# Are Bankrupt Firms Environmentally Dangerous?

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As firms file for bankruptcy, environmental problems come to light. Are these problems chronic or acute? To address the question, we examine emission and production data of bankrupt facilities between 2007 and 2019, using a dynamic diff-in-diff analysis. First, we show that bankrupt facilities are on average larger, more stagnant, inefficient, and more polluting relative to their industry peers, consistent with a chronic effect. Second, we examine whether environmental problems exacerbate around bankruptcy. We do not find significant increase in emission levels either before, during, or after bankruptcy. Taken together, this evidence supports the idea that environmental problems in bankrupt firms are chronic, but legal, financial, and environmental regulations help prevent these issues from becoming more acute.

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**Introduction**

In March 2024 Enviva—the world's largest producer of biomass wood pellets—filed for Chapter 11 bankruptcy after struggling to maintain profitability amid soaring production costs and falling output prices. As the company sought bankruptcy protection, its financial and operational decisions came under scrutiny from firm stakeholders, bankruptcy experts and the press. Important revelations included the company's environmental practices. Despite promoting itself as a leader in green energy, the firm was found to emit excessive toxic waste, clearcut healthy forests, and harm nearby communities through noise and sawdust pollution.

Enviva's environmental practices delivered a significant blow to its stakeholders, with a weakened environmental standing adding to the company's already shaky financial position. The environmental issue is particularly concerning for unsecured creditors, who are likely to become equity holders as part of the restructuring. Since the overall value of the company's assets is directly tied to the environmental impact of their operations, Enviva's poor environmental position has further eroded the recovery potential for creditors.

What drives harmful environmental practices in bankruptcy? How can stakeholders better protect themselves against such environmental risk? To address this question, it is important to understand whether environmental problems in bankruptcy are an acute outcome of financial distress, or whether they reflect chronic firm-specific issues. One possibility is that environmental problems are magnified in financial distress, as firms have stronger incentives to cut abatement costs and shift environmental risk to its creditors. If so, environmentally conscious investors can mitigate their risk by monitoring firm's financial health and implementing covenants designed to signal potential financial trouble. Alternatively, the firm's environmental practices might be chronic and insensitive to financial distress, with bankruptcy merely bringing long-standing vulnerabilities to light. In this case, environmentally conscious investors looking to do well by doing good should try to avoid these firms altogether.

Are environmental problems in bankruptcy chronic or acute? How important are they? In this study, we address these questions by examining firms' environmental decisions before, during, and after bankruptcy. To do so, we analyze all bankruptcy cases in the U.S. filed between 2007 and 2019 in industries known for environmental pollution. Specifically, we integrate bankruptcy data with environmental impact indicators from the Toxic Release Inventory (TRI) database. TRI tracks chemical releases, helping identify contamination sources under the Superfund Law (CERCLA), which oversees cleanup and accountability for hazardous substance releases at contaminated sites. Using a differences-in-differences (diff-in-diff) framework, we explore the relationship between corporate bankruptcy and environmental decision-making to understand the dynamics between financial distress and environmental outcomes.

To construct our sample, we start by identifying all corporations that filed for bankruptcy in the US between 2007–2019 from the Capital IQ bankruptcy database. To ensure that we capture bankrupt firms with economically sizeable operations, we require that each bankrupt firm has at least $50 million in liability at the time of the bankruptcy filing.[1] Next, we identify the facilities that belong to these firms using the National Establishment Time-Series (NETS)-TRI Database, which maps TRI facilities to their Database establishments. NETS also provides information on whether the facility was active in a certain year. We identify a total of 800 facilities across 160 bankruptcies, representing the complete set of facilities that have ever reported under the TRI program and were associated with a firm that declared bankruptcy at any point within our sample period. Our main empirical approach uses a dynamic event window within a difference-in-differences regression framework, comparing variables of interest between facilities (firms) in the pre- and post-bankruptcy periods with control facilities (firms) that were never involved in a bankruptcy event. Consequently, our final sample includes the full universe of NETS-TRI facilities, totaling over 28,000 facilities across over 17,000 different firms.

