

**Table 11. Non-Pollutive Divestitures**

This table provides estimates of difference-in-differences regressions explaining ESG ratings (Panel A), environmental enforcement costs (Panel B), environmental disclosures in earnings conference calls (Panel C), and business ties between buyers and sellers (Panel D) in divestitures of non-pollutive assets. *Seller (NonPollutive)* is an indicator variable that equals 1 if a firm divests a non-pollutive (non-TRI) asset during the sample period. *Post* is an indicator variable that equals 1 in the years following the divestiture. *Firm Char* includes *Size*, *M/B*, *Leverage*, *Cash Holdings*, and *Tangibility*. All variable definitions appear in Appendix A. The 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 (NonPollutive)* × *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. EPA Enforcement**

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

**Panel C. Environmental Disclosure in Earnings Conference Calls**

| Dep. Var.: | *Positive Env Disclosure* | | | *Negative Env Disclosure* | | |
|---|---|---|---|---|---|---|
| Sample: Unmatched | (1) | (2) | (3) | (4) | (5) | (6) |
| *Seller (NonPollutive) × Post* | 0.023 | 0.012 | 0.017 | 0.024 | 0.028 | 0.029 |
| | (0.025) | (0.028) | (0.029) | (0.020) | (0.020) | (0.021) |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | | | Yes | | |
| Industry-Year FE | | Yes | Yes | | Yes | Yes |
| Firm Char | | | Yes | | | Yes |
| Observations | 6,692 | 6,418 | 5,961 | 6,692 | 6,418 | 5,961 |
| $R^2$ | 0.538 | 0.588 | 0.596 | 0.673 | 0.719 | 0.722 |
| Model | OLS | OLS | OLS | OLS | OLS | OLS |

**Panel D. Business Ties**

| | (1) | (2) |
|---|---|---|
| Dep. Var.: | *Buyer (NonPollutive)* | *Develop New Relationship* |
| *Operationally Related* | -0.011 | |
| | (0.014) | |
| *Buyer (NonPollutive)* | | 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. Divestiture Announcement Returns**

This table examines the relation between a divested plant's pollution levels and sellers' cumulative abnormal returns (CARs) in the three-day window surrounding the divestiture announcement date. The unit of observation is a divestiture deal, and the sample includes all publicly traded sellers. We compute abnormal returns in two ways. First, we subtract the market return from firms' equity returns ("Market" benchmark). Second, we compute the residual from regressing total returns on the Fama-French 3-factor model ("FF" benchmark). We consider two measures of pollution. *Quantity* is the total amount of toxic release generated by all the plants sold in the deal. *Intensity* is the ratio of total toxic release to total employment at the sold plants. We sort firms into pollution quartiles ranging from 1 (least pollutive) to 4 (most pollutive). All the regressions include industry fixed effects and year fixed effects. The standard errors are reported in parentheses and 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 Pollution (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 Variable Definitions

### Plant-chemical-level Variable

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

### Plant-Level Variable

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

### Firm-Level Variable

- *Private*: An indicator of a firm being private
- *Unrated*: An indicator of a firm not rated by the KLD
- *No Env. Event*: an indicator variable that equals 1 if the company has not faced an ESG risk incidence in the past or current year.
- *Republican County*: an indicator variable that equals 1 if the company is headquartered in a Republican-leaning county. Republican-leaning counties are those where the majority of the county's votes went to a Republican presidential candidate in the most recent presidential elections.
- *Total Pollution*: The total amount of toxic releases
- *Pollution Intensity*: The total amount of toxic releases divided by the number of employees
- *CSR Score* (KLD): The aggregate net strength and concern counts across six dimensions in KLD
- *Env. Score* (KLD): The net strength and concern counts for the environmental dimension in KLD
- *Size*: The natural log of total assets
- *M/B* : $(at - ceq + csho * prcc_f)/at$
- *Leverage*: $(dlc + dltt)/(dlc + dltt + ceq)$
- *Cash Holdings*: $Cash/at$
- *Tangibility*: $PPENT/at$
- *Log(Sales)*: The natural log of sales (Compustat)
- *RepRisk ESG Event*: An indicator of a firm having an ESG risk event based on RepRisk
- *RepRisk Env. Event*: An indicator of a firm having an environmental risk event based on RepRisk

