Environmental Liabilities, Borrowing Costs, and Pollution Prevention Activities: The Nationwide Impact of the Apex Oil Ruling*

Jianqiang Chen Pei-Fang Hsieh Po-Hsuan Hsu Ross Levine

March 2024

Abstract

The 2008 Apex Oil court decision reduced the circumstances under which specific environmental cleanup obligations were dischargeable in Chapter 11, potentially affecting the securities prices, credit conditions, and pollution practices of corporations not in Chapter 11. We discover that among financially stressed firms with those specific environmental liabilities, bond, and stock prices dropped after *Apex*. Moreover, those firms (1) experienced a tightening of credit conditions (e.g., paying higher risk premia on debts and receiving lower bond ratings), (2) intensified pollution prevention activities, and (3) reduced the emissions of pollutants causing environmental damages no longer dischargeable in Chapter 11. These findings hold among firms nationwide, not only those within the jurisdiction of the Seventh Circuit court, which issued the Apex decision, suggesting that *Apex* had a nationwide impact.

* Chen, School of Economics, Ocean University of China, email: chenjianqiang@ouc.edu.cn; Hsieh, College of Technology Management, National Tsing Hua University, email: pfhsieh@mx.nthu.edu.tw; Hsu, College of Technology Management, National Tsing Hua University, email: pohsuanhsu@mx.nthu.edu.tw; Levine, Haas School of Business, University of California, Berkeley, email: rosslevine@berkeley.edu. We thank Rui Albuquerque, Dyaran Bansraj, Tobias Berg, Adrian Buss, Kornelia Fabisik, Yigitcan Karabulut, Taehyun Kim, Jongsub Lee, Hao Liang, Emanuel Moench, Holger Mueller, Zacharias Sautner, Christoph Schiller, Antoinette Schoar, Kyoungwon Seo, Anand Srinivasan, Laura Starks, Johan Sulaeman, Francesc Rodriguez Tous, Wei Wang, seminar participants at City University of London, Frankfurt School of Finance and Management, National Taiwan University, and Seoul National University, and conferences participants at ABFER, NTHU Symposium on Sustainable Finance and Economics, and TFA for valuable comments. We thank Wan-Chien Chiu and Chi-Yang Tsou for assistance.

1. Introduction

Research demonstrates that corporations produce most of the U.S.'s land and water pollution, increasing cancer rates, reproductive and neurodevelopmental disorders, and premature death (e.g., Schwarzenbach et al. 2010; Environmental Protection Agency (EPA) 2013-16; Landrigan et al. 2018; 2019). This research raises concerns that corporate decision-makers do not fully internalize the social costs of their choices regarding toxic releases (e.g., Bohm 2003; Greenstone 2003; Kolstad and Toman 2005). In this paper, we contribute to research studying the ramifications of court decisions that reassign legal liabilities for firms' environmental damages on firms' securities prices, borrowing costs, pollution prevention activities, and toxic emissions.

Chapter 11 allows financially distressed firms to reduce (i.e., "discharge") claims, including, in some cases, obligations to address environmental damages. In a series of landmark cases (e.g., *Ohio v. Kovacs* (1985) and *U.S. v. Whizco* (1988)), courts ruled that obligations to clean up polluted sites were financial "claims," making those environmental obligations dischargeable in Chapter 11, like other debts. The implications were profound: environmental cleanup liabilities could be shifted from the corporation and its creditors to taxpayers in bankruptcy, leaving more corporate resources available to satisfy the claims of creditors. Among financially distressed firms close to bankruptcy, the dischargeability of environmental liabilities reduced the financial incentives of creditors to limit their firms' toxic releases.

In a pivotal and surprising decision—the 2008 Apex Oil decision, the courts materially reduced the circumstances under which specific environmental liabilities could be discharged in Chapter 11 bankruptcy and, therefore, increased the financial exposure of creditors to their firms' environmental obligations. In *Apex*, the Department of Justice (DoJ) and EPA brought an action under the Resource Conservation and Recovery Act (RCRA). Specifically, they sought injunctive relief requiring the corporate successor of Apex Oil to clean up a site that Apex Oil contaminated before filing for Chapter 11. On July 28, 2008, the U.S. District Court for the Southern District of Illinois ordered Apex Oil Company Inc. (the successor) to clean up the contamination, holding that the environmental obligations under RCRA were not obligations to pay; they were obligations to clean up the site. Consequently, the environmental obligations under RCRA were not "claims" as defined by Chapter 11 and, hence, not dischargeable. While Apex Oil appealed the decision to the Seventh Circuit and the Supreme Court, the lower court ruling stood, meaning legal liability for RCRA-covered environmental damages in bankruptcy shifted from taxpayers to creditors after *Apex* as those liabilities were no longer dischargeable in Chapter 11.

The *Apex* decision offers a unique opportunity to assess the impact of changing creditors' legal liability for environmental damages on firms' securities prices, borrowing costs, pollution prevention activities, and toxic emissions. After *Apex*, firms in Chapter 11 with RCRA-related environmental obligations would have fewer resources available for creditors. Resources would first be used to satisfy environmental obligations and only then to settle creditor claims (e.g., Hayes 2016; Ohlrogge 2020). Besides influencing firms in Chapter 11, *Apex* may have also affected the creditors of firms close to Chapter 11. For firms close to bankruptcy with significant RCRA-related cleanup obligations, *Apex* may have (1) reduced the prices investors would pay for the securities of such firms, (2) induced credit markets to charge higher risk premia, and (3) incentivized creditors to pressure their firms to invest more in pollution prevention activities because any resultant cleanup costs would no longer be dischargeable.

However, there are challenges to this Apex-creditor view of how Apex shaped securities prices, credit conditions, and pollution decisions, as well as questions about whether *Apex* had nationwide repercussions or only influenced firms within the Seventh Circuit. Concerning challenges to the *Apex*-creditor view, markets might view *Apex* as having only minimal effects on the expected returns to creditors even if the firm goes into Chapter 11, reducing the impact of *Apex*. In addition, if the transaction costs are negligible and the assignment of rights to pollute is efficient, then *Apex* may not matter (Coase 1960). Furthermore, even if *Apex* incentivizes creditors to pressure firms to reduce potential environmental liabilities, creditors might have little influence over corporate decisions. There are also questions about whether *Apex* had nationwide effects or whether its effects, if any, were localized. Formally, *Apex* only applied to firms in the Seventh Circuit (e.g., Ohlrogge 2020). However, *Apex* offered a litigation strategy and precedent for state and federal authorities to exploit beyond the Seventh Circuit. Indeed, as discussed in greater detail below, the media, consulting firms, and the DoJ quickly stressed the nationwide ramifications of *Apex*, and the

EPA adjusted its strategies following *Apex*. These observations suggest that *Apex* may have had nationwide effects. Thus, the impact of *Apex* on financial markets and corporate pollution decisions and the geographic boundaries of *Apex*'s effects are empirical questions.

To investigate the effects of *Apex* on securities prices, credit conditions, pollution prevention activities, and toxic emissions, we match data on public firms from the Compustat/CRSP database with information on pollution prevention activities and pollution emissions from the EPA's toxic release inventory (TRI) database. Specifically, we evaluate the *Apex*-creditor view that *Ape*x had an especially large effect on the (1) cumulative abnormal returns (CARs) on bonds and stocks, (2) borrowing costs, (3) pollution prevention activities, and (4) pollution emissions of firms close to bankruptcy with extensive RCRA-covered cleanup obligations. We focus on these firms because (a) *Apex* applied only to firms with environmental cleanup obligations covered by the RCRA; it did not change the dischargeability of non-RCRA-covered damages, and (b) *Apex* would likely have larger effects on firms close to bankruptcy, as *Apex* only reduced the dischargeability of environmental cleanup obligations of firms in bankruptcy and would, therefore, have more muted effects on firms far from bankruptcy. We classify firms as *Heavy RCRA Polluters* if they were above the industry-median emitters of RCRA pollutants during the five years before *Apex* and *Low RCRA Polluters* otherwise. Similarly, we classify firms as *High Default Probability* if their pre-*Apex* default probabilities exceed the corresponding industry-median default probabilities and other firms as *Low Default Probability*. The *High Default Probability* subsample is our primary test sample, and the *Low Default Probability* group serves as a placebo sample.

We first discover that (1) the CARs on the bonds and stocks of heavy-RCRA polluters close to bankruptcy fell significantly in the months and days following *Apex,* and (2) the CARs of these firms fell nationwide, not just among such firms in the jurisdiction of the Seventh Circuit. These findings suggest that *Apex* immediately affected the securities prices of "treated" firms nationwide.

Second, we employ difference-in-differences analyses of the *High Default Probability* sample and find that *Apex* significantly tightened the borrowing costs and credit conditions of firms with extensive RCRA-covered cleanup obligations; however, *Apex* did not significantly alter other firms' borrowing costs and credit conditions. We first show that the total interest rate paid by *Heavy RCRA Polluters* with high default probabilities rises materially after Apex but not among other firms, where each firm's total interest rate equals total interest expenses divided by total interest-bearing liabilities (e.g., Ivanov, Kruttli, and Watugala 2022). Next, we find consistent results when examining interest rate spreads on newly issued bank loans. Consistent with the view that Apex increased the expected loss given default (LGD) for firms close to bankruptcy, we discover that following *Apex*, bank loan spreads for heavy RCRA polluters widened appreciably but not for other firms. The findings remain robust when we estimate synthetic difference-in-differences (Arkhangelsky et al. 2021), use event-based measures for bankruptcy (credit downgrades), and account for time-varying state-level heterogeneity. Furthermore, consistent with the *Apex*-creditor view, our analyses do not reject the parallel trends assumption for the total interest rate and bank loan spread analyses.

We augment these analyses of credit conditions by studying bond ratings. Since rating agencies use ordered categories for bonds, we combine the DID regression structure with an ordered probit estimator. We find a significant decrease in the bond ratings of heavy RCRA polluters with high default probabilities but no change in the bond ratings of heavy RCRA polluters with low default probabilities. The results on total interest rates, bank loan spreads, and bond ratings suggest that creditors readily recognized that *Apex* increased the potential losses from lending to specific firms—those with extensive RCRA-covered cleanup obligations close to bankruptcy—and adjusted their credit terms accordingly.

Third, we discover that *Apex* increased facility-level pollution prevention activities among firms with extensive RCRA-covered cleanup obligations close to bankruptcy. We obtain data on pollution prevention activities and RCRA-regulated emissions from the TRI database, which has been used by Akey and Appel (2021) and Bellon (2021) to gauge firms' investment in pollution abatement and environmental performance. Consistent with the *Apex*-creditor view, pollution prevention activities increased appreciably following *Apex* among heavy RCRA polluters near bankruptcy. There is no evidence of differential trends in pollution prevention activities between treated and non-treated firms before *Apex.*

Finally, we find that, after *Apex*, facilities' RCRA-regulated emissions fell among heavy RCRA polluters relatively close to Chapter 11 but not among the facilities of other firms. Furthermore, we conduct a placebo test examining the release of *non*-RCRA-regulated chemicals. If *Apex* shaped corporate behavior by altering the dischargeability of environmental obligations in Chapter 11, it should only affect RCRA pollutants. Indeed, we find no change in *non*-RCRA-chemical releases after *Apex*.

Our study builds on but substantially differs from Ohlrogge (2020), who focuses on chemical releases by firms in the Seventh Circuit Court following *Apex*. Our study differs as follows. First, we examine whether and discover that (a) *Apex* triggered reductions in the bond and stock CARs of heavy-RCRA polluters close to bankruptcy and (b) these findings hold across firms nationwide, not just among those in the Seventh Circuit. Second, given this finding that *Apex* immediately had immediate, nationwide effects, we expand our analyses to include all public firms (with the requisite data). Thus, our sample of firms is tenfold larger than the limited sample of firms within the Seventh Circuit. Third, we focus on the impact of *Apex* on firms' securities prices, borrowing costs, and pollution prevention activities, not just on pollution. Thus, we evaluate a particular mechanism through which *Apex* spurred firms to reduce pollution: by altering creditors' incentives and firms' pollution prevention activities. Fourth, we employ an enhanced identification strategy. We differentiate firms by their proximity to bankruptcy and the extent of their RCRA-covered cleanup obligations. This methodology improves our ability to identify the impact of a change in legal liability for environmental damages on firms' securities prices, borrowing costs, pollution prevention activities, and toxic emissions.

Our study also relates to Bellon (2021), who evaluates the impact of the 1996 Lender Liability Act on pollution. The Lender Liability Act reduced the circumstances under which secured lenders in the Eleventh Circuit were liable for pollution damages in bankruptcy. Bellon (2021) finds that pollution and violations of environmental regulations increased, and pollution prevention activities decreased following the Act. *Apex* offers a finer set of treated firms by focusing on firms with extensive RCRA-covered cleanup obligations close to Chapter 11. The heterogeneous treatment of firms enhances identification. Our work also differs from Bellon (2021) in that we focus on the *Apex*-creditor view and assess the impact of *Apex* on firms' securities prices, borrowing costs, and credit ratings.

Our work is different from prior studies that focus on (a) shareholders' and managers' interests in environmental issues,[1] (b) how climate and environmental regulatory risks influence equity prices,[2] and (c) bondholders' and banks' preferences for firms with better environmental performance (e.g., Flammer 2021; Gao, Li, and Ma 2021; Kacperczyk and Peydro 2021; Ivanov, Kruttli, and Watugala 2022; Seltzer, Starks, and Zhu 2022). We explore how changes in legal liability for environmental damages alter the risk premia creditors charge. Finally, our work adds to the literature on law and economics by assessing the impact of *Apex* on corporate credit conditions and pollution decisions.[3]

2. Dischargeability and the Case of Apex Oil

2.1 The Apex decision

Under Chapter 11, a financially distressed company (the debtor) files for protection from its creditors with a federal bankruptcy court. Existing shareholders and managers often remain in control of the business (e.g., Eckbo, Thorburn, and Wang 2016) while seeking to restructure the firm's obligations and operations to make it successful, subject to the oversight and jurisdiction of the court. Chapter 11 allows debtors to reduce—"discharge"—claims that arose before the distressed firm filed for bankruptcy. To the extent that the courts define pre-Chapter 11 environmental obligations as claims, firms can discharge those environmental liabilities through Chapter 11. Discharging environment claims can have material financial

[1] Studies document how social norms shape retail and institutional investors (e.g., Renneboog, Ter Horst, and Zhang 2008; Hong and Kacperczyk 2009; Starks, Venkat, and Zhu 2017; Riedl and Smeets 2017; Chen, Kumar, and Zhang 2019; Dyck, Lins, Roth, and Wagner 2019; Hartzmark and Sussman 2019; Cao, Titman, Zhan, and Zhang 2019; Gibson, Krueger, and Mitali 2020; Shive and Forster 2020). Some studies point out that socially responsible firms' reputation can help them survive economic downturns (e.g., Lins, Servaes, and Tamayo 2017; Hoepner, Oikonomou, Sautner, Starks, and Zhou 2018; Albuquerque, Koskinen, and Zhang 2019; Ding, Levine, Lin, and Xie 2021). Dai, Liang, and Ng (2021) examine how the social preferences of customers influence corporate behavior.

[2] For example, see Bansal, Kiku, and Ochoa (2016), Krüger, Sautner, and Starks (2020), Bolton and Kacperczyk (2021), Bansal, Wu, and Yaron (2022), Hsu, Li, and Tsou (2023), and Pástor, Stambaugh, and Taylor (2022).

[3] Our paper adds to the literature on the effectiveness of environmental policies and regulations (e.g., Cohen 1987; Baumol and Oates 1988; Magat and Viscusi 1990; Fowlie 2010; Aghion, Dechezlepretre, Hemous, Martin, and Van Reenen 2016; Boomhower 2019) and how environmental regulations influence economic growth (Jorgenson and Wilcoxen 1990; Jaffe, Peterson, Portney, and Stavins 1995; Jaffe and Palmer 1997; Greenstone 2002; Acemoglu, Aghion, Bursztyn, and Hemous 2012; Acemoglu, Akcigit, Hanley, and Kerr 2016).

ramifications on the debtor as the burden of addressing environmental damages or other liabilities shifts from the debtor to taxpayers, leaving more resources available to satisfy the claims of other creditors (Hayes 2016). Thus, whether courts define environmental obligations as dischargeable claims is a first-order consideration for some creditors.

In defining dischargeable claims, the U.S. Bankruptcy Code stipulates that a claim can be (1) a "right to payment" 11 U.S.C. § 101(5)(A) or (2) a "right to an equitable remedy for breach of performance" but only "if such a breach gives rise to a right to payment" 11 U.S.C. § 101(5)(B). Most financial instruments represent rights to payment and are hence dischargeable in Chapter 11. However, the courts have faced greater challenges in defining the circumstances under which pre-Chapter 11 environmental obligations give rise to a "right to payment" and make it a dischargeable claim.

Consider the landmark 1985 Supreme Court case of *Ohio v. Kovacs* concerning the dischargeability of environmental obligations. The State of Ohio obtained an injunction ordering Kovacs to clean up a hazardous waste disposal site. When Kovacs did not comply, the State directed a receiver to take Kovacs's assets to implement the injunction. Kovacs filed for bankruptcy, and the Bankruptcy Court stayed the execution, precluding Ohio from obtaining those assets. Ohio filed a complaint with the Bankruptcy Court, arguing that the environmental obligation was not dischargeable because it was not a right to payment; it was an obligation to clean up a hazardous waste disposal site. However, the Bankruptcy Court, District Court, Court of Appeals, and Supreme Court ruled that in *Ohio v. Kovacs*, the environmental obligation "gives rise to a right to payment." The Supreme Court argued that it was clear from the case details that Ohio wanted money from Kovacs to defray the cleanup costs. Consequently, the obligation to clean up the hazardous waste disposal site had been converted into an obligation to pay money, making it dischargeable in bankruptcy. Subsequent cases focused on whether the environmental obligation was ultimately a monetary claim and hence dischargeable, e.g., *In re Chateaugay Corp*. and *In re Torwico Elecs.*, Inc. In

U.S. v. Whizco, Inc. (1988), the Sixth Circuit Court ruled that if a cleanup order would force a defendant to spend money, the environmental obligation was a claim and hence dischargeable.[4]

In the significant and surprising *Apex* decision, the courts altered and clarified the circumstances under which they would consider pre-Chapter 11 environmental obligations as dischargeable. Apex Oil Co. filed for Chapter 11 in late 1987 and re-incorporated in 1989. In 2004, the Department of Justice and the EPA brought an action under the Resource Conservation and Recovery Act (RCRA).[5] The action sought injunctive relief requiring the corporate successor to clean up a contaminated site due to Apex Oil's operations before filing for Chapter 11. Critically, the government used the RCRA §7003, 42 U.S.C. §6973(a) to compel Apex Oil Company Inc. (the reorganized entity) to clean up the site. The RCRA does *not* entitle the plaintiff to demand payment instead of cleaning up the site; it only allows the government to sue for an injunction to compel a cleanup. As summarized by Ohlrogge (2020), Apex Oil argued that it could not clean up the site and would have to pay about $150 million to other firms to comply with the EPA cleanup injunction. They stressed that their situation was similar to that in *U.S. v. Whizco, Inc*, where courts decided that such an obligation was ultimately a monetary "claim" and hence dischargeable in bankruptcy.

