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Redeploying Dirty Assets:
The Impact of Environmental Liability

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Redeploying Dirty Assets: The Impact of Environmental Liability

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Abstract

This paper investigates the economic and environmental implications of limiting purchaser liability for past pollution. My empirical setting is the passage of the Brownfields Act, a reform aimed at increasing the liquidity of industrial plants by strengthening liability protection for purchasers. Using a difference-in-difference framework and detailed plant-level data, I find that reducing purchaser liability improves the liquidity treated property. Furthermore, the reform led to a 12 percent decrease in pollution, with distressed firms driving the reduction. The findings indicate that strengthening liability protection for purchasers alleviates the harm-shifting motives associated with financial distress.

JEL Classification: G21, G34, M14, Q50

Keywords: the market for corporate assets, financial distress, social responsibility, environmental economics.

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1 Introduction

A fundamental concept in finance and economics posits that corporations assume excessive risk when they face limited liability. An implication of this concept is that firms in hazardous industries tend to engage in excessive pollution. The rationale is that polluting firms can discharge environmental liability in bankruptcy, effectively capping the maximum cleanup cost that a polluting firm incurs at the firm's net worth. Put differently, while firms bear the full cost of pollution abatement due to limited liability, they only internalize a fraction of the benefits of avoiding contamination. Consequently, they are willing to accept an elevated environmental risk. In finance, this concept is called "risk shifting" (Jensen and Meckling (1976)) and is referred to as the "judgment-proof problem" in the law and economic literature (Shavell (1986)).

An important policy tool used to discourage industrial firms from engaging in such risk-shifting behavior is legal liability (e.g., Shavell (1984)). Existing research shows that a decrease in environmental liability imposed on shareholders and creditors of polluting firms results in worsening corporate environmental practices (e.g., Akey and Appel (2021); Bellon (2020); Bellon (2021)).[1] The economic mechanism documented by this line of research is a *monitoring effect*: when shareholders and creditors face reduced environmental liability, their incentive to monitor their firm's environmental practices decreases, leading to worsening environmental practices.

However, in the U.S., environmental liability extends beyond those with strong control over corporate environmental policy. For example, a purchaser of industrial land may be held responsible for remediating contamination caused by prior owners.[2] Unlike shareholders and creditors, potential purchasers of polluting firms' land have a much weaker direct influence on the firms' policies. In essence, they lack the same "monitoring technology" as

1. For example, Akey and Appel (2021) show that reducing parents' exposure to their subsidiary's liability causes subsidiary plants to pollute more. Bellon (2020) find that private equity-backed companies reduce pollution when the risk of environmental liability is high for shareholders. Bellon (2021) and Ohlrogge (2020) show that reducing lenders' environmental liability reduces their incentive to monitor their borrowers, leading to an increase in pollution.

2. Envrionmental regulations impose liability on "current owners and operators." Since a purchaser becomes a current owner upon acquiring industrial land and, as a result, becomes responsible for cleanup costs, even if the contamination originated from previous owners.

shareholders and creditors. Nevertheless, purchaser liability can significantly impact an industrial firm's environmental policy through the industrial land market. Specifically, a reduction in purchaser liability diminishes the environmental risk of acquiring industrial land, subsequently improving the liquidity and value of such properties (e.g., Sigman (2010); Alberini et al. (2005)).[3] This positive impact on industrial land, in turn, increases the net worth of landowners, which reduces their incentive to engage in harm shifting practices.

Despite the important implications of reducing purchaser liability, there is surprisingly little research on this issue. To fill this gap, this paper studies the implications of a major reform that reduced purchasers' exposure to environmental liability. Using granular plant-level data and a difference-in-difference empirical approach, I find that exempting purchasers from liability leads to more sales of properties affected by the reform and reduces the credit risk of affected subsidiary plants. Furthermore, my analysis reveals that parent firms with a large fraction of plants in affected industries exhibit a decline in pollution, particularly among those close to bankruptcy. I attribute this reduction to a lower incentive to take advantage of limited liability protection. These findings highlight a *net worth effect* associated with environmental liability: by improving the liquidity of the secondary market and the valuation of affected plants, a reduction in purchaser liability pushes distressed landowners away from insolvency, mitigating the moral hazard problem associated with limited liability.

My empirical setting is the Small Business Liability Relief and Brownfields Revitalization Act of 2002 (Brownfields Act hereafter). In the U.S., purchasers of industrial land are exposed to substantial and unpredictable cleanup costs. The average cleanup cost of contaminated sites is $73 million and can range up to billions of dollars (Greenstone and Gallagher (2008)). Moreover, there is significant uncertainty and information asymmetry on the level of contamination even after environmental assessments (Ramsey and Argyraki (1997)). Fear of incurring significant environmental liability resulted in a reluctance to buy industrial property, leading many industrial sites to be abandoned or underutilized—despite many of these

3. Sigman (2010) finds that strict and joint environmental liability reduces industrial land prices by 16 percent and increases the vacancy rate by approximately 40 percent. Using survey evidence, Alberini et al. (2005) documents that purchaser liability relief is worth 21 percent of the median value of a deployment project. See also Wernstedt, Meyer, and Alberini (2006), Howland (2000), Thomas (2002), and McGrath (2000) for how environmental liability affects the liquidity and price of industrial land.

sites being only potentially contaminated (Ramseur (2008)); Alberini et al. (2005); Hayes and Dinkin (1988); Rubenstein (1997)).[4] To address this problem, Congress enacted the Brownfields Act, which clarified and introduced liability defenses for purchasers, allowing them to escape cleanup liability caused by previous landowners. In the presence of frictions, such as information asymmetry or imperfect detection of contamination by regulators, a reduction in purchaser liability should encourage purchasers to enter the industrial land market, positively affecting the liquidity and price of industrial land (Boyd, Harrington, and Macauley (1996)).

I exploit the institutional characteristics of environmental regulation to measure exposure to the reform at the industry level.[5] In the U.S., environmental cleanups are enforced under two environmental statutes: the Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA) and the Resource Conservation and Recovery Act (RCRA). Importantly, the Brownfields Act protects purchasers only from cleanup liability under CERCLA but not RCRA. Given that CERCLA has a broader jurisdiction compared to RCRA (Stoll (1990)),[6] industries exposed CERCLA but have little exposure to RCRA are particularly affected. The reason is that, for these industries, the reform protects purchasers from CERCLA liability, and purchasers are not concerned with the EPA enforcing cleanups using RCRA. Thus, I classify industries exposed to CERCLA enforcement but with a low (high) exposure to RCRA enforcement *prior to reform* as the treated (control) group.

I start by examining the reform's effect on the liquidity of treated plants. To do so, I utilize a granular plant-level dataset from the National Establishment Time Series (NETS), which covers almost the entire universe of plants in the United States. This extensive coverage allows me to track changes in ownership of industrial land even after incumbent plants relocate or shut down by matching the address across different plants. Using the difference-in-difference framework, I find that the propensity to sell real estate increased by 1.3 to 1.7 percentage points for plants in treated industries relative to those in control industries after the reform. The increase is 38 to 50 percent compared to the sample mean, an economically significant increase in liquidity. This finding provides confidence in my classification of the treated and

4. The abandoned sites are labeled as "brownfields," The EPA estimates that there are 450,000 brownfield sites.
5. I thank the EPA for letting me speak to an attorney about the Brownfields Act and environmental statutes.
6. I describe the difference between CERCLA and RCRA in Section 2.1

control groups because the reform's intended goal is to facilitate transactions of industrial property.

Next, I examine the reform's impact on the solvency of subsidiary plants. If the reform positively affects the value of the land, treated plants should be better capitalized after the reform. Using Paydex scores from the NETS database to measure credit quality, I find that treated plants are less likely to have a *high risk* credit score relative to plants in the control industries after the reform.[7] The economic magnitude is again meaningful, representing a 47 to 56 percent decrease relative to the sample mean.

Then, I study how stronger liability protection for purchasers affects industrial pollution. An improvement in the liquidity and value of affected land should positively affect the net worth of firms with a large fraction of their real estate assets in treated industries (hereafter treated firms). This, in turn, reduces treated firms' motive of harm shift because they now internalize a greater fraction of the benefits of preventing environmental contamination. This *net worth effect* should be particularly relevant for *ex-ante* distressed landowners as they have a stronger incentive to engage in risk-shifting behavior. Therefore, I hypothesize that the reform should lead to reductions in pollution, particularly for financially distressed firms.

To test this prediction, I use plant-chemical-level data from EPA's Toxic Release Inventory (TRI) to measure environmental activity. Since the focus of RCRA and CERCLA is soil and groundwater contamination, my outcome of interest is the sum of ground and surface water pollution.[8] I find that treated firms reduce pollution by 12 percent compared to control firms following the passage of the reform. Consistent with the view that the reform lessens risk-shifting motives, I find that the decrease in pollution comes from ex-ante distressed firms. Specifically, I observe that, in response to the reform, distressed firms in the treated group reduce pollution by 15 percent relative to those in the control group. In contrast, for non-distressed firms, there is no difference in pollution rates among treated and control firms.

Next, I investigate how distressed firms reduce pollution. I first examine whether the reduction in pollution comes from increased abatement efforts. Using the EPA's Pollution

7. Duns & Bradstreet classify businesses that have a Paydex below 50 as having a high risk of missing payment for trade credit. I use the same classification in my analysis.

8. See Ohlrogge (2020) and Bellon (2021) for justification.

Prevention (P2) database, I measure abatement efforts at the plant-chemical level. I find that distressed firms increase abatement efforts related to improvements in operation practices by 48 percent.

Then, I test whether firms reduce pollution by transferring hazardous waste to off-site facilities for waste management, which reduces the contamination risk and is generally more environmentally friendly than handling toxic waste on-site (Ohlrogge (2020)).[9] I find that financially distressed firms increase toxic waste transferred to off-site facilities for waste management by 26 percent. In addition, the increase comes from off-site recycling, one of the most preferable ways to handle toxic waste. The alleviated efforts to reduce pollution support the interpretation that the decrease in pollution is due to increased incentives to mitigate contamination risk.

Finally, I test whether changes in pollution are driven by a reduction in economic activity. If the decrease in pollution results from a contemporaneous negative shock to the productivity of the distressed firm, then we should observe a decrease in production by distressed firms relative to non-distressed firms. Contrary to this conjecture, I find no evidence that distressed firms experience a fall in production. Rather, there is some evidence that distressed firms increase production.

This paper makes several contributions. First, the paper adds to a growing strand of literature that studies the effect of environmental liability on corporate environmental activity. Existing research focuses on the impact of imposing environmental liability on shareholders and creditors, who have substantial control over the polluting firms' environmental practices. Bellon (2020) finds that private-equity backed companies reduce pollution when the risk of environmental liability is high for shareholders. Bellon (2021) and Ohlrogge (2020) show that decreasing creditors' exposure to their debtors' environmental liability lessens their incentives to discipline their debtors' environmental activity. Akey and Appel (2021) find that reducing parent companies' exposure to their subsidiary's environmental liability worsens the subsidiary's environmental practices. Boomhower (2019) documents that reducing firms' ability to avoid liability improves environmental outcomes. Collectively, these articles show that re-

9. I verify this by talking to the EPA.

ducing environmental liability leads to increased pollution. I add to this strand of literature by studying the environmental consequences of placing liability on purchasers of land. Unlike other liability regimes studied by prior research, I show that stronger liability protection for purchasers does not lead to poor environmental behavior. Instead, evidence suggests that reducing purchaser liability discourages distressed firms from polluting their land. This result highlights a novel *net worth effect* of environmental liability: a reduction in environmental liability increases the net worth of industrial firms, lessening the moral hazard problems associated with limited liability.

Second, my paper is related to studies on how purchasers' environmental liability affects the industrial land market. Existing empirical studies focus on the effect of purchasers' environmental liability on land prices (Thomas (2002); Howland (2000); Alberini et al. (2005); Sigman (2010)) and the liquidity of industrial land (McGrath (2000); Howland (2000); Howland (2004); Schoenbaum (2002); Sigman (2010)). My paper contributes to this literature in two ways. First, these papers typically use the level of contamination or strictness of environmental liability to measure the extent of purchasers' liability. Such measures could be correlated with other confounding factors that affect the industrial land market, leading to a biased estimate of the effect of purchasers' liability. Unlike these papers, I directly measure changes in purchasers' liability using the Brownfields Act, mitigating omitted variable concerns. Second, I show that purchasers' liability impacts pollution activity and the credit risk of industrial plants.

Third, this paper is related to research on how the financial health of corporations affects non-financial stakeholders (Cohn and Wardlaw (2016); Phillips and Sertsios (2013); Xu and Kim (2022), Cohn and Deryugina (2018), Levine et al. (2019); Goetz (2018); Bartram, Hou, and Kim (2022); Akey and Appel (2021)). Overall, these papers show that firms with poor financial health take actions that harm non-financial stakeholders. I add to this strand of literature by highlighting purchaser liability protection as a novel mechanism that mitigates distressed firms' incentive to engage in activities that are harmful to other stakeholders.