- *RepRisk Soc. or Gov. Event*: An indicator of a firm having a social or governance-related 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
- *Positive Env Disclosure*: Management of a firm discusses improvement in the firm's environmental performance during conference calls in a given year
- *Negative Env Disclosure*: Management of a firm discusses deterioration in the firm's environmental performance during conference calls in a given year
- *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

# Internet Appendix for
# "Sustainability or Greenwashing: Evidence from the Asset Market for Industrial Pollution

Ran Duchin, Janet Gao, Qiping Xu

This document provides additional data descriptions and robustness tests. Section IA.1 provides detailed descriptions of: (1) pollution abatement activities, (2) the procedures used to detect changes in the ownership of pollutive plants, and (3) the industry composition of divested plants. Section IA.2 provides estimates from robustness tests and extensions, including: (1) minimum detectable effect size (MDES) estimates, (2) OLS regression estimates, (3) aggregate plant-level regression estimates, (4) toxicity-weighted regression estimates, (5) estimates from regressions that include financial buyers, (6) estimates from separate regressions for divested and never-divested plants, (7) analyses of new plant acquisitions, and (8) estimates based on alternative ESG ratings.

# IA.1 Data Description

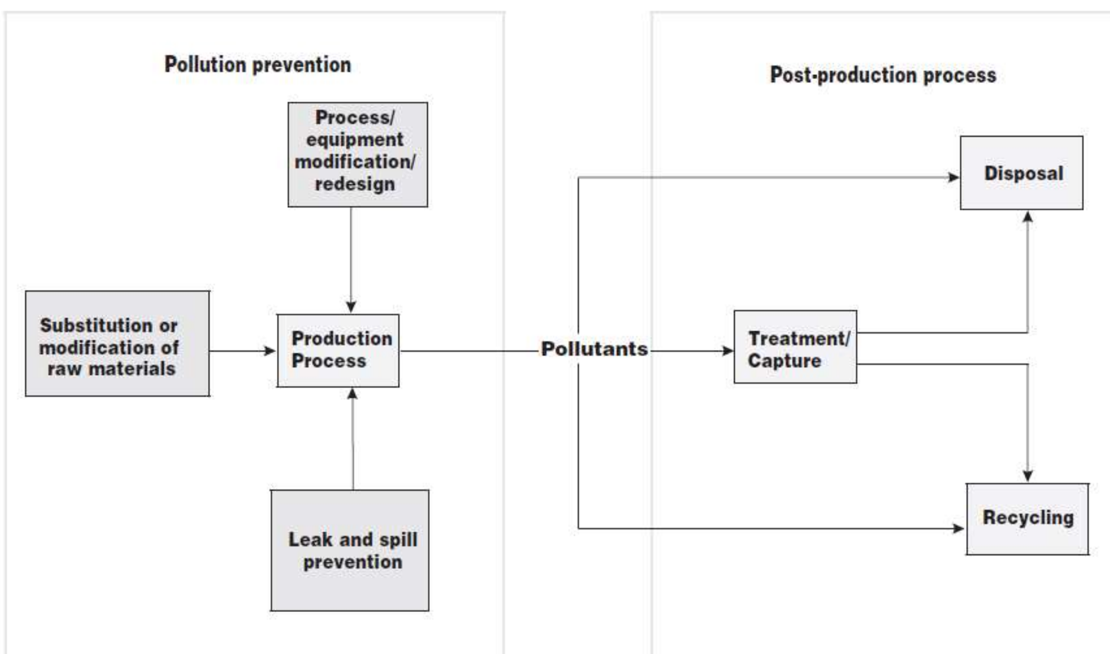
## IA.1.1 Pollution Abatement Activities

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*.

For pollution prevention, facilities must report their newly implemented source reduction activities annually 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; and (3) Treatment, which involves the use of various processes, such as incineration or oxidation, to alter the properties or composition of hazardous materials.

**Figure IA.1. Pollution Abatement Activities**



### IA.1.2 Detecting Changes in the Ownership of TRI Plants

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

First, we flag all cases in which a plant's parent names change, 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 and the ultimate parent level. In this process, we account for the possibility that the TRI data inaccurately captures 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 the TRI database. 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 888 deals.