On July 28, 2008, Chief Judge David R. Herndon of the U.S. District Court for the Southern District of Illinois ordered Apex Oil to clean up the contamination, holding that its environmental obligations were not dischargeable. The court rejected the application of the reasoning in *Whizco* to the RCRA context because, under RCRA, the cleanup obligation does *not* give rise to a right of payment. Apex Oil appealed to the Seventh Circuit, which rejected Apex Oil's argument in August 2009. It held that the obligation to perform a mandatory cleanup injunction under the RCRA was not a claim and hence not discharged in Apex Oil's bankruptcy. The Seventh Circuit further concluded that the fact that it would cost Apex Oil

[4] Most courts did not follow the Sixth Circuit's distinction between money claims and injunctive relief (Seventh Circuit Review, 2010, page 180). Our results hold when excluding firms in the Sixth Circuit (Internet Appendix Tables IC5, ID3, and IE3). In contrast, the Third Circuit tends toward strong nondischargeability (Ohlrogge 2020). Our results continue to hold when we exclude firms in the Third Circuit (see Internet Appendix Tables IC6, ID4, and IE4).

[5] Before the Apex Oil case, federal and state governments unsuccessfully tried using other laws (such as the Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA) and the Surface Mining Control and Reclamation Act (SMCRA) of 1977) to impose environmental liabilities on polluting companies.

money to have the site cleaned up did not make it a "right to payment." Apex Oil appealed the ruling to the Supreme Court. In 2010, the Supreme Court declined to review and let stand the Seventh Circuit decision. The consequence of the Supreme Court's decision not to review *Apex* is that environmental cleanup injunctions brought under RCRA are generally not dischargeable in bankruptcy.

2.2 The impact of the Apex decision

Several observations suggest that the District Court's Apex decision in 2008 was a significant turning point in environmental law that reverberated beyond the Seventh Circuit. First, in deciding that RCRA-related environmental cleanup obligations were not dischargeable in Chapter 11, the District Court offered a litigation strategy and precedent for state and federal authorities to employ outside of the Seventh Circuit. Indeed, the Assistant Attorney General for the Justice Department's Environment and Natural Resources Division, Ronald J. Tenpas, declared the District Court's decision, "a victory for the environment," suggesting that he viewed *Apex* as having national, not simply local, ramifications.[6]

Second, the media extensively covered the decision, and legal and environmental consulting firms quickly alerted their client firms around the country about the ramifications of the District Court's decision.[7] Thus, relevant individuals and institutions nationwide were informed about *Apex* repercussions and could respond accordingly.

---

[6] U.S. Department of Justice, "Court orders Apex Oil Company to perform $150 million environmental cleanup, " press release, July 29, 2008, https://www.justice.gov/archive/opa/pr/2008/July/08-enrd-670.html.

[7] For 2008, see Nick Snow, "Apex Oil to pay for Illinois pollution cleanup," Oil & Gas Journal, August 6, 2008, https://www.ogj.com/refining-processing/article/17267696/apex-oil-to-pay-for-illinois-pollution-cleanup and Amanda Ernst, "Judge Orders Apex Oil To Clean Up Contamination," Law360, July 30, 2008, https://www.law360.com/articles/64332/judge-orders-apex-oil-to-clean-up-contamination. News in 2009 includes Avery Fellow, "Oil Company Stuck With Cleanup, Court Rules," Courthouse News Service, August 27, 2009. https://www.courthousenews.com/oil-company-stuck-with-cleanup-court-rules/.
News released in 2010 include: (i) Seattle Times staff. "Court won't spare Apex from oil spill clean up." The Seattle Times, October 4, 2010. https://www.seattletimes.com/business/court-wont-spare-apex-from-oil-spill-clean-up/.
(ii) Hird, David B. "Supreme Court's Denial of Certiorari in Apex Oil Leaves Standing Seventh Circuit Ruling that Environmental Cleanup Injunctions are Not Dischargeable in Bankruptcy." Weil, Gotshal & Manges LLP. Oct 18, 2010. https://restructuring.weil.com/environmental/supreme-courts-denial-of-certiorari-in-apex-oil-leaves-standing-seventh-circuit-ruling-that-environmental-cleanup-injunctions-are-not-dischargeable-in-bankruptcy/.
(iii) David Bledsoe and Jessica Hamilton, "United States: Supreme Court Lets Stand Seventh Circuit Ruling On Discharging RCRA Cleanup Orders In Bankruptcy," Perkins Coie LLP, October 18, 2010. https://www.mondaq.com/unitedstates/Energy-and-Natural-Resources/113156/Supreme-Court-Lets-Stand-Seventh-Circuit-Ruling-On-Discharging-RCRA-Cleanup-Orders-In-Bankruptcy.

Third, work by lawyers and practitioners indicates that *Apex* (a) shaped the EPA's litigation strategy and court decisions on environmental liabilities beyond the Seventh Circuit[8] and (b) induced market participants nationwide to reduce their expectations that environmental damages associated with RCRA pollutants could ultimately be discharged in bankruptcy (e.g., Fil 2009; Mamis 2009; Rdzanek 2010; Gardner and Pusha III 2014; Light 2019).

We acknowledge that, in a few cases in 2020, courts ruled that specific environmental claims against reorganized debtors were dischargeable under Chapter 11 plans. However, these rulings were based on justifications different from the concept underlying *Apex*. For example, in the Exide Techs. case, the Court judged that because the District's penalties were meant to serve a punitive purpose, the Court ruled that those claims were dischargeable in bankruptcy. As another example, in the Peabody Energy Corp. case, the Court judged this to be a tort claim, not a financial claim, and therefore ruled it be dischargeable. The Apex ruling is different. The Apex decision established that environmental cleanup injunctions brought under RCRA would not generally be dischargeable in bankruptcy.

Consistent with the view that *Apex* shaped national environmental regulatory activities, Figure 1 shows an increase in the frequency of EPA's RCRA evaluation at facilities beyond the Seventh Circuit. Additionally, we show below that the *Apex* decision materially influenced the securities prices of firms with RCRA-covered cleanup obligations outside of the Seventh Circuit.

3. Data

3.1 The TRI

The EPA's Toxic Release Inventory (TRI) database contains facility- and firm-level information on toxic emissions. The EPA requires that facilities in manufacturing industries using TRI-listed chemicals above specified thresholds and employing ten or more full-time equivalent workers report (1) releases of

[8] This is supported by the fact that the Apex Oil ruling is cited by other circuit courts' rulings: In re Peabody Energy Corporation (958 F.3d 717, 8th Cir. 2020) and In re Kaiser Aluminum Corp. (386 Fed.Appx. 201, 3d Cir. 2010). The Apex Oil ruling is also cited by district courts' rulings, including In re Mark IV Industries, Inc. (459 B.R. 173, S.D.N.Y. 2011).

each TRI-listed toxic chemical and (2) pollution prevention activities. The TRI database provides data releases of toxic chemicals (measured in pounds) at the facility-chemical-year level. Thus, a facility may report several chemicals over time, and firms may have multiple facilities in the TRI database. We provide more details on the TRI database in Internet Appendix A1.

We link the TRI database to publicly listed firms in CRSP/Compustat over the 2004-2012 period surrounding the 2008 *Apex* decision. For each TRI facility, we use its parent company name. We use the facility name when the parent company name is missing in the TRI database. Then, we calculate the Levenshtein edit distance scores between these names (parent names or facility names) and public firm names in CRSP/Compustat.[9] We consider the names a match if (1) the Levenshtein edit distance score is less than or equal to 500 and (2) we verify that the names match by reading them. Internet Appendix A2 gives additional details on the matching procedure.

After matching, we have around 120,000 facility-chemical-year observations, covering 5,575 unique facilities owned by 563 unique public firms in our sample.[10] These facility-level observations aggregate to about 4,500 firm-year observations. Concerning the representativeness of our sample, we first note that the proportion of aggregate sales in our sample of firms relative to aggregate sales in the Compustat sample of firms (25%) is about equal to the aggregate market valuation of our firms relative to the aggregate valuation of Compustat firms (23%), suggesting that our sample accounts for a substantial percentage of economic activity as captured by sales and valuations (Internet Appendix Table IA1). Second, our sample covers about 22% of all RCRA-regulated wastes produced by TRI plants (Internet Appendix Table IA2), indicating that we are studying a large proportion of these toxic-emitting facilities. Third, when examining either firm assets or the ratio of market value to sales, the average firm in our sample is not significantly different from average firm in Compustat (Internet Appendix Table IA3).

[9] The Levenshtein edit distance (generalized edit distance) is calculated from the SAS “compged()” function.
[10] We keep firms that release RCRA-regulated toxic chemicals, have complete Compustat data from 2004 to 2012, and are US-based with share codes 10 or 11.

Panel A of Table 1 reports firm-level summary statistics after aggregating each facility's chemicals to the parent firm in each year. Production wastes denote the sum (reported in 1,000 pounds) of chemicals produced by firms' facilities. Since *Apex* only applies to RCRA chemicals, we list RCRA-regulated production wastes separately.[11] These toxic production wastes are either released (to the air, water, or land), recycled, recovered, or treated within facilities.

Panel A shows that about 21% of toxic production wastes were released (i.e., toxic total releases). Air releases, water releases, and land releases account for about 17%, 11%, and 72%, respectively. Thus, non-air toxic releases account for 83% of RCRA toxic releases.

Researchers have expressed concerns that the TRI database is based on firms' self-reported toxic emissions (e.g., De Marchi and Hamilton 2006; Currie et al. 2015; Bellon 2021). We do the following to ameliorate such concerns. First, we focus on non-air toxic emissions. It is more difficult for regulators to verify the accuracy of toxic air emissions because they dissipate, and the nature of the dissipation depends on wind and rain. Nevertheless, the results hold when examining land releases of toxic pollutants. Second, we focus on public firms because they tend to be larger and subject to greater oversight, reducing misreporting. Consistent with this view, Brehm and Hamilton (1996) and Akey and Appel (2021) argue that smaller firms violate EPA rules more frequently than larger firms. Third, in contrast to other research using the TRI data, our study focuses on RCRA-regulated compounds because the Apex ruling only applied to such pollutants. Examining RCRA-regulated compounds helps address measurement concerns because they are generally among the more toxic chemicals covered by the TRI and therefore subject to stricter mandatory reporting requirements and monitoring.

We also note that several studies suggest that the TRI database is not subject to significant measurement errors. In obtaining and surveilling the TRI data, the EPA focuses on ensuring that firms comply with reporting mandates, which is supported by its Office of Enforcement and Compliance

[11] Following Ohlrogge (2020), we use the EPA's Substance Registry Services website to identify RCRA-regulated toxic chemicals (https://ofmpub.epa.gov/sor_internet/registry/substreg/LandingPage.do). Using "RCRA" as a keyword, we find the RCRA chemical lists and corresponding Chemical Abstract Service (CAS) compound IDs. Using these IDs, we retrieve RCRA-regulated toxic releases in the TRI database. See Internet Appendix A3.

Assurance (OECA) (Xu and Kim 2021). The TRI Program supports facilities in submitting high-quality TRI data, offering reporting software with data quality alerts, online training, a hotline for questions, and assistance through the data quality call process. They also created the "GuideME" tool, consolidating all TRI guidance materials. Industry trade associations and facilities often rely on their own guidance documents and site-specific emission factors to ensure compliance and enhance the accuracy of TRI data.[12] Also, the EPA does not use TRI data to levy penalties, reducing incentives for firms to underreport emissions (Greenstone 2003). Indeed, Bui and Mayer (2003) argue that the significance of material, systematic measurement errors in the TRI data is minimal.

A second concern with the TRI database is that the EPA changed industry and chemical coverage or reported thresholds, as discussed in Currie et al. (2015) and the EPA (2019). This concern is less relevant for our sample period because the EPA made few changes during the 2004-2012 period. The EPA did not change industry coverage and changed only 17 chemicals covered by the TRI out of 690.[13] We did the following to address remaining concerns about chemical coverage and reported thresholds. First, we condition on chemical-year fixed effects. Second, we show that the results are robust to (i) filling in zeros for missing RCRA chemicals or (ii) restricting the sample to facility-chemical observations in which a facility reports the chemical in all sample years.

3.2 Firm characteristics and default probabilities

Panel A of Table 1 also provides summary statistics on several other firm characteristics used in our analyses. These traits include *Ln(Total Interest Rate)* (the natural logarithm of 10,000 times total interest payments divided by total liabilities), *Ln(Loan Spread)* (the natural logarithm of the difference between the firms' interest rate on bank loans and the LIBOR times 10,000), *Bond Ratings* (based on data from Standard and Poor's, Moody's, and Fitch), *R&D Intensity* (research and development expenditures divided by total assets), *CAPX/AT* (capital expenditure divided by total assets), *XAD/AT* (advertising expenditures divided

[12] See https://www.epa.gov/toxics-release-inventory-tri-program/tri-data-quality.
[13] See https://19january2017snapshot.epa.gov/toxics-release-inventory-tri-program/tri-listed-chemicals_.html

by total assets), *ROA* (net income divided by total assets), *Leverage* (total debt divided by stockholder equity), *Tangibility* (the book value of property, plant, and equipment divided by total assets), *Tobin's Q* (total assets plus the market value of equity minus book value of equity divided by book value of total assets), *Ln(AT)* (the natural logarithm of the book value of total assets), *Labor/Capital* (the number of employees divided by the book value of property, plant, and equipment), and *Firm Age*. We collect the bank loan data and bond ratings from the DealScan and WRDS Bond Returns databases, respectively. Appendix A provides more detailed variable definitions.

Panels A1 and A2 of Internet Appendix Table IA4 provide summary statistics for the subsamples of high and low default probability firms, respectively. To compute the default probability of each parent firm in 2007, we use the methodology developed by Campbell et al. (2008), which uses a reduced-form econometric model to predict corporate failures. We then define the "High Default Probability" sample consisting of facilities belonging to parent firms with default probabilities above their corresponding industry medians and the "Low Default Probability" sample consisting of facilities belonging to parent firms with default probabilities equal to or below the medians of their respective industries.[14] As shown in Table IA4 in the Internet Appendix, the High and Low Default Probability firms have different characteristics. According to Roberts and Whited (2003) and Yagan (2015), having control and treated groups that are observationally equivalent prior to treatment is not essential for identification in a difference-in-differences analysis. Thus, we include various control variables in our analyses of the impact of *Apex* to mitigate the impact of other firm characteristics.

[14] The "High Default Probability" sample exhibits an average probability of failure that is seven times greater than that of the "Low Default Probability" sample. To further address concerns that the results are driven by firms with medium default probabilities, we also define the "High Default Probability" sample as those firms with default probabilities exceeding the 70th percentile of default probabilities in our sample and the "Low Default Probability" sample as firms with default probabilities equal to or below the 30th percentile of default probabilities in our sample. The results hold and are unreported but they available on request.

4. A Nationwide Effect of *Apex*

This section investigates whether *Apex* affected firms outside of the Seventh Circuit. As explained in Section 2, there are reasons for suspecting that *Apex* had far-reaching effects. First, *Apex* established a precedent for courts other than the Seventh Circuit by determining that RCRA-related environmental clean-up obligations were not dischargeable in Chapter 11. Second, it offered a litigation strategy that could be exploited nationwide. Third, the likely national ramifications of *Apex* were widely disseminated through the media and legal and environmental consulting firms so that companies across the country with RCRA-related cleanup obligations—and investors in those firms—had the information to respond (e.g., Hird 2010; Bledsoe and Hamilton 2010). Finally, as an indication that *Apex* shaped environmental regulations beyond the Seventh Circuit, the EPA altered its litigation and evaluation strategies following *Apex*.

To assess the potential nationwide impact of *Apex*, we examine bond and stock price reactions to *Ape*x across firms within and beyond the Seventh Circuit. Our interpretation of these analyses is based on the following perspective. Suppose the *Apex* decision induced market participants to revise their beliefs about the dischargeability of RCRA-related environmental obligations in Chapter 11. We would expect declines in securities prices among firms with RCRA-related obligations near bankruptcy because those liabilities would no longer be dischargeable in Chapter 11. Moreover, if financial market participants expected *Apex* to alter the legal treatment of environmental obligations of firms nationwide, then we would expect *Apex* to have adverse effects on the securities prices of financially stressed firms with RCRA-related obligations outside of the Seventh Circuit. Thus, we examine the cumulative abnormal returns (CARs) of bonds and stocks for firms within and outside of the Seventh Circuit around the District Court decision, July 28, 2008.

4.1 Bond price reactions

We investigate the impact of *Apex* on the monthly CARs of bonds around the July 2008 District Court decision.[15] When analyzing bonds, we use monthly CARs because the corporate bond market is

[15] We also examine the event time using the Circuit Court Decision in August 2009 and the Supreme Court Decision

illiquid relative to the stock market (and we use daily CARs when examining stock price reactions to *Apex*). Internet Appendix B1 shows how we construct bond CARs by using Dickerson, Mueller, and Robotti (2023) bond factors. Following Bongaerts, de Jong, and Driessen (2017), Cornaggia, Hund, and Nguyen (2022), and Chen, Wu, and Yeh (2022), we also use the repeat-sales method for imputing bond returns to address the illiquidity concern.

We split the sample into high and low default probability firms measured before the Apex decision. We make this distinction because a crucial implication of the *Apex*-creditor view is that *Apex* should primarily affect firms closer to Chapter 11 with RCRA-related environmental obligations. As noted above, we use the methodology developed by Campbell et al. (2008) to compute the default probability of each firm in June 2008 (i.e., in the month before *Apex*) and then categorize firms as "High" or "Low" default probability firms based on whether their default probabilities are above or below (or equal to) the corresponding industry medians.

We also differentiate between heavy RCRA polluters and non-heavy RCRA polluters because *Apex* only applies to RCRA-related environmental damages. Therefore, *Apex* will likely have a larger influence on heavy RCRA polluters since the expected value of future injunctions to address environmental obligations will be greater among heavy RCRA polluters than those with minor toxic releases. We follow the literature in (1) using a firm's recent TRI production wastes to approximate its adverse environmental impact and potential environmental cleanup obligations in bankruptcy (e.g., Li and Zhou, 2017; Li, Wu, and Zhu 2021; Hsu, Li, and Tsou 2023) and (2) defining our treated group as firms polluting relatively more than their industry peers (Berrone et al. 2013). Thus, we classify firms as heavy RCRA polluters if they have total RCRA production wastes during the pre-*Apex* period greater than their industry (SIC 2-digital code) medians. We classify other firms as non-heavy RCRA polluters.