Finally, this paper makes important contributions to understanding the implications of using environmental regulations to protect the environment. The prevailing view is that while stringent environmental regulations benefit the environment, it comes with the cost of adversely affecting economic efficiency. (e.g., Becker and Henderson (2000); Bellon (2021); Greenstone, List, and Syverson (2012); Walker (2013)). My findings show that this trade-off does not necessarily hold for purchaser liability. I document that while the reduction in purchaser liability positively impacts economic efficiency by increasing the liquidity of industrial land, it does not lead to increased emissions from landowners. More broadly, my findings suggest that policies that impose liability on *third parties*, who have little control over pollution, are potentially ineffective: imposing liability on third parties does not lead to greater monitoring of corporate environmental activity and can negatively impact asset value. It is important to note that the findings of the paper do not quantify the full welfare implication of imposing purchaser liability. This is because shielding purchasers from environmental liability can reduce the government's ability to raise funds to clean up contaminated sites, a cost that I do not quantify.

2 Institutional Background

2.1 Environmental Statutes

In the U.S., two statutes regulate environmental cleanups. The first statute, the Resource Conservation and Recovery Act (RCRA), enacted in 1976, gives the Environmental Protection Agency (EPA) the authority to regulate hazardous waste in two ways. First, the EPA can regulate the generation, transportation, treatment, storage, and disposal of hazardous waste. Second, RCRA authorizes the EPA to initiate cleanups of contaminated sites caused by *hazardous waste.* The cleanup enforcement provisions under RCRA are broad and powerful. For example, any time the EPA determines that hazardous waste pollution may have created an imminent danger to public health or the environment, the EPA can bring suit to require any person to take necessary actions to protect public health and the environment.[10] Any person includes any past or present generator, transporter, or present owner or operator of a treatment, storage, or disposal facility.

10. 42 U.S.C.A. §6973

The second statute, the Comprehensive Environmental Response Compensation and Liability Act of 1980 (CERCLA), authorizes the EPA to clean up sites contaminated by *hazardous substances*. Since the EPA has limited resources, it pursues cleanups at sites that may cause the most significant damage to human health and the environment. These sites are known as the National Priorities List (NPL). The EPA conducts assessments on contaminated sites to determine whether the risk of a site meets the requirements to be listed on the NPL. The EPA can put the site on the NPL only when the risk exceeds a certain threshold. When evaluating the risk of a site, the EPA considers the probability that a site has released hazardous substances, the characteristics of the waste, and the population affected by the release. The liability imposed under CERCLA is broad and covers a wide range of parties ("Potentially Responsible Parties" (PRPs)), including owners at the time of disposal, parties involved in transporting hazardous substances, and, notably, the current owner. CERCLA liability imposed on PRPs is joint and several, which means that the EPA can pursue a single party for the total cleanup cost, even if the party contributed a fraction of the contamination.[11] Thus, a purchaser of a contaminated site could be held responsible for cleaning up the site under CERCLA because, by definition, they become the owner of the site after acquisition (Weissman and Sowinski Jr (2015)).

Before 1984, RCRA had traditionally focused on regulating the handling of hazardous waste by operating facilities, and its cleanup provisions were limited. Specifically, the cleanup provisions only applied to certain facilities that received hazardous waste after July 26, 1982. Therefore, when CERCLA was first enacted, it was to fill the gaps left by RCRA by focusing on cleanups. However, over time, RCRA cleanup provisions have become more "CERCLA-like" in scope and effect. In particular, in 1984, Congress expanded the cleanup provision under RCRA to include all releases of hazardous waste regardless of the time at which the waste was placed on the facility (Stoll (1990)).

Although both RCRA and CERCLA enforce environmental cleanups at industrial sites, an important distinction is that CERCLA is a more comprehensive statute. First, a substance must

11. Liability under CERCLA is also strict and retroactive. Strict liability means that a PRP cannot say that it was not negligent or operating according to industry standards. Retroactive implies that parties can be held responsible for acts that occurred before the enactment of CERCLA.

be a "solid waste" to fall under the jurisdiction of RCRA.[12] In contrast, CERCLA encompasses substances considered a waste or product (or something else). Second, CERCLA *hazardous substances* encompass RCRA *hazardous waste* and other toxic pollutants covered by the Clean Air Act, the Clean Water Act, and the Toxic Substance Control Act. Furthermore, any "solid waste" must be listed or meet one of the hazardous characteristics to fall under the jurisdiction of RCRA, which depends on whether the concentration of the substance exceeds a threshold amount. However, CERCLA covers cleanups of any substance that contains any amount of a hazardous substance. Finally, suppose a chemical does not fall under the definition of a hazardous substance. In that case, CERCLA gives the EPA the authority to clean pollutants or contaminants, defined as substances that "will or may reasonably be anticipated to cause" adverse effects or organisms.[13]

2.2 Facts about Environmental Cleanup

In this subsection, I describe the characteristics of environmental cleanups to help understand the environmental liability imposed on purchasers and corporations. First, the cleanup of contaminated land is expensive. Greenstone and Gallagher (2008) estimates that the average cleanup costs at NPL sites is approximately $73 million dollars.[14] Cleanup costs of larger and more complex sites can be even higher, ranging up to billions of dollars (Blair (2011); Ohlrogge (2020)).

Second, environmental cleanups can take a long time, and the duration varies depending on the severity of the contamination. The average duration of cleanup for NPL sites is about a decade (GAO (1997)). Additionally, the average evaluation phase for the clean-up of NPL sites takes 9.4 years (GAO (1997)). As a comparasion, the cleanup of less contaminated sites (ie, Brownfield sites), on average, takes 15 months (Haninger, Ma, and Timmins (2017)).

Finally, cleanup costs are also challenging to estimate ex ante and are often only clear ex-post, partly because it can take decades to complete a cleanup (Goldstein and Ritterling (2001)). According to Greenstone and Gallagher (2008), the actual cleanup costs are, on average, 55

12. See EPA's website for the definition of solid waste and hazardous characteristics.
13. See Stoll (1990) for a more detailed description of the distinction between RCRA and CERCLA jurisdiction.
14. $43 million in year 2000 dollars

percent larger than the expected cleanup costs. In sum, environmental cleanups are costly, uncertain, and can take a long time to complete.

Therefore, purchasers of industrial property face a large and uncertain environmental liability, leading to a reluctance to buy industrial land. This resulted in many abandoned and under-utilized sites known as brownfields. According to the EPA, there are currently at least 450,000 brownfields.

2.3 Small Business Liability Relief and Brownfields Revitalization Act

To address the "brownfields" problem described in the previous subsection, Congress enacted the Small Business Liability Relief and Brownfields Revitalization Act (Brownfields Act) in 2002. As the name suggests, the goal of the Small Business Liability Relief and Brownfields Revitalization Act was twofold. The first goal is to provide liability relief to small businesses. To do so, the Brownfields Act set forth circumstances in which small businesses that sent only small amounts of waste to CERCLA sites will be exempted from CERCLA liability. To mitigate the concern that my analysis might capture the effect of alleviating liability for small businesses, I focus on facilities owned by public firms.

The second goal is to encourage the redevelopment of brownfields. The reform did so in three ways. First, the Brownfields Act clarified the "innocent landowner" defense (ILO defense), which provides liability protection for purchasers without reason to know about past contamination. To establish the defense, the purchaser must show that she had conducted due diligence before the purchase. However, before the Brownfields Act, because Congress did not specify the standards for conducting due diligence, purchasers were often unclear under which circumstances the defense provided protection. As a result, the ILO defense played a limited role in protecting purchasers and facilitating real estate transactions before the Brownfields Act (Beless (1997)).

Second, the reform also introduced a new defense: the "bona fide prospective purchaser" defense. The bona fide prospective purchaser (BFPP) defense protects a purchaser from cleanup liability even if the purchaser knows about a release or potential release of a hazardous substance on the property. This is important because a purchaser might learn about contamination during the environmental assessment, causing the ILO defense to be ineffective in protecting the purchaser from cleanup liability. To exert the BFPP defense, the purchaser must purchase the property after January 11th, 2002, and must satisfy the other criteria outlined in the statute, including pre-acquisition environmental due diligence and handling hazardous substances carefully after the purchase.[15] In sum, by clarifying the ILO defense and introducing the BFPP defense, the Brownfields Act reduced the liability risk associated with purchasing an industrial property.

An important feature of the liability defenses for purchasers is that they protect purchasers only against enforcement cases brought under CERCLA but not RCRA. Combining this feature with the fact that CERCLA is more comprehensive than RCRA, I measure the exposure to the Brownfields Act at the industry level. Since plants in the same industry are likely to use similar production processes and are likely to generate similar toxic waste, industries exposed to CERCLA but with little exposure to RCRA are particularly affected by the reform. This is because the reform protects a purchaser from CERCLA liability, and the purchaser does not have to worry about the EPA imposing clean-up expenses using RCRA. Section 4.1 describes how I construct in the treated and control groups.

Third, the reform also provided grants to assess and clean up brownfields. The amounts are small, with the maximum amount not exceeding 200 thousand dollars. Importantly, the brownfield grants apply to sites contaminated by CERCLA hazardous substances and RCRA hazardous waste. In other words, there is no reason to believe that the likelihood of receiving brownfield grants is related to my classification of the treated and control groups. Therefore, it is unlikely to affect my estimates of the effect of purchaser liability on pollution activity and real estate transactions.

2.4 Number of Defendants After The Brownfields Act

One important question is whether the Brownfields Act reduced purchasers' exposure to CERCLA liability. To shed light on this question, I examine changes in the number of defendants after the reform using enforcement data from the Integrated Compliance Information Sys-

15. Appendix A describes these requirements in more detail.

tem. If the Brownfields Act protects property purchasers against CERCLA enforcement, the number of defendants for CERCLA cases should decrease post-2002. To examine if this is the case, I regress the number of defendants on year dummy variables between 1993 and 2012, controlling for case characteristics (region and law section fixed effects). The coefficients on the year dummy variables indicate the average number of defendants under a CERCLA case in the year relative to 1992, holding case characteristics constant. It is important to control for the characteristics of the cases because the numbers of defendants with different sections of CERCLA differ substantially. For example, the section that allows the EPA to request information or access a site has, on average, 1.5 defendants. In contrast, the section that gives the EPA the authority to sue responsible parties to recover cleanup costs has an average of 4.2 defendants.

Panel A of Figure A1 plots the coefficients on the dummy variables. The number of defendants after 2002 is visibly lower. On average, the reduction is approximately one defendant, corresponding to a 30 percent reduction relative to the sample mean. In 1998 there was a small decrease in the number of defendants (not statistically significant). This could be driven by policy changes in the 1990s that reduced environmental liability for creditors (in 1996, see Bellon (2021)) and parent companies (in 1998, see Akey and Appel (2021).

Panel B of Figure A1 repeats the analysis for RCRA cases. I observe no meaningful changes in the number of defendants for RCRA cases. If anything, there is a slight increase in the number of defendants after 2008, although the magnitude is small (0.2 defendants). This suggests that the reduction in the number of CERCLA defendants observed after 2002 is unlikely driven by time-series factors, such as the EPA being less stringent on environmental enforcement. The findings in Figure A1 provide suggestive evidence that the purchasers' exposure to CERCLA cleanup liability has fallen after the Brownfields Act.

3 Data

I construct two samples. The first sample uses the Toxic Release Inventory (TRI) database to measure pollution activity (hereafter "TRI sample"). The second sample uses the National

Establishment Time-Series (NETS) data to examine how the reform affects the liquidity of real estate (hereafter "NETS sample"). Below, I describe the construction of each sample.

3.1 TRI Sample

I use the EPA's Toxic Release Inventory Program (TRI) data to measure pollution activities.[16] Plants in the United States that meet reporting standards set by the TRI program must report their waste management practices for covered chemicals annually.[17] Although the TRI data is self-reported, the EPA conducts audits to investigate misreporting.

TRI plants report the pounds of ground, water, and air pollution for each covered chemical. Ground pollution includes toxic chemicals released into underground injection wells, landfills, and surface impoundments. Air pollution comprises stack (e.g., confined vents, pipes, and ducts) and fugitive (e.g., evaporative losses) air releases. Water emissions include discharges to streams, rivers, lakes, oceans, and other bodies of water. Since CERCLA and RCRA cleanups target ground and groundwater contamination, my main outcome variable is pounds of ground plus surface water pollution (hereafter "ground & water pollution").[18]

The TRI reports several different ways that a plant manages toxic waste. These methods are summarized in Figure A2, the waste management hierarchy. The most preferable way is source reduction (i.e., pollution abatement), which reduces toxic emissions at its source. Facilities report their abatement efforts in the EPA's P2 database. These abatement activities are reported at the chemical level and are classified into eight broad categories. The list of categories is provided in Table A3. I focus on the most common types of abatement efforts: good operating practices, process modification, and spill and leak prevention. Specifically, I use the number of abatement efforts reported for each of the three types of abatement efforts to measure investment in abatement technology.