**Table IA.1. Industry Composition**

This table reports the distribution of the divestitures of pollutive plants in our sample across industries. Industry classifications are based on three-digit NAICS codes.

| 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 |

## IA.2 Robustness Tests and Extensions

**Table IA.2. MDES for Pollution Estimates**
This table presents minimum detectable effect size (MDES) estimates for the results in Table 2. Panel A corresponds to the generalized DID regression specifications and Panel B corresponds to the stacked regression specifications, which include stacked panels of divested plants and matched never-divested plants within the same NAICS3 industry and state. The unit of observation is a plant-chemical-year. *Total Pollution* is the total amount released for a plant-chemical-year. *Pollution Intensity* is the ratio of total toxic release to the chemical's cumulative production ratio obtained from the TRI. MDES for 80% detect probability is computed as the standard error of coefficient estimates times 2.49, and MDES for 90% detect probability is computed as the standard error of coefficient estimates times 2.93. Each MDES is scaled by the standard deviation of the log of the dependent variable. Standard errors are presented in parentheses and clustered by plant. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

| Dep. Var.: | *Total Pollution* | | | *Pollution Intensity* | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A. Generalized DID Regressions** | | | | | | |
| *Divested* × *Post* Coefficient | 0.035 | 0.030 | 0.038 | 0.044 | 0.035 | 0.050 |
| Std. Err. | (0.032) | (0.034) | (0.032) | (0.041) | (0.041) | (0.042) |
| MDES (80%) | 0.080 | 0.085 | 0.080 | 0.102 | 0.102 | 0.105 |
| Rel. to Std of Log(Dep. Var.): | 2.00% | 2.13% | 2.00% | 2.76% | 2.76% | 2.83% |
| MDES (90%) | 0.094 | 0.100 | 0.094 | 0.120 | 0.120 | 0.123 |
| Rel. to Std of Log(Dep. Var.): | 2.36% | 2.50% | 2.36% | 3.25% | 3.25% | 3.33% |
| **Panel B. Stacked Regressions** | | | | | | |
| *Divested* × *Post* Coefficient | 0.031 | 0.050 | 0.037 | 0.034 | 0.078 | 0.069 |
| Std. Err. | (0.038) | (0.036) | (0.036) | (0.046) | (0.043) | (0.043) |
| MDES (80%) | 0.095 | 0.090 | 0.090 | 0.115 | 0.107 | 0.107 |
| Rel. to Std of Log(Dep. Var.): | 2.38% | 2.25% | 2.25% | 3.10% | 2.90% | 2.90% |
| MDES (90%) | 0.111 | 0.105 | 0.105 | 0.135 | 0.126 | 0.126 |
| Rel. to Std of Log(Dep. Var.): | 2.80% | 2.65% | 2.65% | 3.64% | 3.41% | 3.41% |
| 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 |

**Table IA.3. Changes in Pollution Following Divestitures: Robustness Tests**

Panels A and B provide OLS regressions estimates from plant-by-chemical specifications. Panels C and D provide estimates from regressions that aggregate annual pollution across all the chemicals in each plant. Panels E and F provide estimates from toxicity-weighted measures of chemical emissions. *Divested* is an indicator variable that equals 1 if a plant has been divested by its parent during the sample period. *Post* is an indicator variable that equals 1 in the years following the divestiture. *Total Pollution* is the total amount of toxic release for a plant-chemical-year (or a plant-year in Panels C–F). *Pollution Intensity*) is the ratio of total pollution to a chemical's production ratio (or the number of plant employees in Panels C–F). *RSEI Hazard* is the toxicity weighted pollution amount, while *RSEI Score* incorporates both toxicity weight and modeled population exposure to gauge the impact on public health. Standard errors are presented in parentheses and clustered by plant. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

**Panel A. Pollution, Generalized DID Regressions**

| Dep. Var.: | *Total Pollution* | | | *Pollution Intensity* | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Divested* × *Post* | 1119.094 | 818.396 | 1244.595* | 1509.848 | 1356.195 | 1804.309 |
| | (739.099) | (744.719) | (712.087) | (1364.448) | (1364.210) | (1351.310) |
| Plant-Chemical FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Chemical-Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| State-Year FE | | Yes | Yes | | Yes | Yes |
| Industry-Year FE | | | Yes | | | Yes |
| Observations | 1,035,411 | 1,035,405 | 1,035,311 | 1,035,411 | 1,035,405 | 1,035,311 |
| Adjusted $R^2$ | 0.804 | 0.805 | 0.810 | 0.793 | 0.793 | 0.796 |
| Model | OLS | OLS | OLS | OLS | OLS | OLS |