As explained in Section 3.1, our sample comprises 563 firms based on the intersection of the Compustat and TRI databases. During the period surrounding the Apex decision, 236 of these firms had

in October 2010, as shown in Internet Appendix Table IB3. The results suggest that the market did not react to the *Apex* for these alternative event times.

listed corporate bonds, which constitutes the sample of the bond CAR analyses. Table 1 Panel B reports the summary statistics of bond CARs separately for the entire sample. Panels B1 and B2 of Internet Appendix Table IA4 present summary statistics for the high- and low-default probability subsamples of firms.

We estimate the following cross-sectional regression for subsamples of High- and Low-Default Probability firms to analyze the impact of *Apex* on CARs:

$$\begin{aligned} \mathrm{CAR}_i = \alpha + \beta Heavy\ RCRA\ Polluters_i \\ +\gamma_1 Heavy\ RCRA\ Polluters_i \times Circuit\ Court_i \\ +\gamma_2 Circuit\ Court_i + \delta_1 I_d + \varepsilon_i, \end{aligned} \tag{1}$$

where i indexes firms and d indexes industries. The dependent variable, CAR_i, represents the CAR of each firm's bond(s) from one before until one month after the District Court decision. $Heavy\ RCRA\ Polluters_i$ equals one if firm *i*'s total RCRA production wastes were larger than the industry (SIC 2-digital code) median during the pre-*Apex* (2003-2007) period and zero otherwise.[16] The coefficient, β, estimates the average CAR of heavy RCRA polluters in response to *Apex*, without considering firm location. The coefficient γ_1 provides information on whether the CARs of heavy RCRA polluters in specific circuit courts respond differently to *Apex*. We also include industry fixed effects (I_d) to control for time-invariant industry traits. We use robust standard errors as our CAR sample is a cross-section of firms (Akey and Appel, 2021).

$Circuit\ Court_i$ is composed of three indicator variables, *Seventh Cir.*, *Sixth Cir.*, and *Third Cir.*, for the Seventh, the Sixth, and the Third Circuits, respectively. *Seventh Cir.* equals one if firm *i* is in the Seventh Circuit court's jurisdiction and zero otherwise. *Sixth Cir.* and *Third Cir* are defined analogously. Firms, operating across various circuit court jurisdictions generally initiate bankruptcy filings in the jurisdiction of their primary operations (Cole, 2002). To allocate firms to specific jurisdictions, we adopt the following approach. We assign firm *i* to the Seventh, Sixth, or Third Circuit jurisdiction if 70% or more of its total production wastes during the pre-*Apex* period (2003-2007) are in that jurisdiction.[17] That is, for firm *i*, we set *Seventh Cir.* equal to one if 70% or more of its wastes are produced in the Seventh Circuit's geographic

[16] This simple sum-up (total production wastes) is common in the literature (Hsu, Li, and Tsou 2023).
[17] Our results hold when setting the pollution concentration ratio to 80%, as shown in Internet Appendix Table IB1.

boundaries, with *Sixth Cir.* and *Third Cir.* similarly defined. We set *Seventh Cir.*, *Sixth Cir.*, and *Third Cir.* equal to zero for firm *i* if its total production wastes are not concentrated in these Circuit Court jurisdictions. Table 1 Panel B shows that 7% of firms are located in the Seventh Circuit, 7% in the Sixth Circuit, and 3% in the Third Circuit. We focus on these three circuit courts because (i) the Apex ruling was in the Seventh Circuit; (ii) in deciding *U.S. v. Whizco, Inc*. (1988), the Sixth Circuit Court communicated its view that if a cleanup order implied spending money, the environmental obligation was a claim and dischargeable; and (iii) the Third Circuit revealed a tendency towards nondischargeability in previous cases, as discussed in Ohlrogge (2020).

Table 2 presents the results from estimating Equation (1) for High- and Low-Default Probability firms, yielding two crucial findings. First, there is a sharp reduction in CARs among High-Default Probability firms that are $Heavy\ RCRA\ Polluters_i$. Consistent with the view that *Apex* induced bond markets to reassess the value of claims against firms close to bankruptcy with large RCRA-cleanup obligations downwards, bond CARs fall significantly among these firms but not among other firms. As reported at the bottom of Table 2, we find a statistically significant difference between the impact of *Apex* on $Heavy\ RCRA\ Polluters_i$ in the high and low default probability subsamples using Fisher's permutation test (Cleary 1999; Efron and Tibshirani 1993). The Table 2 estimates indicate that CARs fall by about 2% among Heavy RCRA Polluters with high default probabilities, consistent with *Apex* triggering a reevaluation of loss given default (LGD), which can lead to a major revision of bond prices. Alternatively, firms exhibiting low default probabilities show no response to *Apex*.[18]

Second, the evidence is consistent with the view that *Apex* had nationwide effects; the effects were not limited to the Seventh Circuit. The estimated coefficients on *Heavy RCRA Polluters* × *Seventh Cir., Heavy RCRA Polluters* × *Sixth Cir.,* and *Heavy RCRA Polluters* × *Third Cir.* enter insignificantly. The

[18] We acknowledge that firms can inherit environmental liabilities and hence bankruptcy risk from parent companies. For instance, in 2009, the chemical company Tronox filed for Chapter 11 bankruptcy due to substantial environmental liabilities inherited from its former parent company, Kerr McGee. However, our bond market analyses suggest that such scenarios are isolated and not empirically important.

results do not reject the hypothesis that *Apex* had the same effect on bond CARs across jurisdictions and reveal that the location of the firm does not significantly influence our results.

4.2 Stock market reactions

We also examine stock price reactions to *Apex*. The stock prices of firms with RCRA-environmental obligations near bankruptcy could drop after *Apex* for several interrelated reasons. First, the share prices of firms may mirror the environmental liabilities associated with them (Barth and McNichols, 1994) and negatively react to environmental disasters (Capelle-Blancard and Laguna, 2010). Since pollution liabilities cannot be discharged during bankruptcy due to *Apex*, and meanwhile, creditors demand pollution reduction; all these factors adversely affect firms' cash flows, impacting profits. Second, anticipated costs related to addressing environmental obligations, no longer dischargeable in Chapter 11, and the expected increase in interest rate expenses as creditors re-evaluate the value of these firms post-*Apex*, will elevate firms' operating risk and cost of capital. Shareholders will thus subsequently seek a higher required return on equity, leading to a reduction in current stock prices. Third, the *Apex* case draws market attention to pollution liabilities, discouraging potential investors from investing in polluting firms.

We also examine the reactions of stock prices to *Apex*. *Apex* could trigger a reduction in the stock prices of firms with RCRA-environmental obligations near bankruptcy for several interrelated reasons. First, since RCRA-environmental obligations were no longer dischargeable in bankruptcy after *Apex*, fewer resources would remain for shareholders in the case of bankruptcy, reducing the expected present value of such firms to shareholders. Second, the *Apex* decision meant fewer resources would be available to settle the claims of debtholders of firms with RCRA-environmental obligations in bankruptcy. As a result, creditors of such firms might demand higher interest rates after *Apex* to compensate for the lower expected payout if the firm enters bankruptcy, putting downward pressure on stock prices. Third, the *Apex* case highlighted the importance of RCRA-environmental obligations to investors, potentially discouraging investors from investing in firms with such liabilities with adverse effects on stock prices.

When examining stock prices, we consider an event window (-5,5) from five days before until five days after the July 28, 2008, District Court decision. We use a shorter event window in our stock price analyses because stock markets are more liquid, so stock prices will likely reflect market news, including the Apex decision, more immediately than bond prices. As explained in Section 3.1, our sample includes 563 firms.

To compute the CARs (-5,5) of firms during the event window surrounding the District Court decision, we use the Fama-French-Carhart four-factor model. We estimate the four-factor stock return model using data from 250 to 50 days before July 28, 2008. Based on the resulting parameter estimates, we compute each stock's predicted excess returns (in excess of the monthly T-bill rate) from five days before until five days after the Apex decision. We compute the CAR of each stock as the difference between actual and predicted excess returns (including alphas) for the event window. Finally, we estimate Equation (1) using the CARs from stock prices following the same strategy used in the Table 2 bond analyses.

As shown in Table 3, there are two key results: (1) the CARs on the stocks of heavy-RCRA polluters close to bankruptcy fall significantly in the days following *Apex,* and (2) the CARs of these firms fall nationwide, not just among such firms in the jurisdiction of the Seven Circuit, suggesting that *Apex* had immediate and far-ranging effects on securities prices. The estimates in column (1) indicate that the abnormal stock returns of heavy RCRA polluters with high-default probabilities decrease by 3% after the *Apex* relative to other firms. However, we do not observe any change in the CARs of heavy polluters with low default probabilities. Moreover, we find no heterogeneous *Apex* effects across different specific circuit courts, as the coefficients of *Heavy RCRA Polluters* × *Seventh Cir., Heavy RCRA Polluters* × *Sixth Cir.,* and *Heavy RCRA Polluters* × *Third Cir.* are all insignificant. These results indicate that the adverse impact of *Apex* on heavy-RCRA polluters close to bankruptcy does not differ significantly across jurisdictions. The results of bond and stock price reactions suggest that *Apex* had a nationwide impact on securities prices.[19]

[19] The results are robust at an 80% pollution concentration ratio (Internet Appendix Table IB2).

5. Firms' Interest Rates, Loan Spreads, and Bond Ratings

This section evaluates creditors' responses to *Apex*, which eliminated the dischargeability of RCRA-related environmental cleanup obligations in Chapter 11. The *Apex*-creditor view holds that *Apex* will adversely affect the creditors of firms *close* to Chapter 11 with RCRA-related cleanup obligations because the expected value of their claims against the firm will be lower in bankruptcy after *Apex*. To evaluate the impact of *Apex* on creditors, we study how firms' interest rates, loan spreads, and bond ratings responded to the Apex ruling. Similar to Section 2, we divide the yearly panel into two groups based on firms' failure probabilities (Campbell et al. 2008) in 2007, a year before *Apex*.[20] The results are also robust to using an event-based measures of proximity to bankruptcy: credit downgrades.[21] We then also classify firms as either heavy or non-heavy RCRA polluters.[22] This enables us to examine whether the *Apex* primarily impacted the creditors of RCRA-polluting firms on the brink of bankruptcy.

5.1 Total interest rate

We begin by examining the relationship between *Ape*x and firms' total interest rates, (e.g., Ivanov, Kruttli, and Watugala 2022). Suppose credit markets determine that *Apex* increased the risks associated with lending to heavy RCRA polluters with high default probabilities. In that case, *Apex* should trigger an increase in interest rates for such firms. To assess this view, we estimate the following difference-in-differences regression using a firm-year panel of firms with high default probabilities:[23]

$$\ln\left(Total\ interest\ rate_{it}\right) = \alpha + \beta\left(Apex_t \times Heavy\ RCRA\ Polluters_i\right)$$

---

[20] The results hold when using Merton's (1974) distance to default model to measure firms' default probabilities, as shown in Internet Appendix Table IC1.

[21] We categorize the sample based on their credit rating, using the S&P Domestic Long Term Issuer Credit Rating, which ranges from AAA to D. A firm is classified as a Credit Downgrade firm if it undergoes a credit rating downgrade between the years 2004 and 2008; otherwise, it is labeled as a Credit Non-Downgrade firm. The findings are presented in Internet Appendix Table IC2.

[22] We conducted a robustness test in which we categorized "heavy" RCRA polluters from 1 to 3 using tercile ranks of RCRA production wastes in their industry. The results hold for total interest rates and bank loan spreads but are unreported due to space limitation.

[23] The results reported using these split sample DID regression hold when using a triple-difference model, as shown in Internet Appendix Table IC3. We also find consistent results when (a) excluding firms in the Seventh Circuit (Internet Appendix Table IC4); (b) excluding firms in the Sixth Circuit (Internet Appendix Table IC5); and (c) excluding firms in the Third Circuit (Internet Appendix Table IC6).

$$+\gamma Control_{it} + \delta_1 I_i + \delta_2 I_t + \varepsilon_{it}, \quad (2)$$

where i indexes firms and t represents years. The dependent variable, $\ln(Total\ interest\ rate_{it})$, equals the natural logarithm of 10,000 times total interest expenses divided by total liabilities for firm *i* in year *t*.[24] $Apex_t$ equals one after the 2008 Apex District court decision, i.e., from 2009 onward, and zero before 2009.[25] $Heavy\ RCRA\ Polluters_i$ equals one if firm *i*'s total RCRA production wastes were larger than the industry (SIC 2-digital code) median during the pre-Apex (2003-2007) period and zero otherwise. The coefficient of interest, β, represents the difference-in-differences estimate of how the total interest rates of heavy RCRA polluters differentially respond to *Apex*. $Control_{it}$ denotes the extensive list of control variables defined above and in Appendix A: *R&D Intensity*, *CAPX/AT*, *XAD/AT*, *ROA*, *Leverage*, *Tangibility*, *Tobin's Q*, *Ln(AT)*, *Labor/Capital*, and *Firm Age*. Table 1 Panel A provides summary statistics. We include firm fixed effects (I_i) to control for time-invariant firm traits and year-fixed effects (I_t) to control for common time-varying influences. In robustness checks, we show that the results hold when including state-year fixed effects.[26] We report standard errors clustered at the firm level.

Consistent with the *Apex*-creditor view, total interest rates of heavy RCRA polluters rose significantly more than non-heavy RCRA polluters after *Apex* among high default probability firms but not among firms with low default probabilities. As shown in columns (1) to (4) of Table 4, these results hold when excluding or including the full array controls. When we compare the estimated coefficients on $Apex_t \times Heavy\ RCRA\ Polluters_i$ in the high and low default probability subsamples using Fisher's permutation test, the difference is statistically significant (as shown at the bottom of Table 4).

Taking the estimates from column (3) based on only firms with high default probabilities, the total interest rate of heavy RCRA polluters rose by 27.7% more following *Apex* than otherwise similar firms that

---

[24] The results hold when using either Ln(*1+Total interest rate*), total interest rate, or Ln(*the total amount of interest expenses*) as the dependent variable (Internet Appendix Table IC7).
[25] As shown in Internet Appendix Table IC8, the results hold when using the Seventh Circuit's rejection of the appeal in 2009 as the event date and setting Apex equal to one after 2009.
[26] The construction of the historical firm headquarters' state is derived from SEC 10K/Q filings, as provided by Gao, Leung, and Qiu (2020). Our results hold after controlling for any time-varying, state-level confounding factors in Internet Appendix Table IC9.

were not heavy RCRA polluters. This estimate implies that, when we focus on firms with high default probabilities, an average heavy RCRA polluter pays, on average, \$54 million more in annual interest payments than an average non-heavy RCRA polluter after the ruling than before.[27] Our results suggest that financial markets distinguish the impact of *Apex* across firms and raise interest rates for relevant firms, heavy RCRA polluters subject to greater bankruptcy risk.

The causal interpretation of the difference-in-differences approach relies on the assumption of parallel trends, which requires that the relative pollution outcomes of heavy and non-heavy RCRA polluters in the high default probability subsample would not have changed in the absence of *Apex*. To test the parallel trends assumption, we examine the estimated difference in total interest rates between heavy and non-heavy RCRA-polluting firms in each year among high-default probability firms. In particular, we estimate the following regressions for high-default probability firms:

$$\ln\,(Total\ interest\ rate_{it}) = \alpha + \sum_{t=2005}^{2012} \beta_t (I_t \times Heavy\ RCRA\ Polluters_i)$$

$$+\gamma Control_{it} + \delta_1 I_i + \delta_2 I_t + \varepsilon_{it}, \qquad (3)$$

where I_t denotes an indicator variable for year *t* (except the base year of 2004). The conditioning variables, *Control*, are the same as those in Equation (2).

Figure 2 plots the point estimates for the coefficients on $I_t \times Heavy\ RCRA\ Polluters_i$ and their 90% confidence intervals for each year relative to the base year of 2004. Panels A and B provide the results while excluding and including *Control*. The results are consistent with the parallel trends assumption. The difference in interest rates between heavy and non-heavy RCRA polluters is insignificantly different from zero before *Apex* and does not exhibit a significant trend. After the ruling, the difference in interest rates between heavy and non-heavy RCRA polluters increases appreciably: Heavy RCRA polluters' interest rates rise significantly relative to non-heavy RCRA polluters and remain high.

[27] Since column (3) is estimated using only firms with high default probabilities, we calculate average pre-*Apex* interest payments by multiplying the average total interest rate (310 basis points) by the average total liabilities (\$6.3 billion) in 2007 in our high default probability subsample. The average interest payment among all firms with high default probabilities before Apex was \$195 million.

We employ the synthetic difference-in-differences (SDID) method of Arkhangelsky et al. (2021) as a robust check, using the Equation (2) specification. This approach integrates difference-in-differences and synthetic control methods, reweighting and matching pre-exposure trends to mitigate dependence on parallel trend assumptions. The results hold, and we obtain similar coefficients and significance levels as shown in columns (1) and (3) of Table IC10 in the Internet Appendix for interest rates. More importantly, Figure IC1 in the Internet Appendix shows that the parallel trend assumption still holds.

We then conduct the following placebo test to assess further *Apex*'s impact on interest rates. For the subsample of *High Default Probability* firms, we estimate regressions (1) and (3) in Table 4 using 1,000 simulations for each regression. In each simulation, we randomly assign the *Heavy RCRA Polluters* designation across firms (*Heavy RCRA Polluters (Placebo)*) rather than using the estimate based on our actual measure of *Heavy RCRA Polluters*. We collect each simulation's estimated parameter on *Apex* × *Heavy RCRA Polluters (Placebo)*. We then plot the kernel density distribution of the estimated parameters on *Apex* × *Heavy RCRA Polluters (Placebo)* and the corresponding p-values. We find that the simulated βs are very close to zero, and the "true" β from our non-random designation of heavy RCRA polluters based on RCRA emissions is on the very right tail of the figure (unreported but available upon request). The results from the placebo test suggest that our findings are unlikely to be driven by random variation in the heavy RCRA polluter designation.