The remaining waste management techniques reported in the TRI include recycling, en-

16. The data is used in other papers in the finance literature (e.g., Akey and Appel (2021); Xu and Kim (2022); Bellon (2021)).

17. Currently, the requirements are that the facility is in one of 409 covered NAICS industries, has ten or more full-time employees, and uses one of 770 chemicals in the specified amounts. The list of chemicals is often updated. Industries are updated less frequently. Before 2007, industry requirement was defined using the SIC classification

18. See Bellon (2021) and Ohlrogge (2020) for additional justification for this choice.

ergy recovery (burning chemicals to generate energy), and treatment (putting chemicals through chemical processes to reduce their toxicity). The most preferable is recycling, while the least preferable is treatment. Conversations with the EPA suggest that these waste management techniques are particularly effective if toxic waste is transferred to off-site facilities that specialize in waste management (see Ohlrogge (2020) for additional justification). Thus, I use the pounds of toxic waste transferred to off-site facilities for recycling, energy recovery, and treatment to measure the extent to which plants are engaging in preferable waste management techniques.

I use the EPA's Pollution Prevention (P2) database to measure production at the plant-chemical level. TRI facilities report the production ratio for each chemical, defined as the current year's output divided by the previous year's output. If a chemical is used in the production of refrigerators, the production ratio is equal to $\frac{\#\ of\ refrigerators\ produced_t}{\#\ of\ refrigerators\ produced_{t-1}}$. In some cases, the chemical is not used for production. For example, if a chemical is used for cleaning molds, the productivity ratio is equal to $\frac{\#\ of\ molds\ cleaned_t}{\#\ of\ molds\ cleaned_{t-1}}$. Following Akey and Appel (2021), I exclude production ratios greater than three and less than zero to ensure that reporting errors do not influence my analysis.[19]

As an alternative measure of production, I follow Akey and Appel (2019) and calculate a proxy for total production (*Norm. Production*) by normalizing production to one in the first year a chemical is reported in my sample and "multiply forward" each year. Specifically, normalized production is computed as:

$$Norm.\ Production_{p,c,t} = \prod_{t \neq 1}^{t} 1 \times \frac{Quantity\ Produced_{p,c,t}}{Quantity\ Produced_{p,c,t-1}} = \prod_{t \neq 1}^{t} 1 \times ProductionRatio_{p,c,t}$$

Based on conversations with EPA staff, I aggregate observations to create a plant-chemical-year panel.[20] The same plant may file multiple forms for each chemical in the same year, yielding multiple observations per plant-chemical-year. The majority of the multiple observations are because the reporting plant consists of multiple economic units and is sometimes due to the chemical composition unknown to the reporting plant ("mixtures"). I aggregate

19. In unreported results, I find the results do not change if I truncate at 0 and 5.
20. I would like to thank the EPA for answering questions regarding the TRI database.

multiple observations by summing the pollution and waste quantities reported for the same plant-chemical-year observation.

To measure credit risk at the plant level, I obtain Paydex scores from the NETS database by matching the TRI database with NETS using the Dunsnumber of plants. Paydex is a business credit score based on trade credit performance and ranges between 0 to 100. A score of 80 indicates that, on average, payments are on time according to the trade credit agreement. The score is constructed by surveying a large number of vendors and suppliers. The Paydex score for the current year reflects the credit score for the previous year. Kallberg and Udell (2003) show that Paydex scores strongly predict business survival.

I match the TRI database to Compustat/CRSP to identify plants owned by public companies. I first match the historical parent names reported in TRI with historical names from CRSP and 10-X headers from EDGAR. For observations in which the parent company name is not reported, I use the NETS database and TRI facility names to identify the parent for these plants. In some cases, the EPA parent name is missing in one or two years, while before and after missing years have the same parent name. I use parent names from non-missing years to fill in the missing years. I match the TRI dataset to Compustat to obtain accounting data.

I obtain firm-level financial variables from Compustat. My primary measure of financial distress is Altman's Z score, commonly used in the finance literature to measure bankruptcy risk. (e.g., Akey and Appel (2021); Eisdorfer (2008); Pedersen (2019)).[21] To mitigate reverse causality concerns, I use the pre-treatment average Altman's Z score to measure financial distress. Specifically, I classify firms as distressed if their pre-treatment average Alman's Z score is in the lowest tercile of my sample. For robustness, I consider a variety of other measures of financial distress. The results are reported in Section 7.1.

I exclude observations with missing ex-ante Altman's Z score data and winsorize continuous variables at the 1 and 99 percent levels to mitigate concerns of extreme observations.

21. Akey and Appel (2021) show that parent firms with a low Altman's Z score are more likely to pollute when parent liability is reduced.

3.2 NETS Sample

I use establishment-level data from the National Establishment Time Series (NETS) to measure industrial property transactions. The NETS dataset is maintained by Dun & Bradstreet and marketed by Wall and Associates. The unit observation in NETS is an establishment, defined as a business or industrial unit at a single location. The NETS dataset provides the following information for each establishment: the address (including zip code, state, and street address), industry classification (SIC and NAICS), the current legal status (e.g., non-profit, partnership), number of employees, the parent of the establishment, founding year, and whether the establishment moved location. I identify the ultimate parent company of each establishment by rolling up parent names from the NETS corporate hierarchy. Using the ultimate parent identifier, I match the NETS to Compustat to identify establishments owned by public firms.[22] The financial data for the parent company comes from Compustat.

Using this data, I construct an indicator that a particular establishment sold its real estate in a particular year. The sale of real estate can happen under two different scenarios. The first scenario is when an establishment is sold to another parent company, which I establish by comparing the ultimate parent in subsequent years. The second scenario is that a different establishment, owned by a different parent, starts operating in the same place within a year after the existing establishment is relocated or shuts down.[23] One advantage of the NETS dataset is that it covers nearly all establishments in the U.S., allowing me to track whether a physical location is occupied after the incumbent establishment has closed or moved. I describe this process in more detail in the Appendix B. I treat real estate as sold if either of the two scenarios occurs.

I drop observations with missing SIC code, employment, and establishment age (Current year minus founding year) and exclude non-profit establishments. I also restrict my sample to establishments with parent firms in the TRI database to ensure I capture establishments owned by polluting firms. Continuous variables are winsorized at the 1 and 99 percent levels

22. I thank Tom Griffin for sharing his linking table between NETS and Compustat. I augment his linking table by requiring (1) perfect name matches between CRSP historical name and NETS's ultimate parent name and (2) perfect matches of Zipcode.

23. Alternatively, using occupancy within two years yields the same results.

to mitigate concerns of extreme observations.

3.3 Summary Statistics

Table 1 reports descriptive statistics for the TRI sample. The sample comprises 261,232 plant-chemical observations, with 496 unique chemicals and 9,687 unique plants owned by 847 unique parent firms. Plants, on average, report using 4.95 chemicals each year, and parent firms operate 8.46 plants per year. For a given chemical, a plant emits 7 thousand pounds of toxic pollutants into the ground, 16.5 thousand pounds into the air, and 0.45 thousand pounds onto surface water each year. Each year, the average amount of toxic waste shifted off-site for waste management is 12.86 thousand pounds. Among those shifted off-site, 9.3 thousand pounds are recycled, 2.27 thousand pounds are for energy recovery, and 1.29 thousand pounds are treated. Note that all types of pollution and off-site waste management are highly skewed: the median for ground & water pollution is zero, but the mean is 7.48 thousand pounds. On average, 26 percent of plant-chemical observations have positive ground & water pollution. A total of 10.5 percent of plants report at least one abatement initiative. The mean for the production ratio is 0.95. The average plant in the TRI sample is 38 years old, employs 516 workers, and has a Paydex score equal to 67. The average firm has 4 billion of pre-treatment total assets and has an ex-ante Z-score of 3.48.

Table A2 reports summary statistics for the NETS sample. The sample contains 265,988 establishment-year observations from 53,603 unique establishments owned by 568 ultimate parent companies. The average establishment is about 13 years old and employs 148 people. The likelihood of selling an establishment is 2 percent. The probability of an establishment shutting down and relocating is 4 and 0.8 percent, respectively. The fraction of establishments that sell their real estate each year is 3.4 percent.

4 Research Design

4.1 Measuring Exposure to the Brownfields Act

In this subsection, I describe how I proxy for an industry's exposure to the Brownfields Act. Since the purchasers' defenses under the Brownfields Act only apply to CERCLA and not RCRA, conditional on being exposed to CERLCA, industries exposed less to RCRA are particularly affected by the reform. Thus, the goal is to identify which industries are more exposed to RCRA enforcement among industries that are exposed to CERCLA. Because I measure environmental activity using the TRI database, I begin with industries (3-digit SIC) that report to the TRI database between 1998 and 2006 (181 industries). Second, using enforcement data from EPA's Enforcement and Compamapliance History Online (ECHO) database, I limit my analysis to industries that have experienced cleanup enforcement CERCLA before 2002 (134 industries). Third, I calculate the RCRA exposure score for each industry by scaling the number of RCRA enforcement at the plant level by the number of plants in that industry. Finally, among the 134 industries, I define industries with RCRA exposure below the sample median as the treated group and industries with RCRA exposure above the sample median as the control group.

There are two complications throughout these steps. First, enforced plants may only report their NAICS code in ECHO. To address this, I convert NAICS codes into SIC codes using the NAICS-SIC crosswalk prepared by Schaller and DeCelles (2021). Note that excluding such plants from the analysis yields similar results. Second, a plant can have multiple 3-digit SIC codes. To avoid misclassification and double counting, I assign these cases to the industry with the most RCRA enforcement cases when calculating RCRA exposure. Alternatively, excluding them does not change the results.

Figure A3 plots the density of industry-level RCRA exposure scores, excluding industries with a small number of plants (less than the 25th percentile or 33 plants). RCRA exposure scores to the left of the vertical red line represent exposure scores for treated industries. The treated industries have concentrated exposure scores close to zero, whereas control industries have exposure scores spanning between 0.03 to above 0.2. Table A4 reports 40 industries with the highest and lowest RCRA exposure, excluding industries with few plants (less than the 25th percentile). Sanitary Services (1.46) is most exposed to RCRA enforcement, followed by Public Warehousing & Storage (0.7), Petroleum Refining (0.48), and Electric, Gas & Utility (0.309). In contrast, Musical instruments, Flat glass, Cut Stone & Stone product, Knitting Mills, Mis Food Prep. & Kindred Products, Dyeing & Finishing Textiles, Meat Products, Wood Buildings & Mobile Homes, and Dairy Products have no exposure to RCRA enforcement.

In Section 7.2, I consider alternative measures of exposure to the reform (e.g., Exposure at the 4-digit SIC and NAICS level). The results continue to hold with these alternative measures.

4.2 Empirical Approach

4.2.1 The Effect on Real Estate Transactions

To estimate the reform's effect on the liquidity of industrial real estate, I implement a difference-in-difference (DID) research design. In particular, estimate the following equation using ordinary least squares (OLS):

$$\mathbb{1}(Sell\ RE)_{p,i,j,t} = \beta \cdot Treated_j \times Post_t + X^{'}_{p,t}\gamma_1 + X^{'}_{j,t}\gamma_2 + \alpha_j + +\alpha_i + \alpha_t + \epsilon_{p,j,i,t} \quad (1)$$

where p represents plant, j denotes industry, i denotes parent firm, t represents year at time t. $\mathbb{1}(SellRE)_{p,i,j,t}$ is an indicator equal to one if a plant sold its real estate in year t and is zero otherwise. $Treated_j$ is an indicator of whether the plants' industry is treated by the reform and is zero otherwise. $Post_t$ indicates whether year t is greater or equal to 2002. Since the plant characteristics, such as economic activity and age, might affect the likelihood of real estate transaction, I include a vector of plant controls ($X^{'}_{p,t}$), including (log of) the number of employees, (log of) plant age, and an indicator of whether the plant is the headquarter of the parent firm. Because industry time-varying shocks can influence property sales, I control for observable industry characteristics ($X^{'}_{j,t}$), including industry leverage, Tobin's Q, and HHI. I include industry (α_j), parent (α_i), and year (α_t) fixed effects. The inclusion of industry and year-fixed effects subsume $Treated_j$ and $Post_t$, respectively. Since I proxy for the exposure to the reform at the industry level, standard errors are clustered at the industry level to account for any serial correlation that biases the standard errors downwards. The coefficient of interest β measures the reform's effect on the propensity to sell real estate.