**Panel B. Pollution, Stacked Regressions**

| Dep. Var.: | *Total Pollution* | | | *Pollution Intensity* | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Divested* × *Post* | 51.205 | 1066.408 | 1662.607* | 416.574 | 2146.242 | 2266.818 |
| | (1011.185) | (906.463) | (941.735) | (1567.320) | (1434.128) | (1458.340) |
| 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 | 4,046,477 | 4,046,431 | 4,045,971 | 4,046,477 | 4,046,431 | 4,045,971 |
| Adjusted $R^2$ | 0.805 | 0.806 | 0.808 | 0.780 | 0.781 | 0.782 |
| Model | OLS | OLS | OLS | OLS | OLS | OLS |

**Panel C. Plant Pollution, Generalized DID Regressions**

| Dep. Var.: | *Total Pollution* | | | *Pollution Intensity* | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Divested* × *Post* | 0.043 | 0.049 | 0.041 | 0.030 | 0.049 | 0.031 |
| | (0.047) | (0.048) | (0.046) | (0.105) | (0.104) | (0.104) |
| Plant FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | | | Yes | | |
| State-Year FE | | Yes | Yes | | Yes | Yes |
| Industry-Year FE | | | Yes | | | Yes |
| Observations | 334,852 | 334,838 | 334,683 | 269,656 | 269,635 | 269,474 |
| Model | Poisson | Poisson | Poisson | Poisson | Poisson | Poisson |

**Panel D. Plant Pollution, Stacked Regressions**

| Dep. Var.: | *Total Pollution* | | | *Pollution Intensity* | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Divested* × *Post* | -0.004 | 0.064 | 0.046 | -0.018 | 0.041 | 0.006 |
| | (0.062) | (0.058) | (0.060) | (0.142) | (0.144) | (0.147) |
| 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 | 874,418 | 874,261 | 873,193 | 722,272 | 722,037 | 721,144 |
| Model | Poisson | Poisson | Poisson | Poisson | Poisson | Poisson |

**Panel E. Plant RSEI, Generalized DID Regressions**

| Dep. Var.: | *RSEI Hazard* | | | *RSEI Score* | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Divested* × *Post* | -0.011 | -0.022 | 0.021 | -0.031 | -0.006 | 0.014 |
| | (0.084) | (0.089) | (0.084) | (0.098) | (0.094) | (0.087) |
| Plant FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | | | Yes | | |
| State-Year FE | | Yes | Yes | | Yes | Yes |
| Industry-Year FE | | | Yes | | | Yes |
| Observations | 316,806 | 316,790 | 316,627 | 312,530 | 312,514 | 312,342 |
| Model | Poisson | Poisson | Poisson | Poisson | Poisson | Poisson |

**Panel F. Plant RSEI, Stacked Regressions**

| Dep. Var.: | *RSEI Hazard* | | | *RSEI Score* | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Divested* × *Post* | -0.152 | -0.007 | 0.032 | -0.099 | 0.099 | 0.171 |
| | (0.141) | (0.128) | (0.136) | (0.156) | (0.126) | (0.124) |
| 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 | 849,042 | 848,857 | 847,825 | 849,042 | 848,857 | 847,825 |
| Model | Poisson | Poisson | Poisson | Poisson | Poisson | Poisson |

**Table IA.4. Changes in Pollution Following Divestitures: Including Financial Buyers**
This table presents estimates from difference-in-differences Poisson regressions explaining the pollution levels of divested plants around their divestitures. The unit of observation is a plant-chemical-year. The sample includes deals with financial buyers. Panel A reports generalized DID regression estimates and Panel B reports regression estimates with stacked panels of divested plants and matched never-divested plants within the same NAICS3 industry and state. *Divested* is an indicator variable that equals 1 if a plant has been divested by its parent during the sample period. *Post* is an indicator variable that equals 1 in the years following the divestiture. *Total Pollution* is the total amount of toxic release for a plant-chemical-year. *Pollution Intensity* is the ratio of total toxic release to a chemical's cumulative production ratio obtained from the TRI. A cohort includes all divested plants and matched never-divested control plants sharing the same event year. Standard errors are presented in parentheses and clustered by plant. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