5.2 Bank loan spreads

As a second test of the impact of *Apex* on creditors, we study bank loan spreads. Bank loan spreads reflect banks' perception of the likelihood of default and loss given default (LGD) (Saunders and Allen 2010; James and Kizilaslan 2014). Banks who perceive higher expected LGD raise loan spreads and increase expected borrowing costs. Thus, after *Apex*, banks will likely expect greater LGD among heavy RCRA polluters, increasing bank loan spreads to such borrowers. To test this argument, we use DealScan's bank loan spread database. A firm's bank loan spread equals the number of basis points above LIBOR that banks charge the firm on loans in a year. We aggregate bank loans into firm-year observations by weighting each loan granted to a firm in a year by loan size. We use the Equation (2) regression framework, where the dependent variable is now the logarithm of the firm's bank loan spread.[28]

Consistent with the findings on total interest rates, Table 4 indicates that loan spreads on heavy RCRA polluters rose appreciably relative to loan spreads on non-heavy RCRA polluters after *Apex* among high default probability firms but not among low default probability firms.[29] The estimated coefficient on $Apex_t \times Heavy\ RCRA\ Polluters_i$ is positive and significantly different from zero when excluding or including the control variables, as shown in columns (5) and (7) respectively. In contrast, the estimated coefficient on $Apex_t \times Heavy\ RCRA\ Polluters_i$ enters insignificantly among low default probability firms. We also compare the estimated coefficient on $Apex_t \times Heavy\ RCRA\ Polluters_i$ across the two subsamples using Fisher's permutation test and find that the difference is statistically significant (as shown at the bottom of Table 4). The results indicate that heavy RCRA polluters' loan spreads increase significantly relative to loan spreads on non-heavy RCRA polluters after *Apex* among high default probability firms but not in the low default probability subsample. These results suggest that banks identified which firms *Apex* would impact the most and increased loan spreads accordingly.

Taking the estimates from column (7) based on only firms with high default probabilities, the bank loan spreads of heavy-RCRA polluters rise by 25.43% more following *Apex* than otherwise similar firms that were not heavy-RCRA polluters. This estimate implies that, when we focus on firms with high default probabilities, an average heavy RCRA polluter pays, on average, \$3.03 million more per year on bank loans than an average non-heavy RCRA polluter after the ruling.[30]

---

[28] The results on bank loan spreads are robust to (a) using a triple-difference model, rather than splitting the sample by default probabilities (Internet Appendix Table IC3); (b) excluding firms in the Seventh Circuit (Internet Appendix Table IC4); (c) excluding firms in the Sixth Circuit (Internet Appendix Table IC5); and (d) excluding firms in the Third Circuit (Internet Appendix Table IC6); and (e) using *Ln(1+Loan Spread)* or *Loan Spread* rather than *Ln(Loan Spread)* (Internet Appendix Table IC11)

[29] The results hold when using date of the 2009 Seventh Circuit Court's decision as the event date, i.e., from 2010 onward (Internet Appendix Table IC8).

[30] Since column (7) is estimated using only firms with high default probabilities, we calculate bank loan expenses by multiplying the average bank loan spread (around 118 basis points) by the average total loan amount (around \$1.01 billion) in 2007 in our high default probability subsample. The average bank loan expense among all firms with high default probabilities before *Apex* was \$11.92 million.

To assess the parallel trends assumption, we examine the estimated difference in bank loan spreads between heavy and non-heavy RCRA-polluting firms among high-default probability firms using Equation (3). We plot the estimated coefficients and confidence intervals in Figure 3. Consistent with the parallel trends assumption, the difference in bank loan spreads between heavy and non-heavy RCRA polluters is insignificantly different from zero before *Apex*. It then widens significantly after the 2008 Apex decision.

The findings persist for loan spreads employing the SDID method, as shown in Table IA10 in the Internet Appendix. Columns (5) and (7) display the robust results. Furthermore, Figure IC2 in the Internet Appendix shows that the parallel trend holds when utilizing the method.

We also conduct a placebo test to provide additional information on the impact of *Apex* on bank loan spreads. As described above, we estimate the difference-in-differences regressions for the sample of high default probability firms 1,000 times while randomly assigning the *Heavy RCRA Polluters* designation across firms. We plot the simulated difference-in-differences estimates. The results, when using our actual estimate of *Heavy RCRA Polluters,* are notably different from randomly assigning this designation, with only one stimulated estimate larger than the actual estimate.[31]

5.3 Bond ratings

We also use bond ratings to evaluate the impact of *Apex* on creditors. Suppose credit rating agencies perceive *Apex* as reducing the resources available to the creditors of heavy RCRA polluters in Chapter 11. In that case, the bond ratings of heavy RCRA polluters near bankruptcy will tend to fall after *Apex*. We evaluate this implication of the *Apex*-creditor view by examining monthly bond ratings. Bond rating agencies provide ordered categories of ratings, e.g., AAA, BBB, etc. Consequently, we use an ordered probit estimator while maintaining the difference-in-differences regression structure. We examine the period from March 2008 through January 2009 while dropping July 2008 (the month of the Apex decision).

[31] As a robustness test, we examined a non-price measure of the impact of *Apex* on creditors. We examine loan maturity, calculated as the natural logarithm of the size weighted average of a firm's loan maturities. Loan maturities fell after Apex among heavy RCRA polluters with high default probabilities (Internet Appendix Table IC11).

We collect bond ratings data from the WRDS Bond Returns database. We use Standard and Poor's ratings when available, if not we use Moody's, and if neither of these ratings is available, we use Fitch. We then implement the following for each bond in each month. First, we give a numerical value to each rating category. For example, we assign 1 to a D rating, 5 to a CCC rating, 10 to a BB- rating, 15 to a BBB+ rating, 20 to an AA rating, and 22 to an AAA rating. Second, since many firms have multiple bonds, we calculate the equal-and value-weighted bond ratings for each firm-month. Third, we round that firm-month value to the nearest integer. We implement the ordered probit regressions for the equal- and value-weighted bond ratings based on those ordered ratings. The regressions include firm-level controls from Section 5.1 and monthly dummies. Internet Appendix Table IC13 shows robust results when firm headquarters state-month dummies are included. Similarly, we report standard errors clustered at the firm level.

As shown in Table 5, the results are consistent with the *Apex*-creditor view: Among high default probability firms, the bond ratings of heavy RCRA polluters drop significantly more than non-heavy RCRA polluters after *Apex* (columns (1) and (3)). Also consistent with the *Apex*-creditor view, we find that the coefficient on $Apex_t \times Heavy\ RCRA\ Polluters_i$ enters insignificantly for the sample of low default probability firms, as *Apex* is unlikely to have much of an effect on those firms. As shown, the estimated coefficients on $Apex_t \times Heavy\ RCRA\ Polluters_i$ in the high and low default probability subsamples are significantly different from each other. These results indicate that heavy RCRA polluters' bond ratings fall significantly after *Apex* among high default probability firms near Chapter 11 but not among other firms.

6. Facility-level Analyses

To examine creditors' influence on potential environmental liabilities after *Apex*, we use the TRI database to construct measures for each facility's (1) pollution prevention activities and (2) toxic pollutant emissions. We continue to split the sample between high- and low-default probability firms. We also differentiate facilities between heavy and non-heavy RCRA-polluting facilities. This specification allows us to test a vital implication of the *Apex*-creditor-pollution view: *Apex* should primarily affect the creditors of RCRA-polluting firms near bankruptcy, intensifying the incentives of these creditors to pressure their firms to reduce RCRA pollutants.

6.1 Pollution prevention activities

Facilities that are covered in the TRI database are required to disclose their pollution prevention (P2) practices. Facilities report the extent to which they take actions to prevent pollution by (1) modifying raw material inputs, (2) modifying products and packaging, (3) cleaning and degreasing equipment, (4) adjusting surfaces and finishings, (5) modifying industrial processes and equipment, (6) enhancing spill and leakage prevention practices, (7) improving inventory control and storage, and (8) modifying operational practices and monitoring. For each of these eight pollution prevention categories, facilities select predefined codes (W-codes) to describe the extent of their actions. We use the summation of these codes for each facility in each year (Bellon 2021). Internet Appendix A4 provides more details on the construction of this *Pollution Prevention* measure. This variable, *Pollution Prevention*, is then merged with Compustat and the National Establishment Time-Series (NETS) database (2017 version). The latter provides each facility's number of employees and estimated revenue in every year, which enables us to measure its production scale. We consider a facility-year panel of 21,572 observations from 3,770 unique facilities and 500 unique firms. Panel C of Table 1 reports the summary statistics of these observations. Panels C1 and C2 of Internet Appendix Table IA4 report these summary statistics for the subsamples of high and low default probability firms, respectively.

We estimate the following difference-in-differences Poisson regression:[32]

$$E[Pollution\ Prevention_{it}|\mathcal{X}] = exp(\alpha_0 + \alpha_1 Apex_t \times Heavy\ RCRA\ Polluters_i + \alpha_2 X_{it} + \gamma Facility_i + \delta_1 I_{kt}) \quad (4)$$

[32] The results hold when using Merton's (1974) distance to default to define high and low default probability firms (Internet Appendix Table ID1). The results hold using alternative specifications, including (a) excluding firms in the Seventh Circuit (Internet Appendix Table ID2); (b) excluding firms in the Sixth Circuit (Internet Appendix Table ID3); (c) excluding firms in the Third Circuit (Internet Appendix Table ID4); (c) employing a triple-difference specification rather than splitting the sample between high and low default probability firms (Internet Appendix Table ID5); and (d) clustering standard errors at the firm or state levels (unreported).

where i indexes facilities, k indexes parental company, and t indexes years. The dependent variable $Pollution\ Prevention_{it}$ denotes facility i's pollution prevention activities in year *t*. $Apex_t$ equals one during the years after 2008 and zero otherwise. $Heavy\ RCRA\ Polluters_i$ equals one if facility i's total RCRA production wastes were larger than the industry (NAICS 3-digital code) median during the pre-Apex (2003-2007) period and zero otherwise.[33] X_{it} denotes facility *i*'s control variables (the number of employees in logarithm and the estimated revenue in logarithm) in year *t*. In Equation (4), we also include facility fixed effects ($Facility_i$) to control for time-invariant heterogeneity at the facility level. Furthermore, we add parental company-year fixed effects (I_{kt}) to control for all firm-level characteristics.

We discover that pollution prevention activities increase significantly after *Apex* among heavy RCRA-polluting facilities in firms with comparatively high default probabilities. As shown in Table 6, $Apex_t \times Heavy\ RCRA\ Polluters_i$ enters with a positive and statistically significant coefficient in the specifications without facility-level employees and estimated revenue (column (1)). The estimated coefficient in column (1) for the high default probability subsample suggests that the Apex decision was associated with a 0.5193 increase in the expected log of the number of new pollution prevention activities on average or a 68% increase in engaging in pollution prevention of treated facilities than the control group.[34] For the low default probability subsample (column (2)), $Apex_t \times Heavy\ RCRA\ Polluters_i$ enters with a statistically insignificant coefficient. When comparing the estimated coefficients on $Apex_t \times Heavy\ RCRA\ Polluters_i$ in the two subsamples, the difference is marginally significant, as reported at the bottom of Table 6. The results hold when we add facility-level employees and estimated revenue to regressions to control for production scale, as shown in columns (3) and (4).

[33] In unreported tables, the results hold when (a) we define heavy RCRA polluters are categorized from 1 to 3 based on the lowest tercile to the highest tercile of facility i's RCRA-related production wastes relative to its industry during the pre-Apex period (2003-2007) and (b) we define Heavy RCRA Polluters using a longer period (2000-2007).
[34] We calculate the incidence-rate ratio, which is 1.68 of $Apex_t \times Heavy\ RCRA\ Polluters_i$.

We also check the assumption of parallel trends by examining the following regression to estimate the difference in pollution prevention between heavy and non-heavy RCRA-polluting facilities in each year among high-default probability firms:

$$E[Pollution\ Prevention_{it}|\mathcal{X}] = \ exp\big(\alpha_0 + \textstyle\sum_{t=2005}^{2012} \beta_t (I_t \times Heavy\ RCRA\ Polluters_i) + \alpha_2 X_{it} + \gamma Facility_i + \delta_1 I_{kt}\ \big). \quad (5)$$

where I_t denotes an indicator variable for year *t* (except the base year of 2004).

Figure 4 plots the point estimates for the coefficients on $I_t \times Heavy\ RCRA\ Polluters_i$ and their 90% confidence interval for each year relative to the base year of 2004. Panels A and B provide the results while excluding and including control variables for facility-level production scales. The results are consistent with the parallel trends assumption.

These findings indicate that treated firms engage in more pollution prevention activities after *Apex*, which supports the view that *Apex* increased the costs to creditors of polluting because firms' environmental liabilities were no longer dischargeable in bankruptcy and thus encouraged these creditors to pressure firms to invest more in pollution abatement.

6.2 Toxic emissions

Finally, we examine actual pollution emissions, rather than pollution prevention activities. We use the non-air releases of each RCRA-regulated chemical to measure a facility's pollution. Following Akey and Appel (2021), we consider a facility-chemical-year panel to understand the average effect across all different chemicals. This design allows us to examine the different effects of *Apex* on RCRA-regulated chemicals and other chemicals. Our sample includes 90,830 observations of 4,033 unique facilities and 507 unique firms. Panel D of Table 1 reports the summary statistics on various measures of RCRA-regulated toxic releases. Panels D1 and D2 of Internet Appendix Table IA4 report these summary statistics for the subsamples of high and low default probability firms, respectively.

We estimate the following difference-in-differences regression:[35]

$$ln(Non-air\ Toxic\ Releases_{ict}+1)=\alpha+\beta(Apex_t\times Heavy\ RCRA\ Polluters_i)$$
$$+\gamma Facility_i+\delta_1 I_{ct}+\delta_2 I_{kt}+\varepsilon_{ict}, \qquad (6)$$

where i indexes facilities, c indexes chemicals released in non-air forms, k indexes parental company, and t indexes years. $Non-air\ Toxic\ Releases_{ict}$ denotes the amount of non-air RCRA toxic chemical *c* released by facility i in year t.[36] $Apex_t$ and $Heavy\ RCRA\ Polluters_i$ are defined as in Equation (4).[37] In Equation (6), we also include facility fixed effects ($Facility_i$) to control for time-invariant heterogeneity at the facility level (Greenstone, List, and Syverson 2012). Following Akey and Appel (2021), we add chemical-year fixed effects (I_{ct}) to control for time-varying heterogeneity at the chemical-year level. Adding chemical-year fixed effects allows us to exploit within-chemical-time variation to isolate the impact of the Apex ruling on toxic emissions. This within-chemical-time variation is important because, as Chatterji, Levine, and Toffel (2009) and Di Giuli (2013) mention, researchers lack accepted methods for comparing the environmental impact of each chemical. We cluster standard errors at the facility level to correct for estimation errors related to facility identity.[38]

---

[35] The results hold using alternative specifications, including (a) employing Merton's (1974) distance to default to define high and low default probability firms (Internet Appendix Table IE1); (b) excluding firms in the Seventh Circuit (Internet Appendix Table IE2); (c) excluding firms in the Sixth Circuit (Internet Appendix Table IE3); and (d) excluding firms in the Third Circuit (Internet Appendix Table IE4). Additionally, (e) a triple-difference specification is employed rather than splitting the sample between high and low default probability firms (Internet Appendix Table IE5) and (f) the results hold when we set *Apex* equal to one if it is equal to or larger than 2010 (Internet Appendix Table IE6). We also considered an alternative difference-in-differences setting. We separate the sample into two subsamples, *Heavy RCRA Polluters* and *Light RCRA Polluters*, based on the industry median and define the treatment group as facilities belonging to firms with above the median probability of failure relative to its industry. Consistent with the *Apex*-creditor-pollution view, *Apex* was associated with a drop in RCRA emissions only among high default probability firms in the subsample of heavy RCRA polluters (Internet Appendix Table IE7).

[36] These results hold when using several alternative specifications. Given potential concerns about the dissipation of water pollution, we re-did the analyses using only toxic land releases and the results hold (unreported). We were concerned that nonrandom, noncompliance with TRI reporting mandates around the Apex Oil decision could shape the findings. Thus, we conducted the following two robustness tests. First, we replace a missing value with a zero when (a) a facility reports a missing value for an RCRA toxic chemical release in years t to *t+2* and (b) that same facility reported a non-missing for that chemical in years *t-1* and *t+3*. The results hold (Internet Appendix Table IE8). Second, we limit the sample to facilities that report non-missing values for an RCRA chemical in all years during our sample period. Internet Appendix Table IE9 shows consistent results, reducing concerns that measurement errors associated with changes in compliance around the Apex ruling drive our results.

[37] In unreported tables, we find robust results when (a) heavy RCRA polluters are categorized from 1 to 3 based on the lowest tercile to the highest tercile of facility i's RCRA-related product wastes relative to its industry during the pre-Apex period (2003-2007) and (b) we define *Heavy RCRA Polluters* using a longer period (2000-2007).

[38] The results are robust to clustering at the firm or state level (unreported).

We discover that toxic emissions drop significantly after *Apex* among heavy RCRA-polluting facilities in firms with comparatively high default probabilities. As shown in Table 7, $Apex_t \times Heavy\ RCRA\ Polluters_i$ enters with a negative and statistically significant coefficient in the specifications excluding facility's number of employees and estimated revenue (column (1)). The estimated coefficient in column (1) for the high default probability subsample suggests that the Apex decision was associated with a 37.5% reduction in toxic releases relative to the subsample's mean.[39] For the low default probability subsample (column (2)), $Apex_t \times Heavy\ RCRA\ Polluters_i$ enters with a statistically insignificant coefficient. When comparing the estimated coefficients on $Apex_t \times Heavy\ RCRA\ Polluters_i$ in the two subsamples, the difference is statistically significant, as reported at the bottom of Table 7. The results hold when we control for facilities' production scales, as shown in columns (3) and (4).[40]

We also check the assumption of parallel trends by examining the estimated difference in toxic releases between heavy and non-heavy RCRA-polluting facilities in each year among high-default probability firms by estimating the following regressions:

$$ln(Non-air\ Toxic\ Releases_{ict}+1) = \alpha + \sum_{t=2004}^{2012} \beta_t (I_t \times Heavy\ RCRA\ Polluters_i) + \gamma Facility_i + \delta_1 I_{ct} + \delta_2 I_{kt} + \varepsilon_{ict}, \tag{7}$$

where I_t denotes an indicator variable for year *t* (except the base year of 2004).

Figure 5 plots the estimated coefficients on $I_t \times Heavy\ RCRA\ Polluters_i$ after estimating Equation (7) and the 90% confidence interval for each year relative to the base year of 2004 for high-default probability firms. The results are consistent with the parallel trends assumption because we do not find any

---

[39] Equation (6) can be represented as 1+*Non-air Toxic Releases* = exp(β×*Apex*×*Heavy RCRA Polluters* + *Controls*). When *Apex*×*Heavy RCRA Polluters* = 0, 1+ *Non-air Toxic Releases* = exp(*Controls*); when *Apex*×*Heavy RCRA Polluters* = 1, 1+ *Non-air Toxic Releases* +Δ*Non-air Toxic Releases* = exp(β)×exp(*Controls*). Then, take the difference between the aforementioned two equations: Δ*Non-air Toxic Releases* = exp(*Controls*) [exp(β)-1]. When *Apex*×*Heavy RCRA Polluters* = 0, we assume 1+Mean *Non-air Toxic Releases* = exp(*Controls*). Therefore, *ΔNon-air Toxic Releases* = (1+ Mean *Non-air Toxic Releases*)×[exp(β) – 1]. The Mean of *Non-air Toxic Releases* is 39,990 pounds from Internet Appendix Table IA4 Panel D1.