In tighter specifications, I include county-year fixed effects, which is important because local economic conditions are a critical determinant for the liquidity of real estate (Bernstein, Colonnelli, and Iverson (2019)). One concern is that estimates of β can capture the reform's effect on the demand (e.g., buyers' willingness to purchase industrial land) and supply (e.g., landowners' willingness to sell) of industrial real estate. To isolate the reform's effect on the demand for real estate, I include parent firm-year fixed effects. The inclusion of parent firm-year fixed effects control for any time-varying shocks at the firm level that might affect the propensity of selling real estate, including shifts in the parent firms' willingness to sell real estate. Therefore, the inclusion of firm-year fixed effects allows me to isolate the reform's effect on the demand for industrial land. I also add industry-county fixed effects, which is important because potential buyers of industrial land are frequently other firms that belong to the same industry and reside in the same geographic location (Bernstein, Colonnelli, and Iverson (2019)), including industry-county fixed effect controls for the presidency of the number of potential buyers in the same location. Finally, I add plant fixed effects, controlling for time-invariant characteristics, such as the size of the property.

4.2.2 The Effect on Pollution activity

Since pollution is skewed and left censored at zero, I test the reform's effect on pollution activity by estimating the following DID equation using Poisson pseudo-maximum likelihood (see Cohn, Liu, and Wardlaw (2022) for justification):

$$y_{c,p,i,j,t} = \beta \cdot Treated_i \times Post_t + X^{'}_{i,t-1}\gamma + \alpha_{pc} + \alpha_{ct} + \alpha_i + \epsilon_{c,p,i,t} \tag{2}$$

where c indexes a chemical emitted by a plant p owned by parent firm i at time t. $y_{c,p,i,j,t}$ represents the outcome variables at the plant-chemical level, such as pollution activity and measures of production. $Treated_i$ is an indicator that equals one if a parent firm's industry is treated and is zero otherwise. I measure the industry of a firm using the industry where the firm has the most plants prior to the reform (i.e., in year 2001). This approach is intended to capture the industry in which firms hold most of their real estate assets. According to this industry classification, 45 percent of observations in the sample are considered treated. $Post_t$ is an indicator variable that equals one if the year is greater or equal to 2002 and is zero otherwise. I include plant-chemical fixed effects ($\alpha_{p,c}$) to control for time-invariant factors at the plant-chemical levels. For example, plants with different production technology might use different amounts of a particular chemical. Since there is no clear way to aggregate chemicals and reporting requirements frequently change for different chemicals, I include chemical-year fixed effects ($\alpha_{c,t}$). I also include parent firm fixed effects (α_i) to control for any time-invariant unobservable characteristics at the parent firm level. Standard errors are clustered at the industry level to account for serial correlation within the same industry, which is important because the treatment variable varies only across industries. The variable of interest, β, captures the average effect of the Brownfields Act on outcome variables.

To examine how distressed and non-distressed firms respond to the reform, I separately estimate Equation 2 for distressed and non-distressed firms. Under this approach, β estimates the impact of the reform on the outcome of treated plants with a distressed or non-distressed parent firm. In my baseline specification, a parent firm is distressed if its pre-reform average Altman's Z score is in the lowest tercile and is non-distressed otherwise. Using pre-reform average mitigates concerns that the reform affects distress risk after the reform. As robustness of I consider other measures of incentives to risk shift, such as distance-to-default, market leverage, other liability scaled by assets, and total assets, the results remain unchanged.

I implement a triple-difference framework as an alternative to estimating separate DID regressions. Specifically, I estimate the following regression using Poisson pseudo-maximum likelihood:

$$\begin{aligned} y_{c,p,i,j,t} = {} & \beta_1 Treated_i \times Post_t + \beta_2 Treated_i \times Post_t \times Distressed_i \\ & + \beta_3 Distressed_i \times Post_t + \alpha_{p,c} + \alpha_{c,t} + \alpha_i + \epsilon_{c,p,i,t} \end{aligned} \tag{3}$$

$Distressed_i$ is an indicator equal to one if the parent firm is financially distressed. There are two variables of interest. β_2 captures the reform's effect on distressed firms relative to non-distressed firms. $\beta_2 < 0$ indicates that the outcome variable decreased for distressed firms in the treated group relative to non-distressed firms in the treated group. β_1 estimates the impact of the reform on outcomes by non-distressed firms, and $\beta_1 + \beta_2$ captures total changes in the outcomes of distressed firms in the treated group. Compared to a DID, the advantage of a triple-difference research design is two-fold. First, it is potentially more efficient, as it uses the entire sample. Second, it raises the bar for any alternative story. That is, an alternative story must relate to distressed firms, treated industries, and in the post-period only.

5 Main Results

5.1 The Liquidity Industrial Land

I begin by examining the effect of the reform on the industrial land market. If protecting purchasers from cleanup liability facilitates real estate transactions, treated plants should trade their real estate more often after the policy change. I test this prediction by estimating Equation 1. Table 2 reports the results. Column (1) reports the baseline specification. I gradually add fixed effects in the remaining columns. In column (2), I replace year-fixed effects with county-year fixed effects. Column(3) adds parent firm-year fixed effects, which controls for time-varying firm characteristics that may cause the firm to sell its real estate. Column (4) replaces industry with industry-county fixed effects. Column (5) adds plant fixed effects. Overall, estimates indicate that the reform has a positive effect on the liquidity of industrial land. In particular, the point estimates on *Treated*$\times$*Post* are positive, statistically significant and stable across all specifications, ranging from 0.013 to 0.017. These results show that, after the reform, treated plants' propensity to sell their property increased by 1.3 to 1.7 percentage points compared to control plants. The increase is 38 to 50 percent compared to the unconditional probability of selling industrial land, an economically meaningful change in liquidity. The magnitude of the effect is in line with those documented in previous research (e.g. (McGrath (2000); Howland (2000); Howland (2004); Schoenbaum (2002); Sigman (2010)). For example, Sigman (2010) find that an *increase* in environmental liability is associated with a 40 percent increase in the vacancy rate of industrial property.

The identifying assumption for the DID specification is that the outcome of the treated and control plants would exhibit parallel trends absent the policy change. While this assumption is untestable, I provide indirect evidence that the assumption holds by plotting the coefficient dynamics in Figure 1. I construct this figure by replacing $\sum_{k=1998,k\neq 2001}^{2007} Treated \times \mathbb{1}(Year_t = k)]$. Where $\mathbb{1}(Year_t = k)]$ is a dummy variable that equals one if year t and is zero otherwise. Consistent with the absence of differential pre-trends, we observe that there is no effect of belonging to a treated industry before the reform. On the contrary, after the reform, we observe a sharp increase in the propensity to sell real estate for treated plants relative to control plants.

These findings suggest that reducing purchaser liability substantially improves the liquidity of the land operated by treated plants. Although the result in this subsection may seem unsurprising, since the reform's intended goal was to increase the liquidity of industrial real estate, it is nonetheless important for two reasons. First, it quantifies the impact of the reform on the liquidity of industrial land, indicating that it is substantial. Second, the results help validate my classification of treated and control industries.

5.1.1 Plant Solvency

Next, I examine the effect of limiting purchasers' liability on the solvency of TRI plants. If the reform increases the value of industrial land, treated plants should be better capitalized and further away from insolvency. I use Paydex scores to proxy for plant solvency. Following Dun & Bradstreet, I classify plants as having a high risk of late payment if their Paydex score is below 50.

I estimate Equation 1, except that the outcome variable is an indicator of whether a plant's Paydex score is below 50. The findings are reported in Table 3. The results indicate that the probability that treated plants have a high-risk Paydex score falls by 1.4 to 1.7 percentage points relative to control plants. The decrease is economically significant, representing a 47 to 56 percent decrease in the probability of having a high-risk credit score compared to the sample mean (3 percent).

5.2 Pollution Activity

In this subsection, I test the impact of the reform on pollution activity. The preceding results show that the reform significantly improved the liquidity and credit risk of treated plants. Therefore, parent firms with a significant proportion of their real estate in treated industries should experience an increase in net worth, causing them to internalize a larger fraction of the cleanup costs associated with environmental contamination. This, in turn, should reduce their incentive to pollute the environment. Furthermore, the reduction in pollution should be stronger for ex-ante financially distressed firms as they have a stronger motive to engage in risk-shifting behavior, such as polluting the environment.

5.2.1 Ground & Water Pollution

I begin by verifying that distressed firms pollute more by plotting the raw correlation of pollution against Altman's Z score in Figure 2. I find a negative relation between pollution and Altman's Z-score, indicating firms closer to bankruptcy pollute more.

I next examine the reform's average effect pollution activity by estimating Equation 2. The result is reported in column (1) of Table 4. The point estimate on *Treated*×*Post* is negative (-0.12) and statistically significant at the 5 percent level, indicating that treated firms reduce pollution by 12 percent after the reform.

In the following two columns, I examine the reform's impact on ex-ante distressed and non-distressed firms' pollution activity by estimating Equation 2 separately for the two types of firms. For ex-ante distressed firms, treated firms reduce pollution by 15 percent relative to control firms after the reform. In contrast, ex-ante non-distressed firms experienced no meaningful change in pollution between treated and control firms; The point estimate in column (3) is small and indistinguishable from zero.

In the last two columns, I use the entire sample to estimate a triple difference specification using Equation 3. Column (4) estimates the baseline specification. In column (5), I add state-year fixed effects, which is important because environmental regulation often varies at the state level. The coefficients on *Treated*×*Post*×*Distressed* are negative and statistically significant at the 5 percent level. This indicates that treated firms that are financially distressed reduce pollution relative to treated firms that are non-distressed after 2002. In contrast, the coefficients on *Treated*×*Post* are small and statistically insignificant. This suggests that non-distressed firms in treated industries experience no meaningful change in pollution compared to those in control industries. These findings confirm the results of the sub-sample analysis, indicating that distressed firms drive the reduction in pollution.

The identifying assumption for a DID is that the outcome of treated and control industries should trend similarly without the reform. Although this "parallel trends" assumption is by definition untestable, I plot event study graphs as an indirect test for whether there are pre-trends before the reform. The results are reported in Figure 3. In panel A, I plot event-time coefficients of the average effect and observe no pre-trends, indicating that pollution of treated and control firms trend similarly prior to the reform. After the reform, evidence indicates that treated firms reduce pollution compared to control firms. In Panel B, I plot event-time coefficients using subsamples with distressed and non-distressed firms. The yellow connected line presents dynamics for distressed firms, and the blue dashed line shows dynamics for non-distressed firms. The coefficients for both types of companies did not show a clear trend before the reform. After the reform, non-distressed firms experience no meaningful change in pollution, while distressed firms reduce pollution considerably. The lack of pre-trends suggests that the identifying assumption of an unbiased estimate of the coefficient on *Treated*×*Post* likely holds.

Overall, the findings demonstrate that firms respond to the reform by reducing pollution, and this reduction is entirely driven by distressed firms. These findings are consistent with the view that reducing purchaser liability mitigates distressed firms' incentives to engage in risk-shifting behavior.

5.3 Placebo: Air Pollution

An alternative explanation for the above findings is that perhaps other contemporaneous shocks, such as a negative productivity shock, reduce pollution by distressed firms in treated industries. If this is the case, distressed firms in the treated group should reduce all types of pollution, including air pollution. Unlike ground and water emissions, air pollution does not cause the polluter to incur CERCLA liability and is therefore unaffected by the Brownfields Act. Thus, I use air emissions as a placebo.

The results are reported in Table 5. In general, the findings indicate that the air pollution from the treated firms did not experience a significant change compared to the control companies. Furthermore, distressed firms do not exhibit a reduction in air pollution relative to non-distressed firms. Specifically, the point estimates of *Treated*$\times$*Post* and *Treated*$\times$*Post*$\times$*Distressed* are small and statistically insignificant. This result helps rule out concerns that the reduction in pollution is driven by other time-varying shocks that may have caused distressed firms in the treated industries to reduce pollution.

6 How Do Distress Firms Reduce Pollution?

In this section, I explore how distressed firms achieve a reduction in pollution after the reform. I investigate three non-mutually exclusive channels. First, firms can reduce toxic emissions by investing more in pollution abatement. Second, companies can reduce pollution by redirecting hazardous waste to off-site facilities that specialize in waste management. Lastly, the decline in pollution could be driven by an adverse shock that prompted distressed firms to curtail production.

6.1 Abatement efforts

I first investigate whether investments in abatement technologies drive the reduction in pollution. Because investing in abatement reduces pollution at the source, it is the most preferable way to handle toxic waste. Abatement efforts can be broadly classified into eight types. Table A3 reports a detailed list of activities that fall under each type of abatement effort. I focus on three of the most common types of abatement efforts: abatement related to good operating practices, spill & leak prevention, and process improvements.