**Panel A. Pollution, Generalized DID Regressions**

| Dep. Var.: | *Total Pollution* | | | *Pollution Intensity* | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Divested* × *Post* | 0.025 | 0.021 | 0.033 | 0.045 | 0.039 | 0.059* |
| | (0.028) | (0.028) | (0.027) | (0.035) | (0.034) | (0.035) |
| Plant-Chemical FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Chemical-Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| State-Year FE | | Yes | Yes | | Yes | Yes |
| Industry-Year FE | | | Yes | | | Yes |
| Observations | 992,424 | 992,418 | 992,313 | 992,424 | 992,418 | 992,313 |
| Model | Poisson | Poisson | Poisson | Poisson | Poisson | Poisson |

**Panel B. Pollution, Stacked Regressions**

| Dep. Var.: | *Total Pollution* | | | *Pollution Intensity* | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Divested* × *Post* | 0.003 | 0.014 | 0.025 | 0.013 | 0.042 | 0.056 |
| | (0.034) | (0.033) | (0.032) | (0.042) | (0.039) | (0.040) |
| 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 | 6,611,095 | 6,611,720 | 6,611,114 | 6,611,095 | 6,611,720 | 6,611,114 |
| Model | Poisson | Poisson | Poisson | Poisson | Poisson | Poisson |

**Table IA.5. Divested vs. Never-Divested Plants**

This table presents estimates from Poisson regressions separately explaining the pollution levels of divested plants in Panel A and their never-divested matched plants in Panel B. The unit of observation is a plant-chemical-year. The sample includes stacked panels of divested plants and matched never-divested plants within the same NAICS3 industry and state from the TRI database. *Post* is an indicator variable that equals 1 in the years following the divestiture. *Total Pollution* is the total amount of toxic release for a plant-chemical-year. *Pollution Intensity* is the ratio of total toxic release to a chemical's cumulative production ratio obtained from the TRI. A cohort includes all divested plants and matched never-divested control plants sharing the same event year. Standard errors are presented in parentheses and clustered by plant. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

**Panel A. Divested Plants**

| Dep. Var.: | *Total Pollution* | | | *Pollution Intensity* | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Post* | 0.086** | 0.020 | 0.019 | 0.050 | 0.027 | 0.016 |
| | (0.044) | (0.044) | (0.036) | (0.051) | (0.049) | (0.047) |
| Cohort-Plant-Chemical FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Chemical-Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| State-Year FE | | Yes | Yes | | Yes | Yes |
| Industry-Year FE | | | Yes | | | Yes |
| Observations | 72,174 | 72,172 | 72,151 | 72,174 | 72,172 | 72,151 |
| Model | Poisson | Poisson | Poisson | Poisson | Poisson | Poisson |

**Panel B. Never-divested Plants**

| Dep. Var.: | *Total Pollution* | | | *Pollution Intensity* | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Post* | -0.009 | -0.009 | -0.003 | -0.004 | 0.003 | 0.006 |
| | (0.007) | (0.006) | (0.005) | (0.007) | (0.007) | (0.006) |
| Cohort-Plant-Chemical FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Chemical-Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| State-Year FE | | Yes | Yes | | Yes | Yes |
| Industry-Year FE | | | Yes | | | Yes |
| Observations | 3,942,320 | 3,942,316 | 3,942,266 | 3,942,320 | 3,942,316 | 3,942,266 |
| Model | Poisson | Poisson | Poisson | Poisson | Poisson | Poisson |

**Table IA.6. Acquisition of New Plants**

This table examines new plant acquisitions by sellers around divestitures of pollutive plants. The unit of observation is a firm-year. 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 that have not sold a plant during the sample period. *Seller (Pollutive)* is an indicator variable that equals 1 if a firm divests a pollutive plant during the sample period. *D(New Plant)* is an indicator variable that equals 1 if the firm acquires any new plants in a given year. *Num(New Plant)* is the total number of new plants acquired in a given year. *Post* is an indicator variable that equals 1 in the years following the divestiture. Panel C reports results related to divestitures of other, non-pollutive assets. *Seller (NonPollutive)* is an indicator variable that equals 1 if a firm divests a non-pollutive plant during the sample period. *Firm Char* includes *Size*, *M/B*, *Leverage*, *Cash Holdings*, and *Tangibility*. Standard errors are reported in parentheses and clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