[40] We use the natural logarithm of one plus toxic releases. However, this transformation alters the initial interpretation of a log-level regression. To ensure that this transformation does not affect the results, we utilize an inverse hyperbolic sine transformation (Burbidge, Magee, and Robb 1988) of the total releases. This transformation is expressed as $f(x) = ln\ (x + \sqrt{1+x^2})$, and our results remain consistent as shown in Internet Appendix Table IE10.

difference in toxic releases between heavy and non-heavy RCRA polluters before *Apex*. After the ruling, the difference in toxic releases between heavy and non-heavy RCRA polluters drops significantly among facilities in high default probability firms.

Furthermore, we were concerned that *Apex* might have reduced pollution by lowering production at a facility rather than by reducing the amount of pollution per output (Greenstone 2002; Akey and Appel 2021). However, we find no evidence that employment or sales fall following the Apex decision among heavy emitters of RCRA-pollutants, as shown in Internet Appendix Table IE11.

The results presented in this section suggest that *Apex* triggered increases in pollution prevention activities and reductions in toxic releases at treated facilities with no change in employment or sales.

7. Addressing Additional Concerns and Explanations

The findings in Sections 4-6 indicate that following the Apex decision, borrowing costs rose, bond ratings fell, pollution prevention activities increased, and toxic emissions diminished among firms that were both comparatively (1) heavy-RCRA emitters and (2) close to bankruptcy. One explanation for these findings is that *Apex* reduced the dischargeability of RCRA-based environmental obligations in Chapter 11 bankruptcy, reducing the value of creditor claims on firms in Chapter 11 with RCRA-related clean-up liabilities. From this perspective, firms that were heavy-RCRA emitters and comparatively close to bankruptcy would experience reductions in bond rating and increases in borrowing costs. Furthermore, the creditors of those firms would have stronger incentives to pressure their firm to reduce RCRA-related emissions after *Apex* because such environmental liabilities were longer dischargeable in bankruptcy. Any alternative to this *Apex* explanation must also account for these findings.

One potential alternative explanation is that a confluence of shocks around the time of the 2008 Apex decision accounts for the findings reported above. We consider three possible confounding issues. First, the election of Obama in 2008 might have signaled a tightening of regulatory oversight of chemical releases, especially releases of the most toxic chemicals, such as those covered by the RCRA. Thus, firms that were heavy emitters of the most toxic chemicals prior to Obama's election might have disproportionately engaged in pollution prevention activities and toxic emissions to avoid potential penalties from more intense environmental supervision. Second and relatedly, authorities enacted and implemented new greenhouse gas laws and regulations around 2008 (e.g., Ivanov, Kruttli, and Watugala 2022) that could impede our ability to identify the independent impact of *Apex* on toxic emissions. Third, the global financial crisis (GFC) of 2008 might have exerted especially pronounced effects on the interest rates and bond ratings of firms closer to bankruptcy. To the extent that heavy RCRA polluters tend to rely more on external financing than other firms, on average, this could help explain the surge in interest rates and bond yields among heavy RCRA-polluting firms close to bankruptcy. Thus, the election of Obama, greenhouse gas regulations, and the GFC might together offer an alternative to the *Apex* explanation of the results reported above.

A key component of the first alternative explanation is that the election of Obama triggered expectations of greater regulatory and supervisory scrutiny of toxic releases, especially emissions of the most toxic chemicals, and RCRA-chemicals are among the most toxic pollutants. If this alternative explanation holds, then we should observe a reduction in the release of highly toxic non-RCRA chemicals following *Apex*. That is, the alternative explanation focuses on the most toxic chemicals in general, not RCRA chemicals in particular. In contrast, the *Apex*-creditor-pollution explanation focuses on RCRA chemicals in particular because they are the only ones covered by *Apex*.

Thus, we first conduct the following falsification test. We consider highly toxic chemicals not covered by RCRA.[41] We obtain the list of such toxic chemicals from the EPA's Integrated Risk Information System (IRIS) which classifies chemicals based on risks to humans (Akey and Appel 2021). IRIS was developed by the EPA to provide toxicological information for use in risk assessments, decision-making, and regulatory actions. From IRIS's list of toxic chemicals, we keep chemicals that adversely affect human systems (e.g., respiratory, nervous, and hepatic), including those leading to cancer and premature death, based on the adverse effects information of IRIS chemicals provided by the EPA.[42] We then test whether

[41] The RCRA does not include all toxic chemicals, as documented in https://www.epa.gov/hw/criteria-definition-solid-waste-and-solid-and-hazardous-waste-exclusions.
[42] The EPA provides detailed information on the adverse effects of IRIS chemicals. Available at: https://iris.epa.gov/AdvancedSearch/.

there is a reduction in the release of non-RCRA, IRIS-covered chemicals among firms close to bankruptcy following *Apex*. Consistent with the *Apex*-creditor-pollution explanation but not the Obama-regulation explanation, we discover that the release of non-RCRA, IRIS-covered chemicals did not drop significantly after *Apex* (unreported but available upon request).

Our findings also shed a skeptical empirical light on the second alternative explanation: that the American Clean Energy and Security Act of 2009 (commonly known as the Waxman-Markey bill), the Regional Greenhouse Gas Initiative (RGGI) in 2009, and the California cap-and-trade program implemented in 2013 drive our results on toxic emissions and securities prices.[43] As stressed, we find that *Apex* had a powerful impact on heavy RCRA-polluters close to bankruptcy in particular, not on heavy polluters in general. However, the Waxman-Markey bill, the RGGI, and the California cap-and-trade program are not RCRA-focused regulatory changes. Furthermore, the Waxman-Markey bill failed to gain approval in the Senate on July 22, 2010. The RGGI and California cap-and-trade program are region-specific regulations and thus unlikely to explain our national-level findings.

Nevertheless, to further reduce concerns that the *Apex* results are driven by greenhouse gas regulations, we directly examine greenhouse gas emissions. Suppose greenhouse gas regulations drive reductions in both greenhouse gas and RCRA-pollutant emissions, and it is the greenhouse gas regulations rather than *Apex* ruling that account for our findings of a strong connection between *Apex* and RCRA-pollutant emissions. In that case, we should also find a strong relationship between *Apex* and declines in greenhouse gas emissions. To assess this explanation, we first collect each facility's estimated greenhouse gas from the National Emissions Inventory (NEI), which is available in 2005 and 2011, and each facility's criteria air pollutants in each corresponding year.[44] We then estimate our facility-level difference-in-

[43] For American Clean Energy and Security Act of 2009, see https://www.congress.gov/bill/111th-congress/house-bill/2454/text. For the California cap-and-trade program implemented in 2013, https://ww2.arb.ca.gov/our-work/programs/cap-and-trade-program. For Regional Greenhouse Gas Initiative (RGGI), see: https://www.rggi.org/

[44] Criteria air pollutants include carbon monoxide (CO), nitrogen oxides (NO_x), volatile organic compounds (VOCs), sulfur dioxide (SO_2), ammonia (NH_3) and particulate matter (PM10 and PM2.5). We sum these pollutants at the facility level. We use the carbon monoxide (CO) data provided by NEI to proxy for greenhouse gas emissions because CO is the product of incomplete combustion from burning fossil fuels and standardized industrial processes usually produce CO and CO_2 in constant proportions. We follow the Vulcan Science Methods Documentation (Gurney et al., 2010)

difference regressions using these two variables as the dependent variable, and find that estimated coefficients on $Apex_t \times Heavy\ Polluters_i$ are insignificant (unreported but available upon request). Results do not support the alternative explanation based on greenhouse gas regulation.

The third test focuses on the possibility that (a) the 2008 global financial crisis (GFC) triggered an especially adverse effect on the interest rates and bond ratings of firms relying on external finance and (b) heavy RCRA polluters tend to rely comparatively more on external financing than other firms. We are skeptical that this GFC explanation accounts for the results above, because it seems unlikely that (a) those firms most affected by the GFC-induced tightening of financial constraints are the ones that disproportionately boost pollution prevention activities and pollution abatement, (b) those pollution control efforts are disproportionately concentrated among heavy RCRA polluters close to bankruptcy, and (c) facility employment and estimated sales remain unaffected (see Internet Appendix Table IE11). Nevertheless, we examine whether controlling for financial constraints alters our findings on how firms' borrowing costs respond to *Apex*.

In particular, to our extensive list of control variables, we now include two financial constraint measures, the WW Index (Whited and Wu 2006) and the SA Index (Hadlock and Pierce 2010). The WW Index is created by using the Euler equation approach from a structural model of investment. The WW model exploits a linear combination of six factors: cash flow, a dividend payer dummy, long-term debt ratio, firm size, industry sales growth, and firm sales growth.[45] The SA Index is created by (a) searching through 10-Ks for keywords indicating the degree to which firms are financially constrained and (b) econometrically linking these text-based findings to observable firm characteristics, e.g., firm size, size-squared, and age, to create the SA financial constraint measure.[46] As shown in Internet Appendix Table

---

which provides CO-to-CO_2 conversion factors for industrial processes to estimate facility-level greenhouse gas emissions. The NEI data is available every three years. We use 2005 and 2011 for our tests.

[45] The WW Index = –0.091×CF – 0.062×DIVPOS + 0.021×TLTD – 0.044×LNTA + 0.102×ISG – 0.035×SG, where CF is the ratio of cash flow to total assets; DIVPOS is an indicator that takes the value of one if the firm pays cash dividends; TLTD is the ratio of the long-term debt to total assets; LNTA is the natural log of total assets; ISG is the firm's three-digit SIC industry sales growth; and SG is the firm's sales growth.

[46] The SA Index = –0.737×Size + 0.043×$Size^2$ – 0.040×Age, where Size equals the natural logarithm of book assets, and Age is the number of years the firm is listed on Compustat.

IC12, the estimated coefficients on $Apex_t \times Heavy\ RCRA\ Polluters_i$ when controlling for either of these measures of firms' financial constraints are almost identical to the findings when excluding these controls. These findings are consistent with the Apex-creditor explanation.

8. Conclusion

The 2008 Apex Oil decision reduced the circumstances under which specific environmental liabilities were dischargeable in Chapter 11. In particular, *Apex* established that RCRA-covered environmental cleanup obligations could no longer be discharged in Chapter 11. Among firms in Chapter 11 with RCRA-covered liabilities, *Apex* left fewer resources to settle creditor claims because corporate resources would first settle these specific environmental obligations. Since *Apex* eliminated the ability of firms to discharge RCRA-related clean-up obligations if they were ever to enter Chapter 11, we examine the impact of *Apex* on firms that are not yet in Chapter 11.

For firms relatively to close to Chapter 11 with significant RCRA-related cleanup obligations, we first show that *Apex* triggered a sharp reduction in bond and stock CARs during the narrow event window surrounding the District Court decision on July 28, 2008. Furthermore, these results hold nationwide, not just among firms in the Seventh Circuit. These findings suggest that financial markets expected *Apex* to shape how courts nationwide would treat the dischargeability of RCRA-related cleanup obligations.

Moreover, we discover that *Ape*x significantly affected firms' borrowing costs, pollution prevention activities, and toxic emissions. Among heavy RCRA-polluters close to Chapter 11, their interest rates rose, bank loan spreads widened, and bond ratings deteriorated. Moreover, we show that these firms also increased their pollution prevention activities and reduced their emissions of RCRA-covered pollutants after *Apex*. However, we find no such changes among firms with low probabilities of entering Chapter 11 or with little or no RCRA-covered environmental damages. The reassignment of environmental liabilities substantially influenced corporate credit conditions and pollution decisions.

References

Acemoglu, D., Aghion, P., Bursztyn, L., & Hemous, D. (2012). The environment and directed technical change. American Economic Review, 102(1), 131-66.

Acemoglu, D., Akcigit, U., Hanley, D., & Kerr, W. (2016). Transition to clean technology. Journal of Political Economy, 124(1), 52-104.

Aghion, P., Dechezleprêtre, A., Hemous, D., Martin, R., & Van Reenen, J. (2016). Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry. Journal of Political Economy, 124(1), 1-51.

Akey, P. and Appel, I., 2021. The limits of limited liability: Evidence from industrial pollution. The Journal of Finance, 76(1), pp.5-55.

Albuquerque, Rui, Yrjo Koskinen, and Chendi Zhang, 2019, Corporate social responsibility and firm risk: Theory and empirical evidence, Management Science 65, 4451–4469.

Arkhangelsky, D., Athey, S., Hirshberg, D.A., Imbens, G.W. and Wager, S., 2021. Synthetic difference-in-differences. *American Economic Review*, *111*(12), pp.4088-4118.

Bansal, Ravi, Dana Kiku, and Marcelo Ochoa, 2016, Price of long-run temperature shifts in capital markets, Technical report, National Bureau of Economic Research.

Bansal, R., Wu, D., & Yaron, A. (2022). Socially responsible investing in good and bad times. The Review of Financial Studies, 35(4), 2067-2099.

Bao, J., Pan, J. and Wang, J., 2011. The illiquidity of corporate bonds. The Journal of Finance, 66(3), pp.911-946.

Barth, M.E. and McNichols, M.F., 1994. Estimation and market valuation of environmental liabilities relating to superfund sites. Journal of Accounting Research, 32, pp.177-209.Baumol, W. J., Oates (1988). The theory of environmental policy. Cambridge University Press.

Bellon, A. 2021. Fresh start or fresh water: The impact of environmental lender liability. Working paper. Available at SSRN 3877378.

Berrone, P., Fosfuri, A., Gelabert, L. and Gomez-Mejia, L.R., 2013. Necessity as the mother of 'green' inventions: Institutional pressures and environmental innovations. *Strategic Management Journal*, *34*(8), pp.891-909.

Bledsoe, D. and J. Hamilton, 2010. United States: Supreme Court lets stand Seventh Circuit ruling on discharging RCRA cleanup orders in bankruptcy. Source: https://www.mondaq.com/unitedstates/oil-gas--electricity/113156/supreme-court-lets-stand-seventh-circuit-ruling-on-discharging-rcra-cleanup-orders-in-bankruptcy

Bohm, P., 2003. Experimental evaluations of policy instruments. In Handbook of environmental economics (Vol. 1, pp. 437-460). Elsevier.

Bolton, P. and Kacperczyk, M., 2021. Do investors care about carbon risk? Journal of Financial Economics, 142(2), pp.517-549.

Boomhower, J., 2019. Drilling like there's no tomorrow: bankruptcy, insurance, and environmental risk. American Economic Review, 109(2), 391-426.

Bongaerts, D., De Jong, F. and Driessen, J., 2017. An asset pricing approach to liquidity effects in corporate bond markets. *The Review of Financial Studies*, *30*(4), pp.1229-1269.

Brehm, J. and Hamilton, J.T., 1996. Noncompliance in environmental reporting: Are violators ignorant, or evasive, of the law? American Journal of Political Science, pp.444-477.

Bui, L.T. and Mayer, C.J., 2003. Regulation and capitalization of environmental amenities: evidence from the toxic release inventory in Massachusetts. Review of Economics and statistics, 85(3), pp.693-708.

Burbidge, J.B., Magee, L. and Robb, A.L., 1988. Alternative transformations to handle extreme values of the dependent variable. *Journal of the American Statistical Association*, *83*(401), pp.123-127.

Campbell, J.Y., Hilscher, J. and Szilagyi, J., 2008. In search of distress risk. The Journal of Finance, 63(6), pp.2899-2939.

Cao, Jie, Sheridan Titman, Xintong Zhan, and Weiming Elaine Zhang, 2019, Esg preference and market efficiency: Evidence from mispricing and institutional trading, SSRN Electronic Journal.

Capelle-Blancard, G. and Laguna, M.A., 2010. How does the stock market respond to chemical disasters?. Journal of Environmental Economics and Management, 59(2), pp.192-205.
Chatterji, A.K., Levine, D.I. and Toffel, M.W., 2009. How well do social ratings actually measure corporate social responsibility? Journal of Economics & Management Strategy, 18(1), pp.125-169.
Chen, Y.T., Wu, C. and Yeh, C.Y., 2022. Asset pricing tests of infrequently traded securities: The case of municipal bonds. *The Review of Asset Pricing Studies*, *12*(3), pp.754-807.
Chen, Yao, Alok Kumar, and Chendi Zhang, 2019, Social sentiment and asset prices, SSRN Electronic Journal.
Cleary, S., 1999. The relationship between firm investment and financial status. The Journal of Finance, 54(2), pp.673-692.
Coase, R. H. 1960. The problem of social cost. Journal of Law and Economics, 3, 1-44.
Cohen, M. A., 1987. Optimal enforcement strategy to prevent oil spills: An application of a principal-agent model with moral hazard. The Journal of Law and Economics, 30(1), 23-51.
Cole, M., 2002. Delaware is not a state: Are we witnessing jurisdictional competition in bankruptcy. Vand. L. Rev., 55, p.1845.
Cornaggia, K., Hund, J., and G. Nguyen, 2022. Investor attention and municipal bond returns. Journal of Financial Markets, 60, 2-27.
Currie, J., Davis, L., Greenstone, M. and Walker, R., 2015. Environmental health risks and housing values: evidence from 1,600 toxic plant openings and closings. American Economic Review, 105(2), pp.678-709.
Dai, R., Liang, H., & Ng, L. (2021). Socially responsible corporate customers. Journal of Financial Economics, 142(2), 598-626.
De Marchi, S. and Hamilton, J.T., 2006. Assessing the accuracy of self-reported data: an evaluation of the toxics release inventory. Journal of Risk and uncertainty, 32(1), pp.57-76.
Dickerson, A., Mueller, P. and Robotti, C., 2023. Priced risk in corporate bonds. Journal of Financial Economics, 150(2), 103707.
Di Giuli, A., 2013. Pollution and firm value. Available at SSRN 2227034.Ding, W., Levine, R., Lin, C. and Xie, W., 2021. Corporate immunity to the COVID-19 pandemic. Journal of Financial Economics, 141(2), pp.802-830.
Dyck, Alexander, Karl V Lins, Lukas Roth, and Hannes F Wagner, 2019, Do institutional investors drive corporate social responsibility? international evidence, Journal of Financial Economics 131, 693–714.
Eckbo, B. E., Thorburn, K. S., and Wang, W., 2016. How costly is corporate bankruptcy for the CEO? Journal of Financial Economics, 121(1), 210-229.
Efron, B. and Tibshirani, R.J., 1993. An introduction to the bootstrap. Monographs on Statistics and Applied Probability, 57, pp. 202.
Environmental Protection Agency, 2013. National Rivers and Streams Assessment 2008–2009: A Collaborative Survey.
Environmental Protection Agency, 2014-2016. TRI National Analysis.
Environmental Protection Agency, 2018. Inventory of U.S. Greenhouse Gas Emissions and Sinks, 1990-2016.
Environmental Protection Agency, 2019. Factors to Consider When Using Toxics Release Inventory Data.
Fil, R., 2009. Resource Conservation and Recovery Act vs. Chapter 11: When Is a “Discharge” Not Discharged? American Bankruptcy Institute Journal, 28(9), p.26.
Flammer, C., 2021. Corporate green bonds. Journal of Financial Economics, 142, pp.499-516.
Fowlie, M., 2010. Emissions trading, electricity restructuring, and investment in pollution abatement. American Economic Review, 100(3), pp.837-69.
Gao, H., Li, K., and Ma, Y., 2021. Stakeholder orientation and the cost of debt: Evidence from state-level adoption of constituency statutes. Journal of Financial and Quantitative Analysis 56(6), pp.1908-1944.
Gao, M. Leung, H. and Qiu, B., 2021. Organization Capital and Executive Performance Incentives. Journal of Banking and Finance, 123, p.106017.