Table 6 reports the results. The dependent variables are the count of abatements efforts reported for each type of abatement. I find evidence that distressed firms implement additional operating practices relative to non-distressed firms after the reform. Point estimates of *Treated*×*Post*×*Distressed* are statistically significant and indicate a 48 percent increase in abatement efforts related to good operating practices. Additionally, there is some evidence that distressed firms increase investment in spills & leak prevention: the coefficients range from 0.45 to 0.72 and are marginally significant (p-value = 0.114 in column (4)). However, I do not find evidence that distressed firms alter their investment in abatement efforts related to process modifications.

6.2 Off-site Transfer

Second, I examine whether distressed firms reduce pollution by shifting hazardous waste to off-site facilities. Transferring waste off-site reduces contamination risk and is generally considered better for the environment than emitting toxic chemicals directly into the environment (see Ohlrogge (2020)). The reason is that these off-site facilities typically specialize in waste management and are therefore more capable of handling toxic waste.

The results are reported in Table 7. In column (1), the outcome variable is the total amount of toxic chemicals transferred to off-site plants for waste management, including recycling, energy recovery, and treatment. I find a positive and statistically significant coefficient (0.263) on the triple interaction term, indicating that distressed firms increased off-site waste management by 26.3 percent relative to non-distressed firms after the reform. In the remaining columns, I decompose off-site waste management into recycling (column (2)), energy recovery (column (3)), and treatment (column(4)). Among the three waste management methods, recycling is the most preferable, while treatment is the least favorable option. I find that an increase in off-site waste recycled drives the results, indicating that distressed firms reduce pollution by adopting more environmentally friendly practices.

6.3 Production

Finally, I examine whether the decreases in production drive the reduction in pollution. Table 8. I use two different measures of production: the production ratio (columns (1) and (2)) and the (log of) normalized production (columns (3) and (4)). Across different specifications, the point estimates for *Treated*×*Post*×*Distressed* are positive, ranging between 0.023 and 0.112.

The coefficient is statistically significant at the 5 percent level for the production ratio, but not significant for normalized production. The increase in production ratio is economically meaningful, representing an 11.7 percent increase compared to the sample mean. These findings suggest that, if anything, distressed firms seem to respond to the reform by increasing production.

Collectively, the findings in this section imply that the reduction in pollution is attributed to increased efforts to mitigate contamination risk, rather than to a decline in economic activity.

7 Robustness tests

7.1 Other Measures of Financial Distress

I perform several robustness tests. First, I consider other measures of financial distress. All measures are calculated based on pre-reform average of the measure to mitigate reverse causality concerns.Table A5 presents the results. In column (1), I use distance to default to measure financial distress. The measure is constructed following the method described by Bharath and Shumway (2008). In column (2), I use other liability scaled by assets as a measure of incentive to risk-shift and pollute excessively. Akey and Appel (2021) show that firms with high other liability exhibit risk-shifting behavior. In column (3), I use market leverage to proxy for distress using market leverage (see Gilje, Loutskina, and Murphy 2020 for justification). Finally, in column (4), I use total assets to proxy for incentives to pollute excessively. The economic literature argues that small firms are more likely to engage in harm-shifting activities because legal liabilities are more likely to exceed their asset value (e.g., Boomhower (2019)). Across the different measures, the coefficient on $Treated \times Post \times Proxy$ is negative (between -0.111 and -0.299) and statistically significant. These results indicate that my main findings are robust to alternative measures of risk-shifting motives.

7.2 Other Robustness Tests

Next, I investigate whether my results are sensitive to outliers and the clustering of standard errors. Table A6) reports the results. I find that the main finding is robust to winsorizing the outcome variable at 97.5 percent and 95 percent (columns (1) and (2)), and alternative ways of clustering standard errors (columns (3) to (5)). Specifically, I consider clustering at the industry and parent firm level (column (3)), industry and year level (column (4)), and sector (2-digit SIC) level (column (5)).

Finally, I consider alternative methods for measuring exposure to the reform. Table A7) report the results. In column (1), I exclude industries with RCRA exposure scores greater than the 99 percentile or less than the 1 percentile to mitigate concerns that industries with extreme exposure scores drive the results. In columns (2) and (3), I use 4-digit SIC and 4-digit NAICS, respectively, to calculate industry-level exposure to the reform. Moving to column (4), I use CERCLA minus RCRA cleanup costs as a measure of exposure to the reform.[24] Across these different exposure measures, I observe a negative and statistically significant coefficient on *Treated×Post×Distressed.* Furthermore, the point estimates are stable across the different measures (ranging between -0.138 to -0.183), indicating that the main result is not sensitivity to alternative approaches to measuring the exposure to the Brownfields Act.

8 Conclusion

Legal liability is an important policy tool to discipline industrial firms from polluting the environment. However, stringent liability also comes with the cost of reducing economic activity. This trade-off between environmental protection and economic growth is at the core of the debate on environmental regulation. Existing research has focused on the implications of imposing legal liability on parties with strong control over a firm's environmental policy, such

24. I use cost recovery for CERCLA to measure CERCLA liability because it is the cost incurred by EPA to clean up Superfund sites that are then recovered from the parties responsible. Please refer to the data dictionary of the ECHO database for the definition. This likely overestimates the liabilities imposed on private parties because the EPA does not recover its full cleanup costs. I use penalties to measure RCRA cleanup costs because 42 U.S.C Â§6928 states that "If a violator fails to take corrective action within the time specified in a compliance order, the administrator can assess a civil penalty of not more than $25,000 for each day of continued noncompliance with the order."

as creditors and shareholders. In this paper, I examine a different liability regime: purchaser liability, which differs from other liability regimes because a potential purchaser has a much weaker direct influence over firm policy. Yet, I show that a reduction in purchaser liability substantially dampens landowners' incentives to pollute by positively affecting the industrial land market.

My empirical setting uses the passage of the Brownfields Act, a major reform aimed at boosting the liquidity of industrial land by strengthening liability protection for purchasers. Using detailed plant-level data and a novel identification strategy that takes advantage of the unique characteristics of the reform, I find that the liquidity of treated plants increased by 38 to 50 percent. In addition, treated plants are less likely to have a high-risk credit rating after reform.

After documenting the significant benefits of the reform, I study whether the reform lead to changes in pollution activity. Contrary to the belief that the loosening of environmental liability leads to poor environmental practices, I show that industrial firms respond to the reform by reducing toxic emissions by 12 percent, and the decline is driven by distressed firms, supporting the idea that the positive effects on industrial land mitigate moral hazard problem associated with financial distress.

I also shed light on how distressed firms reduced pollution. I find evidence that the reduction in pollution stems from distressed firms transferring toxic chemicals to off-site facilities for waste management and increasing investment in pollution abatement.

Taken together, my findings highlight the critical role of a net worth effect in influencing pollution incentives. That is, reductions in purchases' exposure to environmental liability can reduce pollution by increasing the net worth of polluting firms.

More broadly, my paper suggests that imposing environmental liability on parties with weak direct influence on polluting firms' environmental policies is potentially ineffective. This is because increasing such parties' exposure to environmental liability does not lead to more monitoring of polluting firms' environmental policy. At the same time, it can reduce the net worth of polluting firms, exacerbating more hazard problems associated with limited liability.

It is worth mentioning that the welfare implications of reducing purchaser liability remain unclear. The reason is that protecting purchasers comes with the potential cost of adversely affecting the government's ability to raise money for cleaning up contaminated sites, a consequence I do not examine in this paper. It is left to future research to quantify such costs.

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Figure 1: **Real Estate Trading Dynamics**

The figure plots coefficients form difference-in-difference regressions that estimate the effect of the Brownfields Act on the propensity to sell real estate. I plot coefficients of year dummy variables (δ_t) estimated from the following equation:

$$y_{p,i,j,t} = \sum_{k=1998, k\neq 2001}^{2006} \delta_k [Treated_j \times \mathbb{1}(Year_t = k)] + X^{'}_{p,t}\gamma_1 + X^{'}_{j,t}\gamma_3 + \alpha_j + \alpha_i + \alpha_t + \epsilon_{p,i,j,t}$$

where $y_{p,i,j,t}$ is an indicator of whether plant p sold its real estate in year t. $X^{'}_{p,t}$, and $X^{'}_{j,t}$ represent time-varying establishment and industry controls, respectively. α_j, α_i, and α_t indicate industry, parent, and year fixed effects, respectively. Vertical bars display 95 percent confidence intervals.

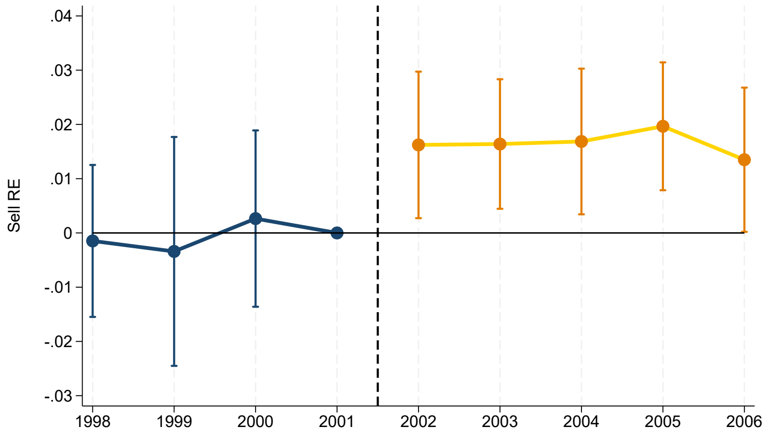


Figure 2: **Bankruptcy risk and pollution**

The figure plots the non-parametric relation between bankruptcy risk and ground & water pollution. Z-score is winsorized at the 1 and 99 percent level.

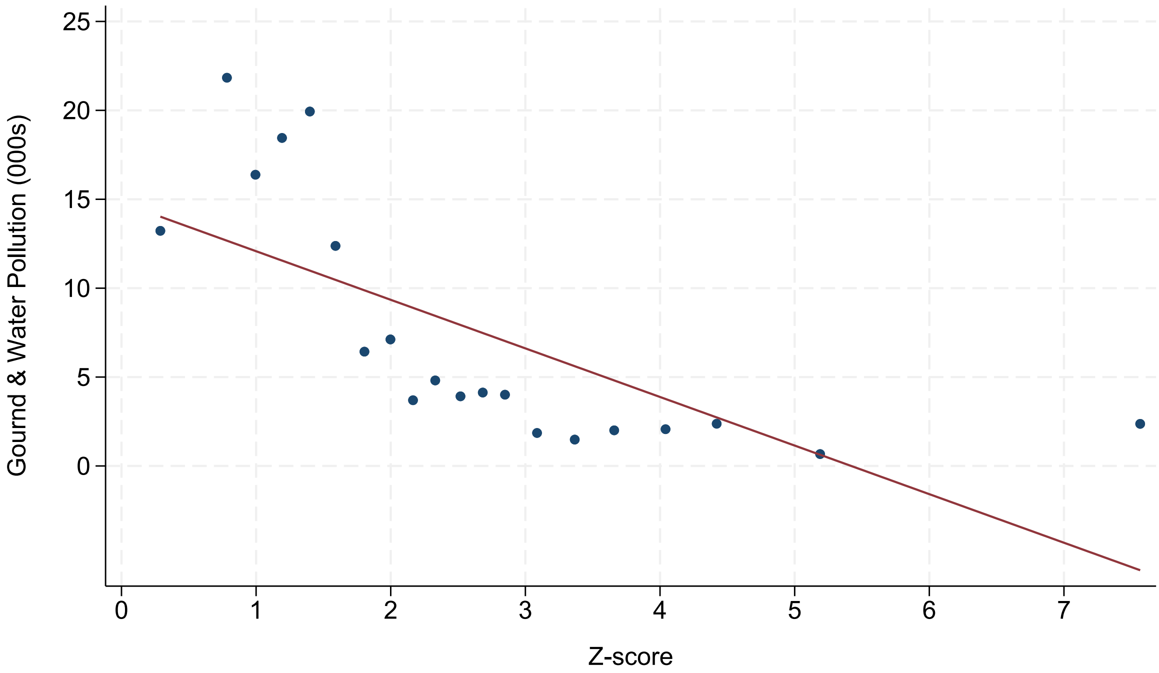


Figure 3: **Pollution Dynamics**

The figure plots the dynamics for the effect of the Brownfields Act on pollution activity surrounding the passage of the reform. Panel A reports the average effect of the Brownfields Act by plotting the coefficients(η_k) from the following Poisson model:

$$y_{c,p,i,t} = \sum_{k=1998, k\neq 2001}^{2006} \eta_k [Treated_p \times \mathbb{1}(Year_t = k)] + \alpha_{pc} + \alpha_{ct} + \alpha_i + \epsilon_{c,p,i,t}$$

The outcome variable, $y_{c,p,i,t}$, is the pounds of ground and water pollution. $\mathbb{1}(Year_t = k)]$ is an indicator variable that equals one when the year in time t equals k. α_{pc}, α_{ct}, α_i represents plant-chemical, chemical-year, and parent firm fixed effects. Panel B reports the heterogenous effects by plotting coefficients(η_k) from the above model estimated using distressed (yellow line) and non-distressed firms (Blue dash line) subsamples. Vertical bars display 95 percent confidence intervals. The vertical (red) dashed line separates pre and post-2002 years.