**Panel A. New Plant Acquisition, Generalized DID Regressions**

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

**Panel B. New Plant Acquisition, Stacked Regressions**

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

**Panel C. New Plant Acquisition, Non-pollutive Divestitures**

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

**Figure IA.2. 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 databases between 1990-2020.

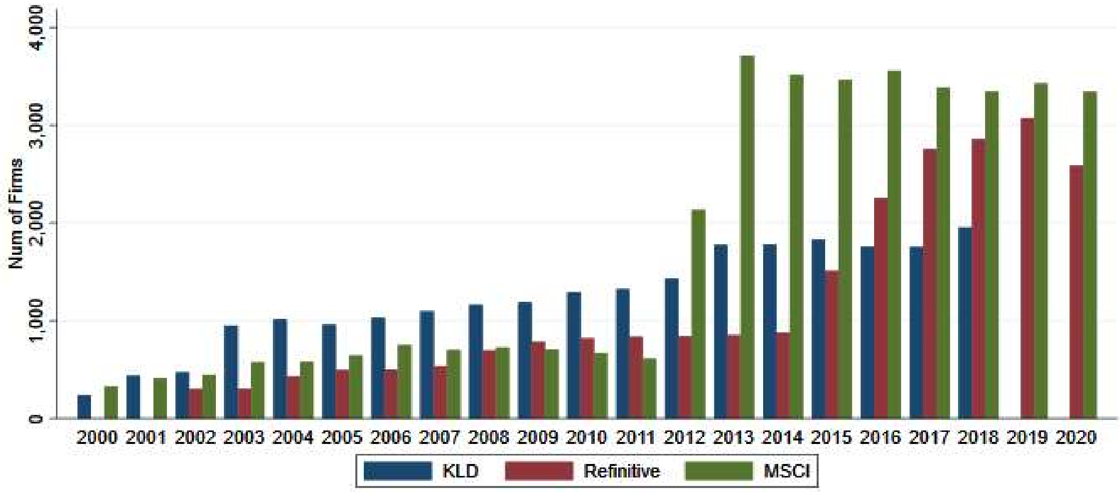


**Table IA.7. Alternative ESG Ratings**

This table presents estimates from difference-in-differences OLS regressions explaining sellers' ESG ratings around divestitures of pollutive plants. we use ratings data from Refinitive and MSCI to augment the ESG ratings from the KLD database. We standardize all rating observations across the three datasets, and fill observations with missing KLD ratings using the standardized ratings from Refinitive and MSCI if available. 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 that have not sold a plant during the sample period. The dependent variable in columns (1)–(3) is *Overall CSR Score*, and the dependent variable in columns (4)–(6) is *Environmental Scores*. *Seller (Pollutive)* is an indicator variable that equals 1 if a firm divests a pollutive plant during the sample period. *Post* is an indicator variable that equals 1 in the years following the divestiture. *Firm Char* includes *Size*, *M/B*, *Leverage*, *Cash Holdings*, and *Tangibility*. All variable definitions appear in Appendix A. A cohort includes all divested plants and matched never-divested control plants sharing the same event year. The 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) |
| *Sell (Pollutive)* × *Post* | 0.309*** | 0.218** | 0.228** | 0.644*** | 0.392*** | 0.369*** |
| | (0.097) | (0.094) | (0.095) | (0.145) | (0.137) | (0.138) |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | | | Yes | | |
| Industry-Year FE | | Yes | Yes | | Yes | Yes |
| Firm Char | | | Yes | | | Yes |
| Observations | 53,250 | 53,111 | 49,880 | 53,242 | 53,103 | 49,871 |
| $R^2$ | 0.518 | 0.545 | 0.547 | 0.410 | 0.456 | 0.459 |
| 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) |
| *Sell (Pollutive)* × *Post* | 0.219** | 0.209** | 0.246** | 0.436*** | 0.375** | 0.367** |
| | (0.104) | (0.101) | (0.100) | (0.158) | (0.150) | (0.150) |
| Cohort-Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Cohort-Year FE | Yes | | | Yes | | |
| Cohort-Industry-Year FE | | Yes | Yes | | Yes | Yes |
| Firm Char | | | Yes | | | Yes |
| Observations | 162,694 | 162,655 | 160,962 | 162,670 | 162,631 | 160,938 |
| $R^2$ | 0.553 | 0.564 | 0.567 | 0.433 | 0.455 | 0.456 |
| Model | OLS | OLS | OLS | OLS | OLS | OLS |