Gardner, R.W. and Pusha III, R., 2014. The west Virginia chemical spill and environmental liabilities in a post-apex world. American Bankruptcy Institute Journal, 33(4), p.38.
Gibson, Rajna, Philipp Krueger, and Shema F Mitali, 2020, The sustainability footprint of institutional investors: ESG driven price pressure and performance, Swiss Finance Institute Research Paper.
Greenstone, M., 2002. The impacts of environmental regulations on industrial activity: Evidence from the 1970 and 1977 clean air act amendments and the census of manufactures. Journal of Political Economy, 110(6), pp.1175-1219.
Greenstone, M., 2003. Estimating regulation-induced substitution: The effect of the Clean Air Act on water and ground pollution. American Economic Review, 93(2), pp.442-448.
Greenstone, M., List, J.A. and Syverson, C., 2012. The effects of environmental regulation on the competitiveness of US manufacturing (No. w18392). National Bureau of Economic Research.
Gurney, K. R., D. L. Mendoza, Y. Zhou, M. L. Fischer, C. C. Miller, S. Geethakumar, and S. de la Rue du Can, 2009, High resolution fossil fuel combustion CO2 emission fluxes for the United States, Environmental Science & Technology 43, 5535-5541.
Hadlock, C.J. and Pierce, J.R., 2010. New evidence on measuring financial constraints: Moving beyond the KZ index. The Review of Financial Studies, 23(5), pp.1909-1940.
Hartzmark, Samuel M, and Abigail B Sussman, 2019, Do investors value sustainability? A natural experiment examining ranking and fund flows, The Journal of Finance 74, 2789–2837.
Hayes, D.W., 2016. Environmental liabilities in § 363 Sales and the Priority of environmental claims. National Conference of Bankruptcy Judges American Bankruptcy Institute Conference Roundtable. https://ncbjmeeting.org/2016/
Hird, D. B., 2010. Supreme court's denial of certiorari in Apex Oil leaves standing seventh circuit ruling that environmental cleanup injunctions are not dischargeable in bankruptcy. Source: https://restructuring.weil.com/environmental/supreme-courts-denial-of-certiorari-in-apex-oil-leaves-standing-seventh-circuit-ruling-that-environmental-cleanup-injunctions-are-not-dischargeable-in-bankruptcy/
Hoepner, A. G., Oikonomou, I., Sautner, Z., Starks, L. T., & Zhou, X. (2018). ESG shareholder engagement and downside risk. Working paper.
Hong, Harrison, and Marcin Kacperczyk, 2009, The price of sin: The effects of social norms on markets, Journal of Financial Economics 93, 15–36.
Hsu, P.H., Li, K. and Tsou, C.Y., 2023. The pollution premium. The Journal of Finance, 78(3), pp.1343-1392.
Huang, S., and A. Kopytov, 2023, Sustainable finance under regulation, Available at SSRN 4231723.
Ivanov, I., Kruttli, M. S., & Watugala, S. W. 2022. Banking on carbon: Corporate lending and cap-and-trade policy. Available at SSRN 3650447.
Jaffe, A.B. and Palmer, K., 1997. Environmental regulation and innovation: a panel data study. Review of Economics and Statistics, 79(4), pp.610-619.
Jaffe, A.B., Peterson, S.R., Portney, P.R. and Stavins, R.N., 1995. Environmental regulation and the competitiveness of US manufacturing: what does the evidence tell us? Journal of Economic Literature, 33(1), pp.132-163.
James, C. and Kizilaslan, A., 2014. Asset specificity, industry-driven recovery risk, and loan pricing. Journal of Financial and Quantitative Analysis, 49(3), pp.599-631.
Jorgenson, D. W., & Wilcoxen, P. J. (1990). Environmental regulation and US economic growth. The Rand Journal of Economics, 314-340.
Kacperczyk, M. T. and Peydro, J., 2021. Carbon emissions and the bank-lending channel. Working paper.
Keller, W. and Levinson, A., 2002. Pollution abatement costs and foreign direct investment inflows to US states. Review of economics and Statistics, 84(4), pp.691-703.
Kolstad, C.D. and Toman, M., 2005. The economics of climate policy. Handbook of environmental economics, 3, pp.1561-1618.
Krüger, P., Sautner, Z. and T Starks, L.T. 2020, The importance of climate risks for institutional investors, Review of Financial Studies 33, 1067–1111.

Landrigan, P.J., Fuller, R., Acosta, N.J., Adeyi, O., Arnold, R., Baldé, A.B., Bertollini, R., Bose-O'Reilly, S., Boufford, J.I., Breysse, P.N. and Chiles, T., 2018. The Lancet Commission on pollution and health. The lancet, 391(10119), pp.462-512.

Landrigan, P.J., Fuller, R., Fisher, S., Suk, W.A., Sly, P., Chiles, T.C. and Bose-O'Reilly, S., 2019. Pollution and children's health. Science of the Total Environment, 650, pp.2389-2394.

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

Li, X. and Zhou, Y.M., 2017. Offshoring pollution while offshoring production? *Strategic Management Journal*, *38*(11), pp.2310-2329.

Light, S.E., 2019. The law of the corporation as environmental law. Stan. L. Rev., 71, p.137.

Magat, W. A., & Viscusi, W. K. (1990). Effectiveness of the EPA's regulatory enforcement: The case of industrial effluent standards. The Journal of Law and Economics, 33(2), 331-360.

Mamis, Rachel, 2009. United States of America v. Apex Oil Company, Inc., 579 F.3d 734, (7th Cir. Aug. 25, 2009). The New York Environmental Lawyer, 29(4), pp.59-60.

Merton, R.C., 1974. On the pricing of corporate debt: The risk structure of interest rates. The Journal of finance, 29(2), pp.449-470.

Ohlrogge, M., 2020. Bankruptcy claim dischargeability and public externalities: Evidence from a natural experiment. Available at SSRN 3273486.

Pástor, Ľ., Stambaugh, R. F., & Taylor, L. A., 2022. Dissecting green returns. Journal of Financial Economics, 146(2), 403-424.

Rdzanek, D.E., 2010. Discharge of RCRA Injunctive Claims in Bankruptcy: The Seventh Circuit's Decision in United States v. Apex Oil Co., Inc. Seventh Circuit Review, 6(1), p.163.

Renneboog, Luc, Jenke Ter Horst, and Chendi Zhang, 2008, The price of ethics and stakeholder governance: The performance of socially responsible mutual funds, Journal of Corporate Finance 14, 302–322.

Riedl, Arno, and Paul Smeets, 2017, Why do investors hold socially responsible mutual funds?, The Journal of Finance 72, 2505–2550.

Roberts, Michael R., and Toni M. Whited, (2013). Chapter 7 - Endogeneity in empirical corporate finance, in George M. Constantinides, Milton Harris, and Rene M. Stulz, eds.: Handbook of the Economics of Finance (Elsevier)

Saunders, A. and Allen, L., 2010. Credit risk management in and out of the financial crisis: new approaches to value at risk and other paradigms (Vol. 528). John Wiley & Sons.

Schwarzenbach, R.P., Egli, T., Hofstetter, T.B., Von Gunten, U. and Wehrli, B., 2010. Global water pollution and human health. Annual review of environment and resources, 35(1), pp.109-136.

Seltzer, L.H., Starks, L. and Zhu, Q., 2022. Climate regulatory risk and corporate bonds. NBER Working Paper 29994.

Shive, S.A. and Forster, M.M., 2020. Corporate governance and pollution externalities of public and private firms. The Review of Financial Studies, 33(3), pp.1296-1330.

Starks, Laura T, Parth Venkat, and Qifei Zhu, 2017, Corporate esg profiles and investor horizons, Available at SSRN 3049943 .

Xu, Q. and Kim, T., 2022. Financial constraints and corporate environmental policies. *The Review of Financial Studies* 35(2), pp.576-635.

Whited, T.M. and Wu, G., 2006. Financial constraints risk. *The review of financial studies*, 19(2), pp.531-559.

Yagan, D., 2015. Capital tax reform and the real economy: The effects of the 2003 dividend tax cut. *American Economic Review*, *105*(12), pp.3531-3563.

Figure 1 RCRA evaluations

This figure shows the yearly count of evaluations conducted by the EPA under the RCRA. The evaluations include both non-self-disclosure and self-disclosure evaluations of facilities in the Seventh Circuit and facilities in Other Circuits. Non-self-disclosure evaluations comprise Compliance Evaluation Inspections (CEI), Financial Record Reviews, Non-Financial Record Reviews, Compliance Assistance Visits, among others. On the other hand, Facility Self-Disclosure evaluations denote instances where a facility has self-reported the existence of a violation and/or performed an audit and subsequently submitted the information to the appropriate authorities at the State or EPA. CEI is the most prevalent evaluation between 2002 and 2014 and accounts for about 50% of evaluations. CEI is an on-site review of a facility's compliance status with all relevant RCRA regulations and permits, aimed at conducting an overall assessment of a site's performance. See: https://echo.epa.gov/system/files/ndv_eval_type_0.pdf and the data could be downloaded from https://echo.epa.gov/files/echodownloads/rcra_downloads.zip.

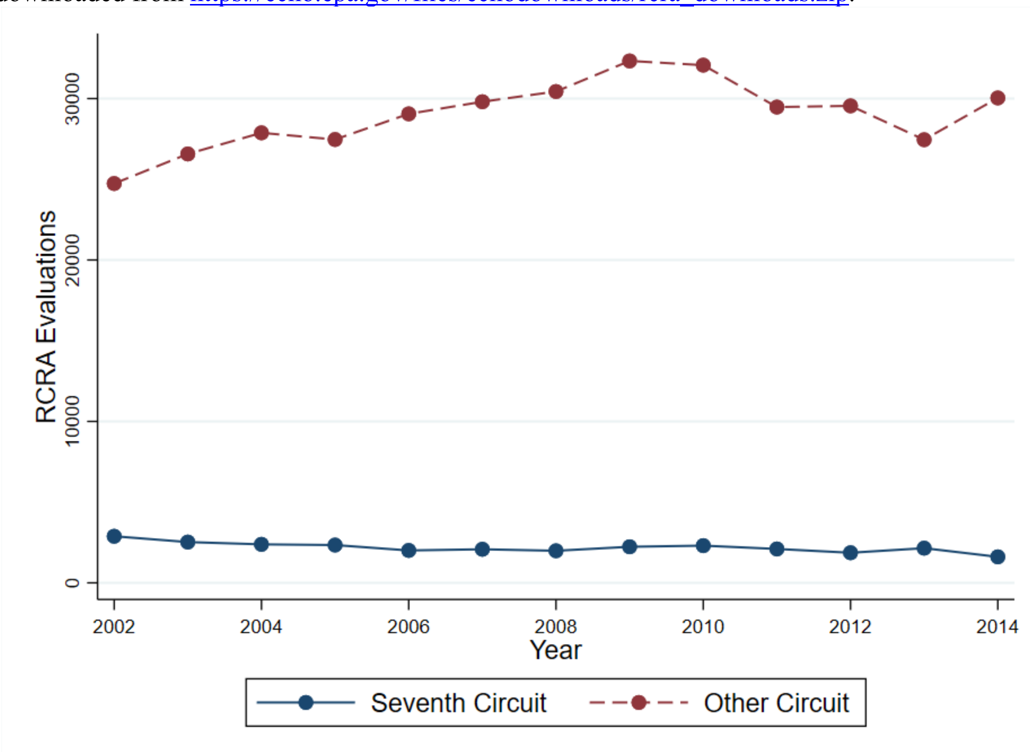
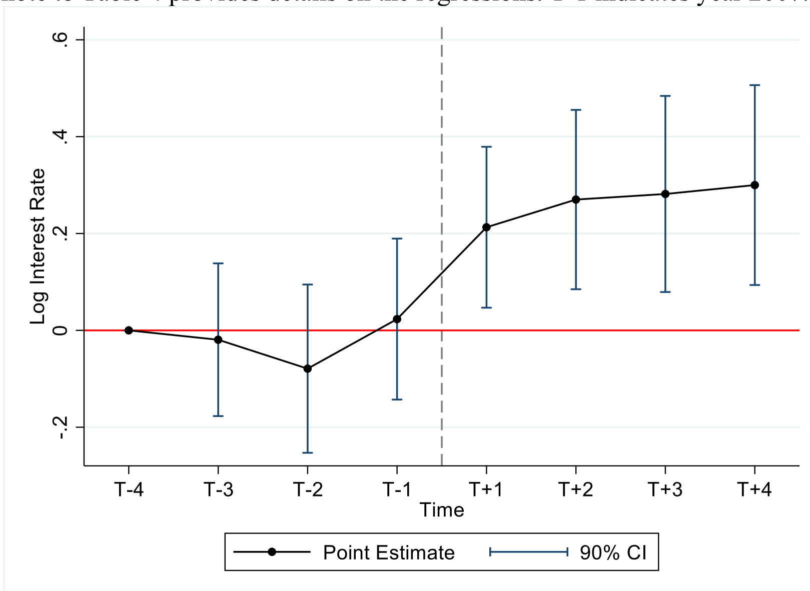


Figure 2 Parallel trend plots of total interest rates

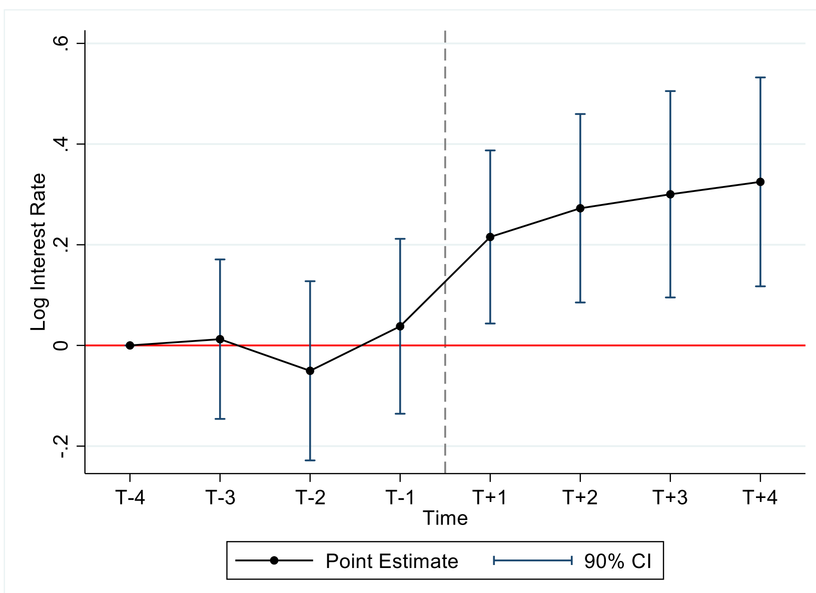
These plots depict the evolving differences in the total interest rates paid by heavy and non-heavy emitters of RCRA pollutants among high default probability firms. We plot the estimated β_t's from the following regression:

$\ln(Total\ interest\ rate_{it}) = \alpha + \sum_{t=2005}^{2012} \beta_t (I_t \times Heavy\ RCRA\ Polluters_i) + \gamma Control_{it} + \delta_1 I_i + \delta_2 I_t + \varepsilon_{it}$.

The two figures use different control variables, with the top figure based on the Table 4 column 1 regression and the bottom figure based on the column 3 specification. Vertical lines in the plots depict 90% confidence intervals for the estimated β_t's. The note to Table 4 provides details on the regressions. T-1 indicates year 2007.



Panel A. Table 4 Column (1)



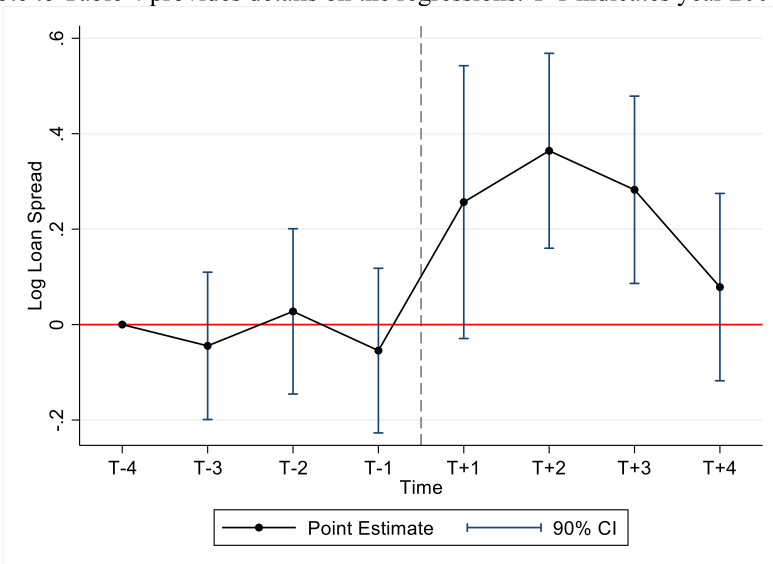
Panel B. Table 4 Column (3)

Figure 3 Parallel trend plots of bank loan spreads

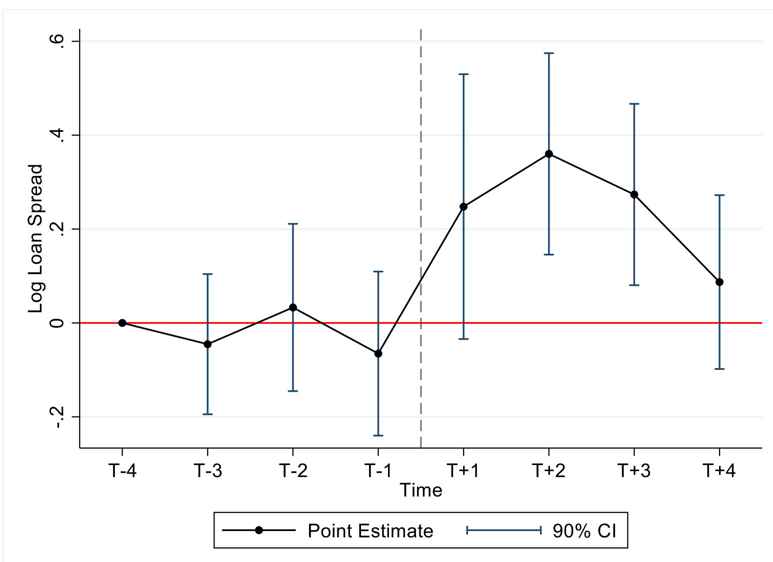
These plots depict the evolving differences in the bank loan spreads paid by heavy and non-heavy emitters of RCRA pollutants among high default probability firms. We plot the estimated β_t's from the following regression:

$\ln(Loan\ spread_{it}) = \alpha + \sum_{t=2005}^{2012} \beta_t (I_t \times Heavy\ RCRA\ Polluters_i) + \gamma Control_{it} + \delta_1 I_i + \delta_2 I_t + \varepsilon_{it}$,.