(A) Average effect **(B) Heterogenous effect**

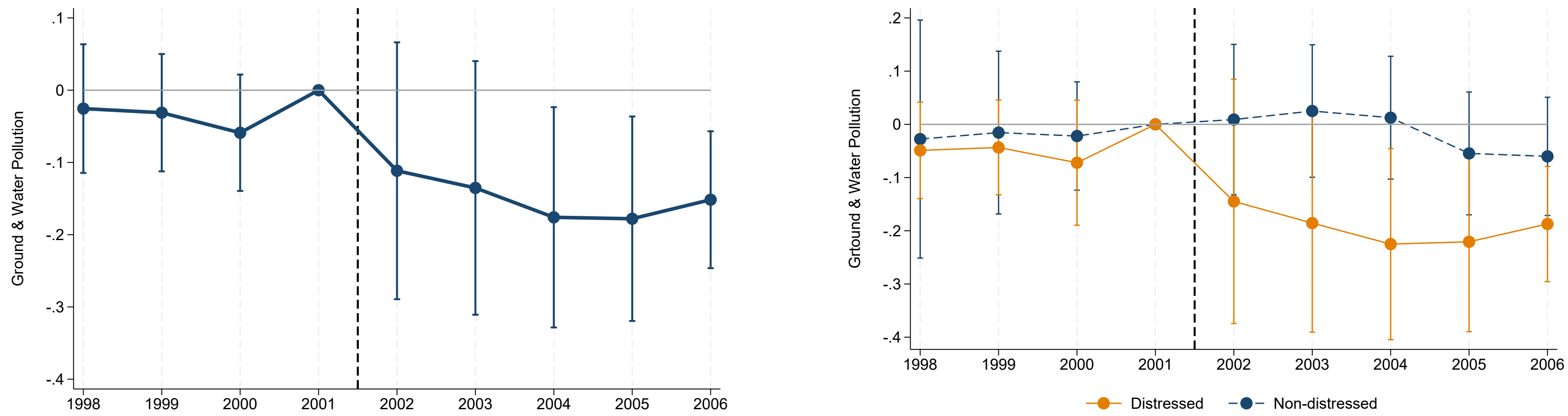


Table 1: **Summary Statistics**

The table reports the summary statistics for the TRI sample (Plant-chemical level). Table A1 in the Appendix lists definitions for variables.

Variable	Mean	Median	SD	N
Chemical-level				
Ground Pollution (1000s)	7.03	0.00	37.00	261232
Water Pollution(1000s)	0.45	0.00	2.87	261232
Air Pollution(1000s)	16.48	0.14	68.54	261232
Ground & Water Pollution(1000s)	7.48	0.00	37.39	261232
Off-site managed(1000s)	12.86	0.00	51.21	261232
Off-site recycled (1000s)	9.30	0.00	48.18	261232
Off-site energy recovery(1000s)	2.27	0.00	12.58	261232
Off-site treated (1000s)	1.29	0.00	7.67	261232
$\mathbb{1}$(Ground Pollution)	0.14	0.00	0.35	261232
$\mathbb{1}$(Water Pollution)	0.19	0.00	0.39	261232
$\mathbb{1}$(Air Pollution)	0.75	1.00	0.44	261232
$\mathbb{1}$(Ground & Water pollution)	0.26	0.00	0.44	261232
$\mathbb{1}$(Abate)	0.105	0.000	0.31	261232
$\mathbb{1}$(Operating practice)	0.052	0.000	0.22	261232
$\mathbb{1}$(Spill prevention)	0.023	0.000	0.15	261232
$\mathbb{1}$(Process Mod.)	0.030	0.000	0.17	261232
#Abate	0.167	0.000	0.58	261232
#Operating Practice	0.057	0.000	0.26	261232
#Spill preventions	0.027	0.000	0.19	261232
#Process Mod.	0.034	0.000	0.20	261232
Production ratio	0.95	1.00	0.44	232764
Plant-level				
#Emp	516.092	200.000	1195.18	38346
Age	37.623	17.000	37.61	38346
Paydex	66.923	68.000	7.93	35213
Firm-level				
Total assets (Mil$)	4038.329	918.711	7803.29	6232
Mkt Leverage	0.318	0.292	0.22	6232
Merton DD	0.032	0.000	0.09	6025
Other Liability / AT	0.068	0.045	0.08	6232
Z-score	3.484	2.790	2.54	6232

Table 2: **The Effect of the Brownfields Act on the Propensity to Sell Real Estate**

This table estimates the effect of the Brownfields Act on the propensity to sell real estate using ordinary least squares. The dependent variable indicates whether real estate is sold in year t. *Treated* is a dummy variable that equals one if the plant's industry (3-digit SIC) is treated and zero otherwise. *Post* is a dummy variable that takes value one after 2002 and is zero otherwise. *log(Emp)* represents the log of the number of employees of the plant. *log(Age)* is log of plant age. $\mathbb{1}$*(HQ)* is an indicator for headquarter. *Ind leverage* and *Ind Q* represents average industry leverage and Tobin's Q, respectively. HHI is the Herfindahl-Hirschman Index of sales at the 3-digit SIC level, calculated using Compustat firms. Fixed effects are indicated in the table. Standard errors clustered by industry level are reported in parentheses. The symbols $*$, $**$, and $***$ indicate significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Outcome:	$\mathbb{1}$***(Sell RE)***				
	(1)	(2)	(3)	(4)	(5)
Treated×*Post*	0.017**	0.016**	0.013***	0.016***	0.017***
	(0.007)	(0.007)	(0.003)	(0.003)	(0.004)
log(Emp)	-0.004***	-0.004***	-0.003***	-0.004***	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
log(Age)	-0.001	-0.000	-0.001	0.001*	0.022***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.003)
$\mathbb{1}$*(HQ)*	-0.018***	-0.022***	-0.019***	-0.025***	-0.107
	(0.003)	(0.002)	(0.002)	(0.003)	(0.173)
Ind leverage	0.057**	0.052**	0.010	0.001	0.005
	(0.023)	(0.023)	(0.022)	(0.022)	(0.022)
Ind Q	0.005	0.005	0.000	-0.000	-0.003*
	(0.005)	(0.006)	(0.001)	(0.001)	(0.001)
HHI	0.021*	0.020*	0.003	0.003	0.002
	(0.012)	(0.011)	(0.009)	(0.008)	(0.007)
Year FE	Yes	No	No	No	No
Industry FE	Yes	Yes	Yes	No	No
Firm FE	Yes	Yes	No	No	No
County×Year FE	No	Yes	Yes	Yes	Yes
Parent Firm×Year FE	No	No	Yes	Yes	Yes
Industry×County FE	No	No	No	Yes	Yes
Plant FE	No	No	No	No	Yes
Adjusted R^2	0.045	0.038	0.114	0.128	0.171
Observations	265988	265988	265988	265988	265988

Table 3: **The Effect of the Brownfields Act on Plant Solvency**

This table estimates the Brownfields Act's effect on subsidiary plants' solvency using ordinary least squares. Observations are at the plant level. The dependent variable is an indicator of whether the plant's Paydex score is less than 50. *Treated* is a dummy variable that equals one if the plant's industry (3-digit SIC) is treated and is zero otherwise. *Post* is a dummy variable that takes value one after 2002 and is zero otherwise. Fixed effects are indicated in the table. *Ind leverage* and *Ind Q* represents average industry leverage and Tobin's Q, respectively. HHI is the Herfindahl-Hirschman Index of sales at the 3-digit SIC level, calculated using Compustat firms. Industry is 3-digit SIC. Standard errors clustered by industry level are reported in parentheses. The symbols $*$, $**$, and $***$ indicate significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Outcome:	$\mathbb{1}$(***Paydex***< 50)	
	(1)	(2)
Treated×*Post*	-0.017**	-0.014**
	(0.008)	(0.007)
log(Age)	-0.016	-0.018
	(0.012)	(0.011)
Ind leverage	-0.038	-0.030
	(0.040)	(0.040)
Ind Q	-0.000	-0.000
	(0.002)	(0.002)
Ind leverage	-0.021	-0.017
	(0.026)	(0.025)
Plant FE	Yes	Yes
Year FE	Yes	No
Parent Firm FE	Yes	Yes
State×Year FE	No	Yes
Adjusted R2	0.196	0.193
Observations	25541	25541

Table 4: **The Effect of the Brownfields Act on Pollution**

This table estimates the effect of the Brownfields Act on ground and water pollution using Poisson pseudo-maximum-likelihood. Observations are at the plant-chemical level. The dependent variable is pounds of ground and water pollution. *Treated* is a dummy variable that equals one if the parent firm's industry (3-digit SIC) is treated and is zero otherwise. *Post* is a dummy variable that takes value one after 2002 and is zero otherwise. *Distressed* is a dummy variable that equals one if the parent company is financially distressed (i.e., pre-treatment Altman's Z in the bottom tercile) and is zero otherwise. Column (1) uses the full sample to test the average effect of the Brownfields Act. Columns (4) and (5) report triple-difference analyses by pooling the distressed and non-distressed subsamples. Fixed effects are indicated in the table. Standard errors clustered by industry level are reported in parentheses. The symbols $*$, $**$, and $***$ indicate significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Outcome:	**Ground & Water pollution**				
Sample:	*Avg. effect*	*Distressed*	*Non-distressed*	*Pooled*	
	(1)	(2)	(3)	(4)	(5)
Treated×*Post*	-0.120**	-0.150**	0.005	0.010	0.069
	(0.058)	(0.066)	(0.046)	(0.050)	(0.052)
Treated×*Post*×*Distressed*				-0.161**	-0.231**
				(0.068)	(0.114)
Chemical×Year FE	Yes	Yes	Yes	Yes	Yes
Plant×Chemical FE	Yes	Yes	Yes	Yes	Yes
Parent Firm FE	Yes	Yes	Yes	Yes	Yes
State×Year FE	No	No	No	No	Yes
Observations	261232	87707	173525	261232	261232

Table 5: **Placebo: the Effect of the Brownfields Act on Air Pollution**

This table estimates the effect of the Brownfields Act on air pollution. Observations are at the chemical level. The dependent variable is pounds of air pollution. *Treated* is a dummy variable that equals one if the parent firm's industry (3-digit SIC) is treated and is zero otherwise. *Post* is a dummy variable that takes value one after 2002 and is zero otherwise. *Distressed* is a dummy variable that equals one if the parent company (i.e., pre-treatment Altman's Z in the bottom tercile) is financially distressed and is zero otherwise. Fixed effects are indicated in the table. Standard errors clustered by industry level are reported in parentheses. The symbols $*$, $**$, and $***$ indicate significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Outcome:	**Air Pollution**		
	(1)	(2)	(3)
Treated×*Post*	-0.018	0.004	0.013
	(0.024)	(0.040)	(0.041)
Treated×*Post*×*Distressed*		-0.048	-0.032
		(0.044)	(0.048)
Chemical×Year FE	Yes	Yes	Yes
Plant×Chemical FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
State×Year FE	No	No	Yes
Observations	261232	261232	261232

Table 6: **The Effect of the Brownfields Act on Abatement Investment**

This table estimates the effect of the Brownfields Act on pollution abatement efforts. Observations are at the chemical level. The dependent variables are the number of abatement efforts implemented for a particular chemical: Good operating practices (Column (1)-(2)), spill and leak preventions (Column(3)-(4)), and process modifications (Column (5)-(6)) *Treated* is a dummy variable that equals one if the parent firm's industry (3-digit SIC) is treated and is zero otherwise. *Post* is a dummy variable that takes value one after 2002 and is zero otherwise. *Distressed* is a dummy variable that equals one if the parent company is financially distressed (i.e., pre-treatment Altman's Z in the bottom tercile) and is zero otherwise. Fixed effects are indicated in the table. Standard errors clustered by industry level are reported in parentheses. The symbols $*$, $**$, and $***$ indicate significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Outcome:	**#Good Operating**		**#Spill preventions**		**#Process modifications**	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated×*Post*	-0.286*	-0.284	0.187	0.074	0.238	0.205
	(0.155)	(0.177)	(0.340)	(0.354)	(0.170)	(0.165)
Treated×*Post*×*Distressed*	0.488**	0.488*	0.446	0.724	-0.264	-0.354
	(0.229)	(0.253)	(0.420)	(0.458)	(0.324)	(0.284)
Chemical×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Plant×Chemical FE	Yes	Yes	Yes	Yes	Yes	Yes
Parent Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
State×Year FE	No	Yes	No	Yes	No	Yes
Observations	261232	261232	261232	261232	261232	261232