The two figures use different control variables, with the top figure based on the Table 4 column (5) regression and the bottom figure based on the column (7) specification. Vertical lines in the plots depict 90% confidence intervals for the estimated β_t's. The note to Table 4 provides details on the regressions. T-1 indicates year 2007.



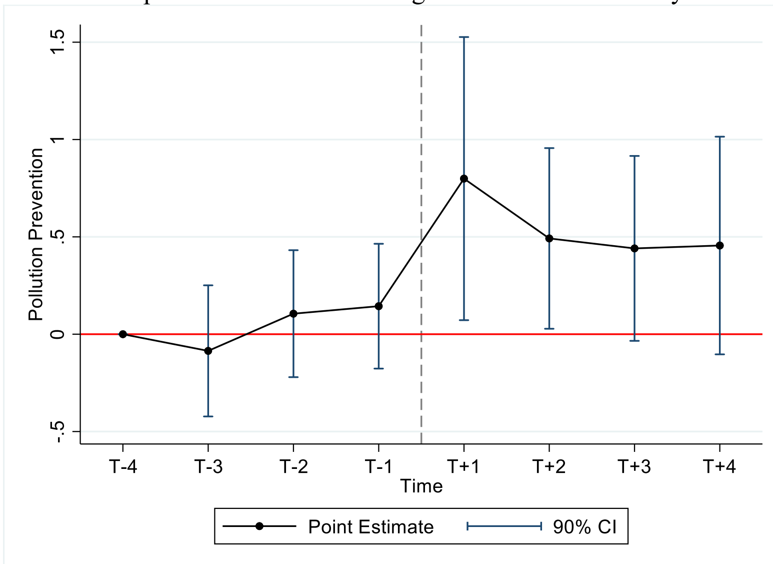
Panel A. Table 4 Column (5)



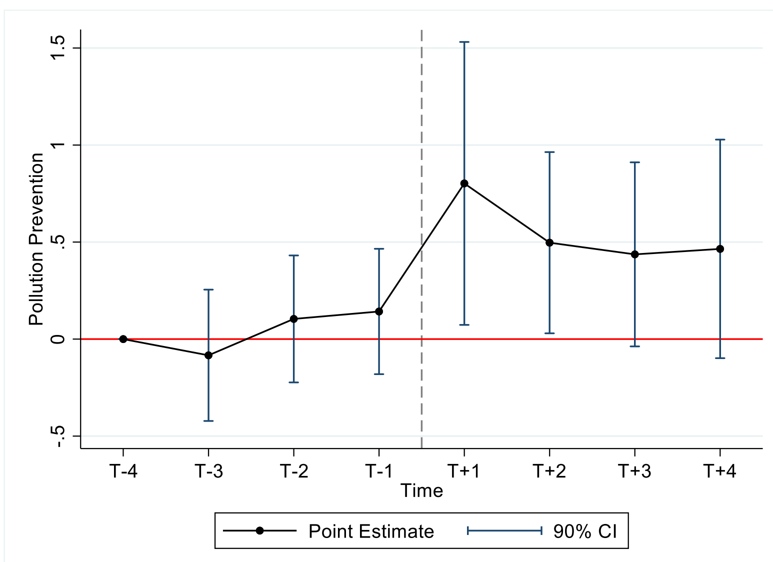
Panel B. Table 4 Column (7)

Figure 4 Parallel trend plots of facility pollution prevention activities

These plots depict the evolving differences in facility pollution prevention activities between heavy and non-heavy emitters of RCRA pollutants among high default probability firms. We plot the estimated β_t's from the following Poisson regression: $[Pollution\ Prevention_{it}|\mathcal{X}] = \ exp(\alpha_0 + \sum_{t=2005}^{2012} \beta_t(I_t \times Heavy\ RCRA\ Polluters_i) + \alpha_2 X_{it} + \gamma Facility_i + \delta_1 I_{kt}\ ),$. where i indexes facilities, k indexes parental company, and t indexes years. The two figures use different control variables, with the top figure based on the Table 6 column (1) regression and the bottom figure based on the column (3) specification. Vertical lines in the plots depict 90% confidence intervals for the estimated β_t's. The note to Table 6 provides details on the regressions. T-1 indicates year 2007.



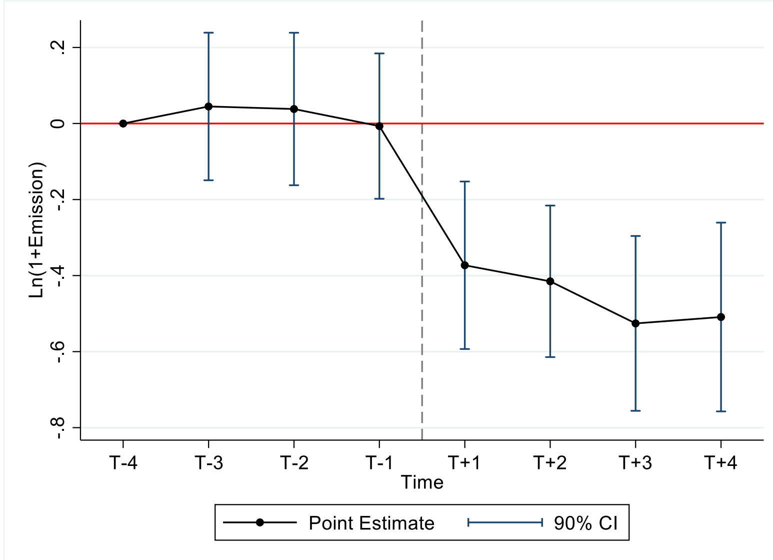
Panel A. Table 6 Column (1)



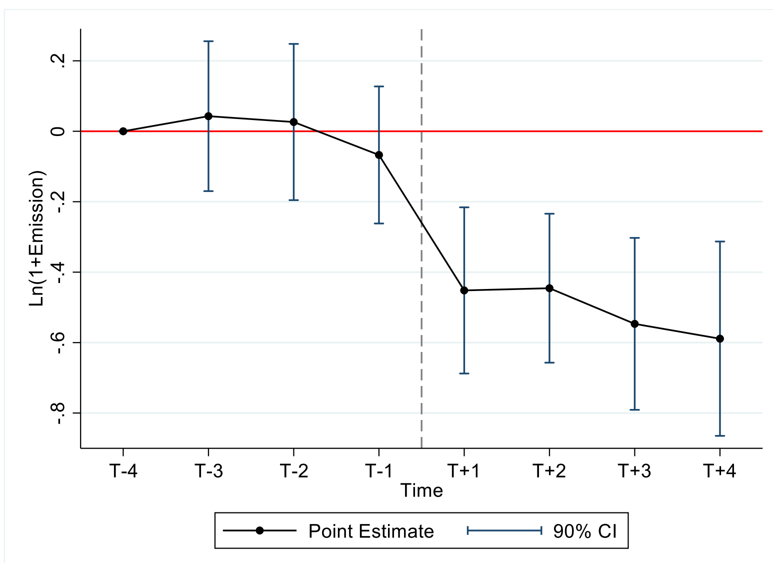
Panel B. Table 6 Column (3)

Figure 5 Parallel trend plots of Non-air Toxic Releases

These plots depict the evolving differences in non-air toxic releases produced by heavy and non-heavy emitters of RCRA pollutants among high default probability firms. We plot the estimated β_t's from the following regression: $ln(Non-air\ Toxic\ Releases_{ict}+1) = \alpha + \sum_{t=2004}^{2012} \beta_t (I_t \times Heavy\ RCRA\ Polluters_i) + \gamma Facility_i + \delta_1 I_{ct} + \delta_2 I_{kt} + \varepsilon_{ict}$,. where *i* indexes facilities, *k* indexes parental company, *c* indexes chemicals, and *t* indexes years. The two figures use different control variables, with the top figure based on the Table 7 column (1) regression and the bottom figure based on the column (3) specification. Vertical lines in the plots depict 90% confidence intervals for the estimated β_t's. The note to Table 7 provides details on the regressions. T-1 indicates year 2007.



Panel A. Table 7 Column (1)



Panel B. Table 7 Column (3)

Table 1 Summary statistics

The table presents summary statistics of the stock and bond cumulative abnormal returns (CAR), as well as the characteristics of firms and facilities, for the full (All) sample. Panels A, C, and D provide statistics at the firm level, facility level, and facility-chemical levels, respectively, spanning the years from 2004 to 2012, except for the year 2008. Panel B of the table presents an overview of the stock and bond CAR in the vicinity of July 2008, along with information regarding the locations of the firms. Toxic Air Releases consist of fugitive air releases and stack air releases of RCRA chemicals. Toxic Water Releases refer to surface water discharges of RCRA chemicals. Toxic Land Releases refer to toxic (RCRA) chemicals disposed of in underground wells, landfills, and surface impoundments et al. Toxic Air, Water and Land releases make up the Toxic Total Releases. Non-air Toxic Releases consist of Toxic Water and Land Releases. Toxic Production Wastes consist of Toxic Total Releases, wastes recycling, energy recovery, and wastes treatment. Production Wastes consist of Toxic Production Wastes and other non-RCRA chemicals Production Wastes. The releases are measured in pounds and reported in thousands (1000s). Ln(Total Interest Rate) is the natural logarithm of the basis points of firms' total interest rates. Ln(Loan Spread) is the natural logarithm of the basis points of firms' bank loan spread based on LIBOR. Bond Ratings are value-weighted bond ratings of the firm in monthly frequency. Pollution Prevention is the summation of the number of pollution prevention practices (W codes) of facility *i* in year *t*. Ln(1+Toxic Non-air Releases) is natural logarithm of one plus the amount of Toxic Non-air Releases. Firm characteristics include R&D Intensity, capital expenditure/total assets (CAPX/AT), advertising expenditures/total assets (XAD/AT), ROA, Leverage, Tangibility, Tobin's Q, the natural logarithm of the book value of total assets (Ln(AT)), labor/capital intensity (Labor/Capital), and firm age (Firm Age). Appendix A provides variable definitions. Facility characteristics include Employment (the number of employees) and Facility Sales (reported in thousands). Stock CAR refers to the cumulative abnormal returns (CAR) of each firm's stock over the (-5,5) day event window surrounding the District Court Apex decision of July 28th, 2008. Bond CAR, on the other hand, measures the cumulative abnormal returns (CAR) of each firm's bond over the (-1,1) month event window surrounding the July 2008 District Court Apex decision. Heavy RCRA Polluters is a binary variable that takes a value of one if firm i's RCRA production wastes were larger than the industry (SIC 2-digital code) median during the pre-Apex period (2003-2007), and zero otherwise. The binary variable Seventh Cir. (Sixth Cir. or Third Cir.) identifies a firm's jurisdiction based on its RCRA production waste between 2003-2007, with a value of one assigned if more than 70% of the waste was produced in the Seventh (Sixth or Third) Circuit, and zero otherwise. The interaction term Heavy RCRA Polluters × Seventh Cir. (× Sixth Cir. Or × Third Cir.) is the product of the variables Heavy RCRA Polluters and Seventh Cir. (Sixth Cir. Or Third Cir.), representing their combined effect.

Panel A. Firm level

Variables	Obs	Mean	Median	SD	% of Toxic Total Releases	% of Toxic production Wastes
Toxic Air Releases (1000 pounds)	4504	247.65	2.86	1643.39	17.35%	3.66%
Toxic Water Releases (1000 pounds)	4504	154.04	0.00	1654.65	10.79%	2.28%
Toxic Land Releases (1000 pounds)	4504	1025.50	0.95	5452.10	71.85%	15.17%
Non-air Toxic Releases (1000 pounds)	4504	1179.54	1.04	5923.29	82.65%	17.45%
Toxic Total Releases (1000 pounds)	4504	1427.18	12.99	6388.20	100.00%	21.11%
Toxic Production Wastes (1000 pounds)	4504	6760.62	129.98	29495.48		100.00%
Production Wastes (1000 pounds)	4504	11742.50	250.28	51851.64		
Ln(Total Interest Rate)	4188	5.27	5.48	0.89		
Ln(Loan Spread)	1631	4.68	4.83	0.85		
Bond Ratings (monthly)	2296	13.77	14.00	3.39		
R&D Intensity	4504	0.03	0.01	0.04		
CAPX/AT	4504	0.04	0.03	0.03		
XAD/AT	4504	0.01	0.00	0.02		
ROA	4504	0.05	0.05	0.08		
Leverage	4504	0.70	0.44	1.41		
Tangibility	4504	0.28	0.23	0.19		
Tobin's Q	4504	1.67	1.44	0.77		
Ln(AT)	4504	7.53	7.47	1.85		
Labor/Capital	4504	0.02	0.02	0.02		
Firm Age	4504	30.17	32.00	15.36		

Panel B. CAR Part

Variables	Obs	Mean	Median	SD
Stock CAR	563	0.00	0.00	0.11
Bond CAR	236	0.01	0.01	0.03
Heavy RCRA Polluters	563	0.48	0.00	0.50
Seventh Cir.	563	0.07	0.00	0.25
Sixth Cir.	563	0.07	0.00	0.26
Third Cir.	563	0.03	0.00	0.18
Heavy RCRA Polluters × Seventh Cir.	563	0.04	0.00	0.19
Heavy RCRA Polluters × Sixth Cir.	563	0.04	0.00	0.21
Heavy RCRA Polluters × Third Cir.	563	0.01	0.00	0.12
Panel C. Facility level				
Toxic Air Releases (1000 pounds)	21572	37.64	0.03	198.50
Toxic Water Releases (1000 pounds)	21572	25.45	0.00	440.62
Toxic Land Releases (1000 pounds)	21572	138.41	0.01	1033.45
Toxic Non-air Releases (1000 pounds)	21572	163.86	0.01	1147.18
Toxic Releases (1000 pounds)	21572	201.49	0.60	1185.05
Toxic Production Wastes (1000 pounds)	21572	978.90	17.12	7079.26
Employment	21572	521.24	220.00	1197.78
Facility Sales (1000 dollars)	21572	191673.10	53194.40	547128.40
Pollution Prevention	21572	0.54	0.00	2.46
Panel D. Facility-Chemical level				
Toxic Air Releases (1000 pounds)	90830	10.16	0.03	93.06
Toxic Water Releases (1000 pounds)	90830	6.53	0.00	215.76
Toxic Land Releases (1000 pounds)	90830	35.39	0.00	367.09
Toxic Non-air Releases (1000 pounds)	90830	41.92	0.00	425.53
Toxic Releases (1000 pounds)	90830	52.08	0.42	436.35
Toxic Production Wastes (1000 pounds)	90830	267.22	8.76	3048.56
Employment	80155	639.12	250.00	1502.11
Facility Sales (1000 dollars)	80155	344937.00	67536.00	912112.00
Ln(1+Toxic Non-air Releases)	90830	3.73	1.39	4.36

Table 2 Bond price reactions

This table reports regression results evaluating how the cumulative abnormal returns (CARs) on firms' bond respond to *Apex*. The dependent variable is the *CAR* of each firm's bond over the (-1,1) month event window surrounding the July 2008 District Court Apex decision. The analysis employs the bond market factor and the traded liquidity factor (Dickerson, Mueller, and Robotti 2023) to calculate monthly bond CARs. The estimation period spans 14 months, with a gap of 1 month preceding the event window. $Heavy\ RCRA\ Polluters_i$ equals one if firm i's RCRA production wastes during the pre-Apex (2003-2007) period were larger than the industry (SIC 2-digital code) median and zero otherwise. *Seventh Cir.* (*Sixth Cir.* or *Third Cir.*) indicates that firm i's RCRA production waste relative to total production waste during the pre-Apex period in the specified Circuit were larger than 70%. The analyses include two subsamples: High Default Probability firms, which are firms with above-median levels of Campbell et al. (2008) failure probabilities relative to other firms in their industries, and Low Default Probability firms. The table also reports the results of tests of the hypothesis that the coefficient estimates on Heavy Polluters for the High-Low Default probability subsamples are equal. Detailed variable definitions can be found in Appendix A. We report t-statistics based on robust standard errors in parentheses. Based on the estimated coefficient p-values (p), * denotes p < 0.1, ** denotes p < 0.05, and *** denotes p < 0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Subsample	High Default Prob.	Low Default Prob.	High Default Prob.	Low Default Prob.	High Default Prob.	Low Default Prob.	High Default Prob.	Low Default Prob.
Dependent var.	CAR(-1,1)	CAR(-1,1)	CAR(-1,1)	CAR(-1,1)	CAR(-1,1)	CAR(-1,1)	CAR(-1,1)	CAR(-1,1)
Heavy RCRA Polluters	-0.0199**	-0.0070	-0.0203**	-0.0052	-0.0202**	-0.0069	-0.0205**	-0.0069
	(-2.2362)	(-1.4780)	(-2.1297)	(-1.0804)	(-2.1002)	(-1.3862)	(-2.2297)	(-1.3998)
Heavy RCRA Polluters × Seventh Cir.			-0.0052	-0.0208				
			(-0.3045)	(-1.0365)				
Seventh Cir.			0.0130	0.0234				
			(1.1442)	(1.5184)				
Heavy RCRA Polluters × Sixth Cir.					0.0080	-0.0087		
					(0.3914)	(-0.6378)		
Sixth Cir.					-0.0125	0.0095		
					(-0.8622)	(1.0086)		
Heavy RCRA Polluters × Third Cir.							0.0319	-[47]
							(1.2750)	-
Third Cir.							-0.0210	0.0023
							(-1.0980)	(0.1637)
Observations	111	125	111	125	111	125	111	125
R-squared	0.148	0.199	0.151	0.222	0.151	0.200	0.151	0.199
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
High – Low Default Prob.	0.087*		0.053*		0.086*		0.084*	

[47] The omission is made without sufficient observation.