Table 7: **The Effect of the Brownfields Act on Off-Site Waste Management**

This table estimates the effect of the Brownfields Act on toxic waste transferred to off-site facilities using Poisson pseudo-maximum-likelihood. Observations are at the plant-chemical level. In column (1), the dependent variable is pounds of toxic waste (recycled+energy recovery+treatment) transferred to off-site facilities. In column (2), the dependent variable is pounds of toxic waste transferred to off-site facilities for energy recovery. In column (3), the dependent variable pounds of toxic waste to transferred to off-site facilities for energy recovery. In column (4), the dependent variable is pounds of toxic waste transferred to off-site facilities for treatment. *Treated* is a dummy variable that equals one if the parent firm's industry (3-digit SIC) is treated and is zero otherwise. *Post* is a dummy variable that takes value one after 2002 and is zero otherwise. *Distressed* is a dummy variable that equals one if the parent company is financially distressed (i.e., pre-treatment Altman's Z in the bottom tercile) and is zero otherwise. Fixed effects are indicated in the table. Standard errors clustered by industry level are reported in parentheses. The symbols $*$, $**$, and $***$ indicate significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Outcome:	**Off-site managed**	**Off-site recycled**	**Off-site energy recovery**	**Off-site treatment**
	(1)	(2)	(3)	(4)
Treated×*Post*	-0.050	-0.078	-0.081	0.281**
	(0.036)	(0.053)	(0.080)	(0.133)
Treated×*Post*×*Distressed*	0.263***	0.289**	-0.050	-0.003
	(0.096)	(0.113)	(0.147)	(0.257)
Chemical×Year FE	Yes	Yes	Yes	Yes
Plant×Chemical FE	Yes	Yes	Yes	Yes
Parent Firm FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes
Observations	261232	261232	261232	261232

Table 8: **The Effect of the Brownfields Act on Production**

This table estimates the effect of the Brownfields Act on production. Observations are at the plant-chemical level. The dependent variables are the production ratio (columns (1) and (2)) and the log of normalized production (columns (3) and (4)). *Treated* is a dummy variable that equals one if the parent firm's industry (3-digit SIC) is treated and is zero otherwise. *Post* is a dummy variable that takes value one after 2002 and is zero otherwise. *Distressed* is a dummy variable that equals to if the parent company is financially distressed (i.e., pre-treatment Altman's Z in the bottom tercile) and is zero otherwise. Fixed effects are indicated in the table. Standard errors clustered by industry level are reported in parentheses. The symbols $*$, $**$, and $***$ indicate significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Outcome:	**Production ratio**		**log(Norm. Prod.)**	
	(1)	(2)	(3)	(4)
Treated$\times$*Post*	-0.053*	-0.065**	0.051	0.053
	(0.030)	(0.028)	(0.037)	(0.034)
Treated$\times$*Post*$\times$*Distressed*	0.112**	0.111**	0.023	0.028
	(0.050)	(0.043)	(0.058)	(0.052)
Chem$\times$Year FE	Yes	Yes	Yes	Yes
Plant$\times$Chemical FE	Yes	Yes	Yes	Yes
Parent Firm FE	Yes	No	Yes	No
State$\times$Year FE	No	Yes	No	Yes
Adjusted R^2	0.238	0.248	0.768	0.773
Observations	232764	232764	249807	249807

Internet Appendix

A Requirements for Purchaser Liability Defenses

The bona fide prospective purchaser and the innocent landowner defense shield the purchaser from CERLCA liability as long as the purchaser satisfies the criteria outlined in the statute. I discuss the most important and relevant requirements in this section.

An important requirement for establishing the purchaser liability defense is that before the purchaser buys the property, the purchaser must conduct "all appropriate inquires" (AAI) into the previous ownership and use the property consistent with good commercial or customary practices. The AAI requirement existed before the Brownfields Act. Specifically, AAI was a requirement established for the "innocent landowner defense" in 1986, allowing property owners to escape cleanup liability. The rationale of AAI was for an innocent landowner to show that he had no knowledge or reason to know of the disposal before purchasing the property (Weissman and Sowinski Jr (2015)).

Before the Brownfields Act, to comply with "good commercial or customary practices," the industry had adopted standards set by a private entity: ASTM (American Society of Testing Materials). The Brownfields Act directed the EPA to define AAI by regulation within two years. Meanwhile, allowing AAI to follow ASTM standards. In August 2004, the EPA published its proposed rule, setting standards for AAI in the Federal Register.[1] The proposed AAI Rule resembles the ASTM standard but requires a broader scope of inquiring and stricter standards for professionals conducting AAI. The more stringent requirements raised some concerns. For instance, "the EPA received a significant number of comments regarding the statutory requirements for qualifying for the CERCLA liability protections".[2] Ultimately, in November 2005, the EPA published its final AAI rule relaxing some of the requirements in the proposed rule.

Another critical requirement is that the purchaser must meet "continuing obligations," including (1) exercising "appropriate care" concerning hazardous substances, (2) taking reasonable steps to stop the continuous release, (3) preventing any future or threatened releases, and (4) limit human and environmental exposure to previously released pollutants.

1. See 69 FR 52542
2. See 70 FR 66069

In sum, to assert the defenses, a purchaser must conduct environmental due diligence and adopt good environmental practices.

B Tacking Changes in Real Estate Ownership in the NETS Database

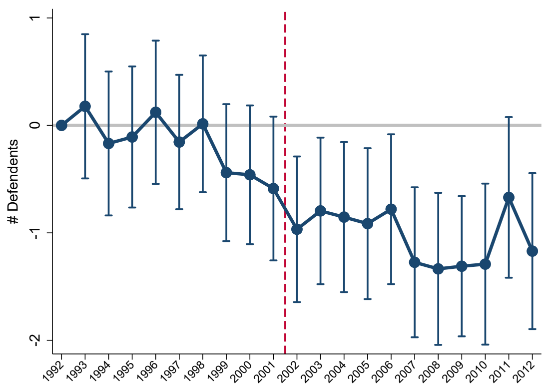
I take the following steps to determine whether real estate is occupied after the incumbent establishment shuts down or is relocated. First, I clean all addresses by standardizing abbreviations (e.g., Street to ST). Second, using STATA's reclick2 command, I perform a fuzzy matching algorithm on the address of the sold property to the address of other establishments not owned by the same parent company. The address matching requires perfect street number and zip code matches and allows for fuzzy matching based on city and street name. Since newborn establishments often have missing addresses in the first few years, when the address is missing, I use future addresses up to four years after the establishment shuts down. Then, I manually inspect potential matches with high fuzzy matching scores (greater than 0.80) to validate each possible match. In some cases, multiple establishments, including existing, newborn, or those that relocate, share the same address. To mitigate potential measurement error, I exclude observations with many establishments (greater than 99 percentile or 107 establishments) operating at the same address the year before the property is shut down. Finally, a property that shuts down is coded as sold if a new establishment starts operating at the same address or an existing establishment relocates to the same address in the following year.[3]

3. In unreported results, I also consider a newborn or relocation at the same address within two years of shutdown as the real estate being sold. The results do not change.

Figure A1: **Evolution of Number of Defendants Under CERCLA and RCRA**

This figure plots the number CERCLA and RCRA defendants between 1992 and 2012. I plot coefficients of year dummy variables (δ_t) estimated from the following equation: $\#Defendents_{ct} = \sum_{k=1993}^{2012} \delta_k \mathbb{1}(Year_t = k)] + \alpha_s + \alpha_r + \#statutes_{ct} + \epsilon_{ct}$ where c is an enforcement case, t represents a year, s denotes a law section, r denotes an EPA region. α_s and α_r are fixed effects for law section and EPA region (including 10 regional offices + headquarters), respectively. $\#statutes_{ct}$ is the number of statutes brought under case c. I winsorize $\#Defendents$ at the 95 percent level. Vertical bars represent 95 percent confidence intervals. The vertical (red) dashed line separates the pre- and post-2002 years.

(A) CERCLA



(B) RCRA

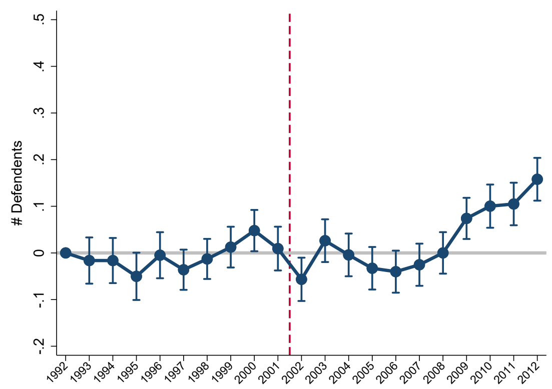


Figure A2: **Waste Management Hierarchy**

This figure presents the waste management hierarchy from the EPA. It ranks waste management methods from the most to the least environmentally preferred. Source: United States Environmental Protection Agency

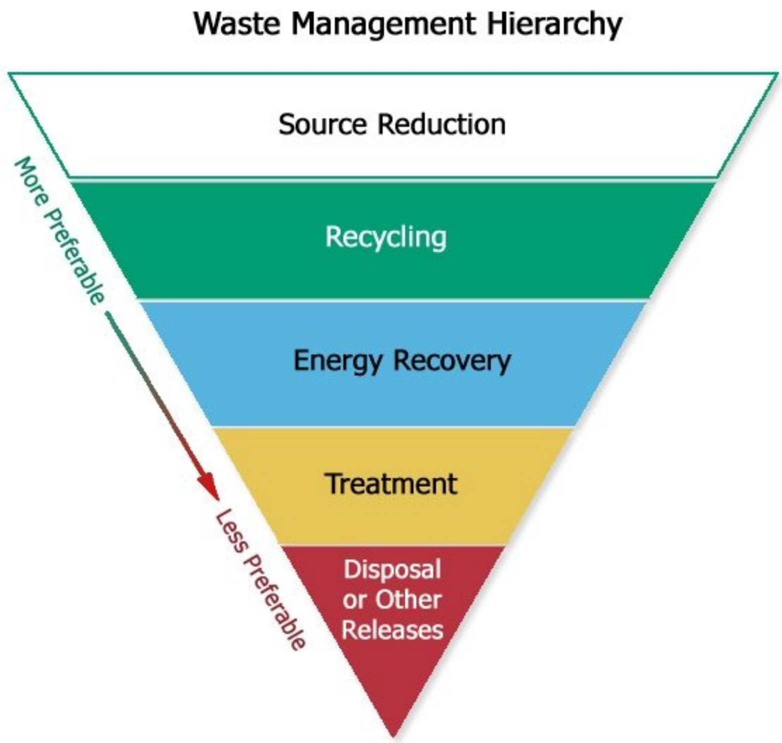


Figure A3: **Distribution of RCRA Enforcement Exposure**

The figure plots the density of the industry (3-digit SIC) level exposure to RCRA enforcement. RCRA exposure is the number RCRA enforcements prior to 2002 scaled by number of TRI plants for each industry. The figure omits small industries: the number of plants in that industry falls below the 25^{th} percentile or 34 plants. Industries with RCRA exposure equal to 0.2 represents scores above 0.2. Five industries have scores above 0.2: Sanitary Services (1.46), Petroleum Refining (0.348), Electric, Gas, & Utility (0.309), and National Security (0.219). The red vertical line represents the median of the RCRA exposure score (0.0323). Industries to the left of the red vertical line are treated industries.

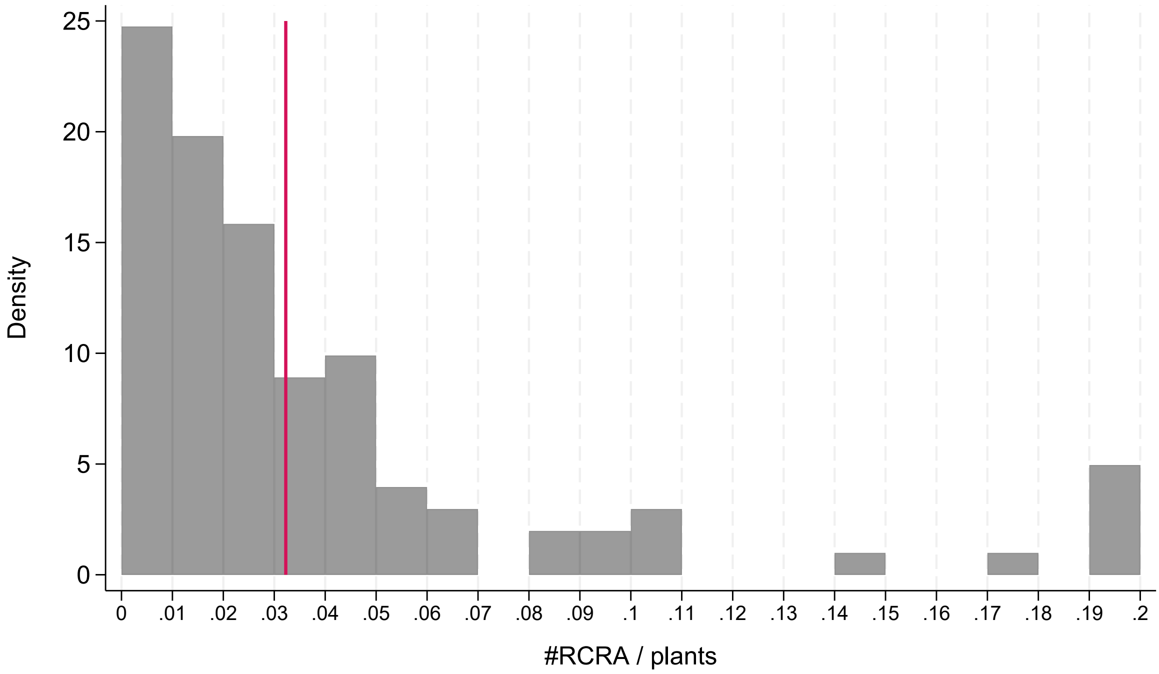


Table A1: **Description of Variables**

Variable	**Description**
Treatment variables	
Treated	Indicator of equal to one if an industry is treated by the Brownfields Act and is zero otherwise
Post	Indicator that equals one for years after 2002 (including), and zero otherwise. 2002 is the year in which the Brownfields Act was passed.
NETS variables	
$\mathbb{1}$*(Close Est)*	Indicator of whether an establishment closed
$\mathbb{1}$*(Move Est)*	Indicator of whether an establishment moved
$\mathbb{1}$*(Sell RE)*	Indicator of whether a plant sold its real estate
$\mathbb{1}$*(Sell Est)*	Indicator of whether an establishment is acquired
Age	Plant age (current year − founding year)
Emp	Number of Employees
Paydex	Minimum Paydex score
TRI variables	
Ground pollution	Pounds of ground pollution
Water pollution	Pounds of surface water pollution
Air pollution	Pounds of air pollution (stack + fugitive emissions)
Ground & water pollution	Pounds of ground + water pollution
Off-site recycled	Pounds of toxic waste transferred to other facilities for recycling
Off-site energy recovery	Pounds of toxic waste transferred to other facilities for energy recovery
Off-site treatment	Pounds of toxic waste transferred to other facilities for treatment
Off-site managed	Pounds of toxic waste transferred to other facilities for waste management (recycling + energy recovery $treatment$)
Productivity Ratio	Current year's output / prior year's output
Normalized Production	Total production
Firm variables	
Altman's Z	Altman's Z score (3.3×pre-tax income + sales + 1.4×retained earnings+ 1.2×Working capital/assets + Market value of equity /Total Liability
Distressed	An indicator equal to one if the parent firm's average Altman's Z score before the reform is in the lowest tercile and is zero otherwise

Variable	Description
Total assets	Total assets
Merton DD	Merton model distance-to-default estimated following (Bharath and Shumway 2008)
Mkt Leverage	Long-term debt plus debt in current liabilities / Market value of assets
Other Liab.	Other liability / assets
Industry controls	
HHI	Herfindahl-Hirschman Index calculated by summing the squared market shares of firms within each 3-digit SIC industry-year.
Ind leverage	Industry leverage, calculated by averaging leverage across all firms within each industry-year (3-digit SIC).
Ind Q	Industry Q, calculated using market value-weighted Tobin's Q across all firms within each industry-year (3-digit SIC).

Table A2: **NETS Sample Summary Statistics**

The Table reports summary statistics for the NETS sample (establishment level) Table A1 lists definitions for variables.

	Mean	Median	SD	N
#Emp	148.188	24.00	507.996	265988
Age	12.645	10.00	15.999	265988
$\mathbb{1}$(HQ)	0.015	0.00	0.121	265988
$\mathbb{1}$(Sell RE)	0.034	0.00	0.181	265988
$\mathbb{1}$(Sell Est)	0.020	0.00	0.140	265988
$\mathbb{1}$(Close Est)	0.040	0.00	0.197	265988
$\mathbb{1}$(Move Est)	0.008	0.00	0.089	265988

Table A3: **Abatement Categories**

This table lists and describes various abatement categories

Abatement category	Examples
Good Operating Practices	Improved maintenance scheduling, record keeping, or procedures Changed production schedule to minimize equipment and feedstock changeovers
Inventory Control	Instituted procedures to ensure that materials do not stay in inventory beyond shelf-life Instituted clearinghouse to exchange materials that would otherwise be discarded
Spill and Leak Prevention	Installed overflow alarms or automatic shut-off valves Improved procedures for loading, unloading, and transfer operations; Improved storage or stacking procedures
Raw Material Modifications	Increased purity of raw materials Substituted raw materials
Process Modifications	Used a different process catalyst Modified equipment, layout, or piping
Cleaning and Degreasing	Changed to mechanical stripping/cleaning devices (from solvents or other materials) Modified stripping/cleaning equipment
Surface Preparation and Finishing	Modified spray systems or equipment Substituted coating materials used
Product Modifications	Changed product specifications Modified design or composition of product; Modified packaging

Table A4: **Industries with Highest and Lowest RCRA Exposure**

This table reports the industries (3-digit SIC) with the highest and lowest RCRA exposure. RCRA/Plant is the number RCRA enforcements scaled by the number of TRI plants for each industry prior to 2002.

SIC3	Industry name	$\frac{RCRA}{Plants}$	#Plants
Highest 20			
495	Sanitary Services	1.460	161
422	Public Warehousing and Storage	0.700	40
291	Petroleum Refining	0.348	221
493	Electric, Gas & Utility	0.309	55
971	National Security	0.219	210
333	Primary Smelting & Refining of Nonferrous	0.174	86
331	Blast Furnace & Basic Steel Product	0.146	602
348	Ordnance and Accessories	0.109	110
286	Industrial Organic Chemicals	0.106	827
517	Petroleum & Petroleum Products	0.102	753
738	Mis. Business Services	0.097	144
283	Drugs	0.093	453
372	Aircraft and Parts	0.088	536
324	Cement, Hydraulic	0.081	124
347	Coating, Engraving, & Allied Services	0.064	2036
386	Photographic Equipment & Supplies	0.064	94
249	Mis. Wood Products	0.063	756
281	Inorganic Chemicals	0.060	1040
282	Plastics Materials and Synthetic Resins, Synthetic Rubber	0.052	712
299	Products of Petroleum and Coal	0.052	291
Lowest 20			
263	Paperboard mills	0.007	145
295	Asphalt Paving & Roofing Materials	0.006	337
308	Mis. Plastics Products	0.005	2685
267	Converted Paper & Paperboard Products	0.005	393
262	Paper mills	0.004	254
207	Fats & Oils	0.004	256
208	Beverages	0.004	559
265	Paperboard Containers and Boxes	0.003	288
204	Grain Mill Products	0.003	868
203	Canned, Frozen, & Preserved Fruits, Veg., & Food Specialties	0.002	452
393	Musical instruments	0.000	34
321	Flat glass	0.000	35
328	Cut Stone and Stone Products	0.000	36
104	Gold & Silver Ores	0.000	60
222	Broadwoven Fabric Mills, Manmade Fiber & Silk	0.000	70
225	Knitting Mills	0.000	109
245	Wood buildings and mobile homes	0.000	245
226	Dyeing & Finishing Textiles	0.000	247
209	Mis. Food Prep. & Kindred Products	0.000	325
201	Meat Products	0.000	605
202	Dairy Products	0.000	801

Table A5: **Robustness: Alternative Measures of Risk-Shifting**

The table considers alternative measures of risk-shifting motives. All measures are calculated based on pre-treatment averages. The dependent variable is ground plus water pollution. *Treated* is a dummy variable that equals one if the parent firm's industry (3-digit SIC) is treated and is zero otherwise. *Post* is a dummy variable that takes value one after 2002 and is zero otherwise. *Proxy* is a dummy variable that equals to one if the parent company is distressed/faces judgment-proof problem and is zero otherwise. In column (1), a firm is classified as distressed if its Merton distance-to-default (Bharath and Shumway (2008)) is in the top tercile of its industry. In column (2), a firm is deemed to have a high incentive to risk-shift if its other liability over assets belongs to its industry's top tercile. In column (3), a firm is classified as distressed if its market leverage belongs to its industry's top tercile. In column (4), a firm is considered to face a judgment-proof problem if its total asset is below its industry median. Fixed effects are indicated in the table. Standard errors clustered by industry level are reported in parentheses. The symbols $*$, $**$, and $***$ indicate significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Measure:	Merton DD	Ohter Liab. / AT	Mkt Leverage	Total Assets
	(1)	(2)	(3)	(4)
Treated×*Post*	-0.107*	-0.074*	-0.102	-0.038
	(0.065)	(0.039)	(0.065)	(0.045)
Treated×*Post*×*Proxy*	-0.111*	-0.252*	-0.169***	-0.299***
	(0.058)	(0.151)	(0.049)	(0.110)
Chemical×Year FE	Yes	Yes	Yes	Yes
Plant×chemical FE	Yes	Yes	Yes	Yes
Parent Firm FE	Yes	Yes	Yes	Yes
Observations	259971	261232	261232	261232

Table A6: **Robustness: Alternative Specifications**

The table performs robustness tests. The dependent variable is ground & water pollution. *Treated* is a dummy variable that equals one if the parent firm's industry (3-digit SIC) is treated and is zero otherwise. *Post* is a dummy variable that takes value one after 2002 and is zero otherwise. *Distressed* is a dummy variable that equals one if the parent company is financially distressed and is zero otherwise. In columns (1) and (2), the dependent variable is winsorized at the 97.5 and 95 percent levels. In columns (1) and (2), standard errors are clustered at the 3-digit SIC level. In columns (3)-(5), I test whether the main results are robust to alternative ways of clustering standard errors. Standard errors are clustered at the 3-digit SIC and parent firm levels in column (3), 3-digit SIC and year levels in column (4), and at the 2-digit SIC level in column (5). Fixed effects are indicated in the table. The symbols $*$, $**$, and $***$ indicate significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Outcome:	**Ground & Water Pollution**				
Specification	*Winsorize*		*Clustering*		
	(1) 97.5 percent	(2) 95 percent	(3) SIC3 & Parent Firm	(4) SIC3 & Year	(5) SIC2
Treated×*Post*	0.084*	0.085	0.085	0.085	0.085**
	(0.050)	(0.053)	(0.053)	(0.063)	(0.040)
Treated×*Post*×*Distressed*	-0.182***	-0.155***	-0.155***	-0.155**	-0.155***
	(0.057)	(0.058)	(0.058)	(0.077)	(0.054)
Chemical×Year FE	Yes	Yes	Yes	Yes	Yes
Plant×Chemcial FE	Yes	Yes	Yes	Yes	Yes
Parent Firm FE	Yes	Yes	Yes	Yes	Yes
Observations	261232	261232	261232	261232	261232

Table A7: **Robustness: Exposure to the Brownfields Act**

The table tests whether results are robust to alternative measures of exposure to the Brownfields Act by estimating Poisson Pseudo-Maximum Likelihood. The dependent variable is the pounds of ground plus water pollution. *Treated* is a dummy variable that equals one if the parent firm's industry is treated and is zero otherwise. *Post* is a dummy variable that takes value one after 2002 and is zero otherwise. *Distressed* is a dummy variable that equals one if the parent company is financially distressed and is zero otherwise. Columns (1) exclude 3-digit SIC industries with RCRA exposure scores (RCRA enforcement/Plants) exceeding the 1st and 99th percentiles. Column (2) measures exposure to the reform using 4-digit SIC. Column (3) measures exposure to the reform using 4-digit NAICS. Column (4) measures exposure to the reform at the 3-digit SIC level using the difference between CERCLA and RCRA cleanup costs. Fixed effects are indicated in the table. Industry is 3-digit SIC. Standard errors clustered by industry level are reported in parentheses. The symbols $*$, $**$, and $***$ indicate significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Outcome:	**Ground & Water Pollution**			
Exp. measure:	Exc. Extreme	4-digit SIC	4-digit NAICS	CERCLA−RCRA($)
	(1)	(2)	(3)	(4)
Treated×*Post*	-0.003	0.116*	-0.013	0.099
	(0.051)	(0.066)	(0.069)	(0.067)
Treated×*Post*×*Distressed*	-0.138**	-0.183**	-0.148*	-0.150*
	(0.062)	(0.073)	(0.085)	(0.080)
Chemical×Year FE	Yes	Yes	Yes	Yes
Plant×Chemical FE	Yes	Yes	Yes	Yes
Parent Firm FE	Yes	Yes	Yes	Yes
Observations	251539	217058	237963	261232