Table 3 Stock price reactions

This table reports regression results evaluating how the cumulative abnormal returns (CARs) on firms' stock respond to *Apex*. The dependent variable is the *CAR* of each firm's stock over the (-5,5) day event window surrounding the July 28th, 2008, District Court Apex decision. The analysis uses the Fama-French-Carhart four factors model, with 200 days the of estimation period and 50 days of gaps between the estimation period and the event window to compute daily stock CARs. $Heavy\ RCRA\ Polluters_i$ equals one if firm i's RCRA production wastes during the pre-Apex (2003-2007) period were larger than the industry (SIC 2-digital code) median and zero otherwise. *Seventh Cir.* (*Sixth Cir.* or *Third Cir.*) indicates that firm i's RCRA p production waste relative to total production waste during the pre-Apex period in the specified Circuit were larger than 70%. The analyses include two subsamples: High Default Probability firms, which are firms with above-median levels of Campbell et al. (2008) failure probabilities relative to other firms in their industries, and Low Default Probability firms. The table also reports the results of tests of the hypothesis that the coefficient estimates on Heavy Polluters for the High-Low Default probability subsamples are equal. Detailed variable definitions can be found in Appendix A. We report t-statistics based on robust standard errors in parentheses. Based on the estimated coefficient p-values (p), * denotes p < 0.1, ** denotes p < 0.05, and *** denotes p < 0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Subsample	High Default Prob.	Low Default Prob.	High Default Prob.	Low Default Prob.	High Default Prob.	Low Default Prob.	High Default Prob.	Low Default Prob.
Dependent var.	CAR(-5,5)	CAR(-5,5)	CAR(-5,5)	CAR(-5,5)	CAR(-5,5)	CAR(-5,5)	CAR(-5,5)	CAR(-5,5)
Heavy RCRA Polluters	-0.0338**	-0.0039	-0.0330**	-0.0037	-0.0356**	-0.0053	-0.0338**	-0.0046
	(-2.2181)	(-0.3460)	(-2.0780)	(-0.3067)	(-2.2162)	(-0.4445)	(-2.1415)	(-0.3925)
Heavy RCRA Polluters × Seventh Cir.			0.0322	0.0040				
			(0.3855)	(0.1235)				
Seventh Cir.			-0.0715	0.0183				
			(-0.9273)	(0.8358)				
Heavy RCRA Polluters × Sixth Cir.					-0.0017	0.0326		
					(-0.0302)	(0.8816)		
Sixth Cir.					0.0477	-0.0381		
					(1.0308)	(-1.1731)		
Heavy RCRA Polluters × Third Cir.							-0.0064	0.0194
							(-0.1075)	(0.8601)
Third Cir.							-0.0160	-0.0070
							(-0.4018)	(-0.3572)
Observations	270	293	270	293	270	293	270	293
R-squared	0.136	0.131	0.149	0.134	0.145	0.135	0.137	0.132
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
High − Low Default Prob.	0.047**		0.064*		0.055*		0.062*	

Table 4 Total interest rates and bank loan spreads

This table reports regression results evaluating how firms' total interest rates and bank loan spreads responded to *Apex.* The sample runs from 2004 to 2012 and excludes 2008, the year of the Apex decision. The dependent variables are (a) *Ln(Total interest rate)*, calculated as the natural logarithm of total interest expenses divided by average total liabilities in *t-1* and *t* (in basis points), and (b) *Ln(Loan Spread)*, calculated as the natural logarithm of the number of basis points above LIBOR that banks charge the firm. *Apex* equals one after the 2008 Apex District Court decision, and zero before 2009. $Heavy\ RCRA\ Polluters_i$ equals one if firm i's RCRA wastes during the pre-Apex (2003-2007) period were larger than the industry median and zero otherwise. All regressions include firm and year fixed effects. Regressions (3), (4), (7) and (8) also include: R&D Intensity, CAPX/AT, XAD/AT, ROA, Leverage, Tangibility, Tobin's Q, Ln(AT), (Labor/Capital), and Firm Age. Appendix A provides variable definitions. Regressions (1), (3), (5) and (7) include the sample of High Default Probability firms, i.e., firms with above the median levels of Campbell et al. (2008) failure probabilities relative to other firms in their industries. Regressions (2), (4), (6) and (8) include the corresponding sample of Low Default Probability firms. The table reports the results of tests of the hypothesis that the coefficient estimates on *Heavy RCRA Polluters* for the High-Low Default probability subsamples are equal. Dependent variables and controls are winsorized at the 1% and 99% levels. Parentheses include t-statistics based on robust standard errors clustered at the firm level. Using estimated coefficient p-values (p), * denotes $p < 0.1$, ** denotes $p < 0.05$, and *** denotes $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Subsample	High Default Prob.	Low Default Prob.	High Default Prob.	Low Default Prob.	High Default Prob.	Low Default Prob.	High Default Prob.	Low Default Prob.
Dependent var.	Ln(Total Interest Rate)	Ln(Total Interest Rate)	Ln(Total Interest Rate)	Ln(Total Interest Rate)	Ln(Loan Spread)	Ln(Loan Spread)	Ln(Loan Spread)	Ln(Loan Spread)
Apex × Heavy RCRA Polluters	0.2817***	0.0480	0.2770***	0.0058	0.2555***	-0.0018	0.2543***	-0.0294
	(3.3356)	(0.5543)	(3.4632)	(0.0712)	(2.9325)	(-0.0209)	(3.0436)	(-0.3697)
Observations	2,055	2,122	2,055	2,122	737	824	737	824
R-squared	0.697	0.676	0.716	0.700	0.816	0.851	0.831	0.869
Firm Controls			YES	YES			YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
High − Low Default Prob.	0.020**		0.004***		0.015**		0.004***	

Table 5 Bond ratings

This table reports ordered probit regression results evaluating how firms' bond ratings responded to *Apex*. Using monthly data, the sample runs from March 2008 to January 2009 and excludes July 2008, the month and year of the Apex decision. Using the ordered bond ratings from Standard and Poor's, Moody's, and Fitch for individual bonds, we (a) assign and integer value for each bond-month observation, (b) construct equal-weighted and value-weighted bond ratings for each firm-month, and (c) round that firm-month rating to the nearest whole number. *Apex* equals one after the July 2008 Apex District Court decision and zero before July 2008. $Heavy\ RCRA\ Polluters_i$ equals one if firm i's RCRA wastes during the pre-Apex (2003-2007) period were larger than the industry median and zero otherwise. Regressions (1) and (3) include the sample of High Default Probability firms, i.e., firms with above the median levels of Campbell et al. (2008) failure probabilities relative to other firms in their industries. Regressions (2) and (4) include the corresponding sample of Low Default Probability firms. Regressions (1) and (2) are based on equal-weighted ratings, and Regressions (3) and (4) are based on value-weighted ratings. They include the following firm control variables: R&D Intensity, CAPX/AT, XAD/AT, ROA, Leverage, Tangibility, Tobin's Q, Ln(AT), (Labor/Capital), and Firm Age. Appendix A provides variable definitions. The table reports the results of tests of the hypothesis that the coefficient estimates on *Heavy RCRA Polluters* for the High-Low Default probability subsamples are equal. Parentheses include t-statistics based on robust standard errors clustered at the firm level. Using estimated coefficient p-values (p), * denotes $p < 0.1$, ** denotes $p < 0.05$, and *** denotes $p < 0.01$.

	(1)	(2)	(3)	(4)
Subsample	High Default Prob.	Low Default Prob.	High Default Prob.	Low Default Prob.
Dependent var.	Equal-Weighted Bond Ratings	Equal-Weighted Bond Ratings	Value-Weighted Bond Ratings	Value-Weighted Bond Ratings
Apex × Heavy RCRA Polluters	-0.1699***	0.0787	-0.1808***	0.0688
	(-2.6043)	(1.1889)	(-2.7402)	(0.8994)
Apex	0.0244	-0.0840	0.0223	-0.0243
	(0.3695)	(-0.8978)	(0.3269)	(-0.2383)
Heavy RCRA Polluters	0.2572	-0.3679*	0.2644	-0.2766
	(1.3052)	(-1.6932)	(1.3429)	(-1.2589)
Observations	1,048	1,254	1,045	1,251
Pseudo R2	0.181	0.228	0.174	0.214
Firm Controls	YES	YES	YES	YES
Month Dummy	YES	YES	YES	YES
High − Low Default Prob.	0.004***		0.006***	

Table 6 Facility pollution prevention activities

This table reports regression results evaluating how facilities' pollution prevention activities responded to the Apex decision based on the Poisson model. The dependent variable is $Pollution\ Prevention_{it}$ which is the summation of the number of pollution prevention practices (W codes) of facility *i* in year *t*. The sample runs from 2004 to 2012 and excludes 2008, the year of the Apex decision. *Apex* equals one after the 2008 Apex District Court decision and zero before 2009. $Heavy\ RCRA\ Polluters_i$ equals one if facility i's RCRA production wastes during the pre-Apex (2003-2007) period were larger than the industry (NAICS 3-digital code) median and zero otherwise. As indicated, regressions control for Facility and Parent-Year fixed effects. Regressions (3) and (4) also include Ln(Emp) and Ln(Sales) from NETS, which are defined in Appendix A. Regressions (1) and (3) include the sample of High Default Probability firms, i.e., firms with above the median levels of Campbell et al. (2008) failure probabilities relative to other firms in their industries. Regressions (2) and (4) include the corresponding sample of Low Default Probability firms. The table also reports the results of tests of the hypothesis that the coefficient estimates on *Apex × Heavy RCRA Polluters* for the High-Low Default probability subsamples are equal. Appendix A provides detailed variable definitions. We report t-statistics based on robust standard errors clustered at the facility level in parentheses. Based on the estimated coefficient p-values (*p*), * denotes $p < 0.1$, ** denotes $p < 0.05$, and *** denotes $p < 0.01$.

	(1)	(2)	(3)	(4)
Subsample	High Default Prob.	Low Default Prob.	High Default Prob.	Low Default Prob.
Dependent var.	Pollution Prevention	Pollution Prevention	Pollution Prevention	Pollution Prevention
Apex × Heavy RCRA Polluters	0.5193**	-0.0875	0.5222**	-0.0840
	(2.1882)	(-0.4540)	(2.1879)	(-0.4386)
Ln(Emp)			-0.1085	-0.1940
			(-0.4740)	(-0.8486)
Ln(Sales)			0.1612	0.1346
			(0.8240)	(0.6509)
Observations	1,825	2,870	1,825	2,870
Pseudo R2	0.555	0.611	0.555	0.611
Facility FE	YES	YES	YES	YES
Parent-Year FE	YES	YES	YES	YES
High − Low Default Prob.	0.090*		0.091*	

Table 7 Non-air Toxic Releases

This table reports regression results evaluating how facilities' emission of RCRA-regulated toxic pollutants responded to the Apex decision. The dependent variable is *Ln(1 + Non-air Toxic Releases$_{ict}$)*, where *Non-air Toxic Releases$_{ict}$* equals the amount of non-air RCRA toxic chemical *c* released by facility *i* in year *t*. The sample runs from 2004 to 2012 and excludes 2008, the year of the Apex decision. *Apex* equals one after the 2008 Apex District Court decision and zero before 2009. $Heavy\ RCRA\ Polluters_i$ equals one if facility i's RCRA production wastes during the pre-Apex (2003-2007) period were larger than the industry (NAICS 3-digital code) median and zero otherwise. As indicated, regressions control for Facility, Chemical-Year, and Parent-Year fixed effects. Regressions (3) and (4) also include Ln(Emp) and Ln(Sales) from NETS, which are defined in Appendix A. Regressions (1) and (3) include the sample of High Default Probability firms, i.e., firms with above the median levels of Campbell et al. (2008) failure probabilities relative to other firms in their industries. Regressions (2) and (4) include the corresponding sample of Low Default Probability firms. The table also reports the results of tests of the hypothesis that the coefficient estimates on *Apex × Heavy RCRA Polluters* for the High-Low Default probability subsamples are equal. Appendix A provides detailed variable definitions. We report t-statistics based on robust standard errors clustered at the facility level in parentheses. Based on the estimated coefficient p-values (*p*), * denotes $p < 0.1$, ** denotes $p < 0.05$, and *** denotes $p < 0.01$.

	(1)	(2)	(3)	(4)
Subsample	High Default Prob.	Low Default Prob.	High Default Prob.	Low Default Prob.
Dependent var.	Ln(1+Non-air Toxic Releases)	Ln(1+Non-air Toxic Releases)	Ln(1+Non-air Toxic Releases)	Ln(1+Non-air Toxic Releases)
Apex × Heavy RCRA Polluters	-0.4701***	0.0415	-0.5047***	0.0778
	(-3.8930)	(0.3945)	(-3.8997)	(0.7668)
Ln(Emp)			0.1033	0.0606
			(0.7595)	(0.3753)
Ln(Sales)			-0.0053	-0.0585
			(-0.0419)	(-0.3756)
Observations	34,918	54,261	30,614	47,893
R-squared	0.799	0.736	0.801	0.748
Facility FE	YES	YES	YES	YES
Chemical-Year FE	YES	YES	YES	YES
Parent-Year FE	YES	YES	YES	YES
High − Low Default Prob.	0.004***		0.000***	

Appendix A Variables Definition

Variables	Definition	Source
Bond CAR	Cumulative abnormal returns (CAR) of each firm's bond over the (-1,1) month event window surrounding the July 2008 District Court Apex decision. CAR is calculated as the difference between the actual monthly excess returns (in excess of the monthly T-bill rate) of the bond and the expected excess returns based on bond market factors and traded liquidity factors (Dickerson, Mueller, and Robotti 2023). We use the value weighted return of firms' bonds. The estimation period for the model spans 14 months, with a gap of 3 month preceding the event window to establish a baseline for expected returns.	WRDS Bond Returns
Stock CAR	Cumulative abnormal returns (CAR) of each firm's stock over the (-5,5) day event window surrounding the July 28th, 2008, District Court Apex decision. CAR is calculated as the difference between the actual daily excess returns (in excess of the monthly T-bill rate) of the stock and the expected excess returns based on the Fama-French-Carhart four factors model. The model is estimated using 200 days of the estimation period, and there is a 50-day gap between the estimation period and the event window.	CRSP
Ln(Total Interest Rate)	The natural logarithm of the basis points (times 10,000) of total interest rates. Total interest rates equal total interest expenses divided by average total liabilities in year t-1 and year t.	Compustat
Ln(Loan Spread)	The natural logarithm of the basis points (times 10,000) of firms' bank loan spread based on LIBOR. All loans are aggregated into firm-year level data by weighting all loans granted to a firm in a given year based on loan size.	DealScan
Bond ratings	A numerical bond rating (from the S&P, if missing, use Moody's or Fitch equivalent) of 1 corresponds to a D rating, a rating of 5 to a CCC rating, a rating of 10 to a BB- rating, a rating of 15 to a BBB+ rating, a rating of 20 to an AA rating, and a rating of 22 to an AAA rating. Equal- and value-weighted bond ratings are calculated for firms with multiple bonds and rounded the number to the nearest whole number.	WRDS Bond Returns
Ln(1+Non-air Toxic Releases)	Natural logarithm of one plus the amount of facility total RCRA chemical releases excluding air-related releases.	TRI
Pollution Prevention	The summation of the number of pollution prevention practices (W codes) of facility i in year t in the TRI database (Bellon 2021).	TRI
Ln(Emp)	Natural logarithm of the employment of the facility.	NETS
Ln(Sales)	Natural logarithm of sales of the facility.	NETS
Apex	Apex equals one when year>=2009 and set to zero otherwise	-
Heavy RCRA Polluters	For firm level data, $Heavy\ RCRA\ Polluters_i$ equals one if firm i's RCRA production wastes were larger than the industry (SIC 2-digital code) median during the pre-Apex (2003-2007) period and zero otherwise. For facility-chemical level data, $Heavy\ RCRA\ Polluters_i$ equals one if facility i's RCRA production wastes were larger than the industry (NAICS 3-digital code) median during the pre-Apex (2003-2007) period and zero otherwise.	TRI
High/Low Default Prob.	For firm level data, High Default Prob. includes firms with probabilities of failure (Campbell et al. 2008) at the end of December 2007 being larger than SIC 2-digital code industry median, and the Low Default	CRSP/Compustat

	Prob. includes all others. To increase the sensitivity of our analysis, we adjusted the date to June 2008, one month prior to the Apex decision, for both daily and monthly analysis. This adjustment applies to the stock CAR, bond CAR, and bond rating sections of the analysis. For facility-chemical level data, High Default Prob. includes facilities belonging to firms with probability of failure (measured by Campbell et al. 2008) in December 2007 being larger than industry (NAICS 3-digital code) median. All other facilities are assigned to the Low Default Prob.	
High/Low Expected Default	For firm level data, High Expected Default includes firms with the expected default frequency of Merton's (1974) distance to default model at the end of December 2007 being larger than SIC 2-digital code industry median, and the Low Expected Default includes all others. For facility-chemical level data, High Expected Default includes facilities belonging to firms with the expected default frequency of Merton's (1974) distance to default model in December 2007 being larger than industry (NAICS 3-digital code) median. All other facilities are assigned to the Low Expected Default.	CRSP/Compustat
Seventh Cir.	Seventh Cir. is a binary variable that identifies the jurisdiction of a firm i based on its RCRA production wastes during the pre-Apex period (2003-2007). Specifically, the variable takes a value of one if the percentage of the firm's RCRA production wastes generated in the Seventh Circuit was greater than 70% of its total production wastes, and zero otherwise.	TRI
Sixth Cir.	Sixth Cir. is a binary variable that identifies the jurisdiction of a firm i based on its RCRA production wastes during the pre-Apex period (2003-2007). Specifically, the variable takes a value of one if the percentage of the firm's RCRA production wastes generated in the Sixth Circuit was greater than 70% of its total production wastes, and zero otherwise.	TRI
Third Cir.	Third Cir. is a binary variable that identifies the jurisdiction of a firm i based on its RCRA production wastes during the pre-Apex period (2003-2007). Specifically, the variable takes a value of one if the percentage of the firm's RCRA production wastes generated in the Third Circuit was greater than 70% of its total production wastes, and zero otherwise.	TRI
R&D Intensity	Research and development expenditures divided by total assets, set to zero if missing.	Compustat
CAPX/AT	Capital expenditure scaled by the book value of total assets, set to zero if missing.	Compustat
XAD/AT	Advertising expenditures divided by total assets, set to zero if missing.	Compustat
ROA	Net income scaled by the book value of assets, set to zero if missing.	Compustat
Leverage	The ratio of total debt to stockholder's equity, set to zero if missing.	Compustat
Tangibility	Property, Plant and Equipment divided by total assets, set to zero if missing.	Compustat
Tobin's Q	Total assets plus the market value of equity minus book value of equity divided by book value of total assets, set to zero if missing.	Compustat
Ln(AT)	Natural logarithm of the book value of total assets (million-dollar), set to zero if missing.	Compustat
Labor/Capital	The ratio of the number of employees over Property, Plant and Equipment, set to zero if missing.	Compustat
Firm Age	Years on Compustat.	Compustat