Aside from broad coverage of industries and facilities, the NETS-TRI dataset has two additional advantages that are absolutely critical for a proper empirical study of bankruptcy. First, NETS precisely identifies facility ownership and also precisely tracks changes in ownership over time. Since firms in bankruptcy often sell facilities, tracing the ownership at a given point of time is essential. Second, the TRI reporting includes disclosure of the changes in production levels of each facility from the previous year. This variable is crucial since facility-level emission is highly dependent on facility-level production. To the extent that bankruptcy is almost always associated with decline in production, a drop in the level of emissions before or during bankruptcy might indicate that production levels have changed rather than firms produce less emission.

[1] This threshold is consistent with the criteria used by credit analysts to flag default cases significant enough to warrant coverage. See, for example, Moodey's recovery database https://www.moodys.com/sites/products/DefaultResearch/2006600000428092.pdf.

We begin our analysis by validating the empirical design. If our data accurately represents the scope and production activities of bankrupt firms, we should be able to confirm key patterns, which characterize firms that go bankrupt. First, firms that ultimately file for bankruptcy tend to be larger than their peers, as bankruptcy often reflects overexpansion and unsustainable growth. Second, we expect to observe a decline in firm size and production levels leading up to bankruptcy. We indeed find that at a firm level, bankrupt firms operate more facilities than their industry peers. We also find that firms close and sell facilities around bankruptcy, consistent with the idea that distressed firms reduce their overall scope to streamline operations and improve efficiency. At a facility-level, we find a significant reduction in production around the time of bankruptcy. This supports the notion that bankruptcy often coincides with economic distress, leading to lower demand and reduced production. This pattern also underscores the importance of controlling for facility-level production when assessing bankruptcy's impact on emissions; otherwise, we risk attributing emission reductions solely to decreased production activity. Lastly, in line with human-capital costs of bankruptcy, we observe increased managerial turnover in bankrupt facilities, further suggesting that our data and empirical design are both reliable and timely.

We then turn to our main question and examine (1) whether bankrupt firms are on average large emitters and (2) whether emission levels increase as these firms approach bankruptcy, while controlling for facility production levels. Our findings indicate that bankrupt firms are on average emitting more toxic waste than other firms in the industry. However, there is no increase in emission levels as firms approach bankruptcy. For robustness, we measure emission levels using two additional methodologies: (1) scaling emissions by toxicity of each chemical, and (2) scaling by both toxicity and environmental impact scope (such as mode of dissemination and local population size). Across all methodologies, we find no significant effect of bankruptcy—or financial distress more broadly—on emission levels. These results hold when including industry-year and facility fixed effects and using alternative industry classifications. Since the TRI database provides data on toxic waste management activities, we next analyze changes in toxic waste management around bankruptcy. Controlling for production levels, we observe no significant increase or decrease in the volume of managed toxic waste in bankrupt firms, supporting our finding of no impact on toxic waste emissions. Our main results are thus consistent with the premise that bankrupt firms have chronic emission problems.

After confirming that financial distress pre-bankruptcy is not associated with increased emission levels, we investigate whether possible acute environmental changes might be obscured by the diversity of bankrupt firms in our sample. To explore this, we conduct a series of cross-sectional tests. First, we compare bankruptcies during the financial crisis period to those occurring outside of it. Although our setting does not have a method to single out bankruptcies caused by events exogenous to the firm from bankruptcies that were anticipated or planned for, bankruptcies during the financial crisis are likely driven by a more sudden and large shock to firms' financial health and therefore, are more likely to be unexpected. Consistent with this idea, we find that the facility-level production declines and personnel turnover were more pronounced among financial crisis bankruptcies than in non-crisis bankruptcies. However, we still find no significant differences in emissions between these groups.

Next, we create subsets of bankrupt firms based on the duration of bankruptcy. We expect longer bankruptcies to involve firms that are consistently less profitable and therefore, face more chronic economic challenges, such as operating in declining industries (Denis et al., 2009). We perform our analysis across three bankruptcy groups: long (lasting two years or more), regular (one to two years), and short (under one year). Once again, we find no consistent increase in emissions around bankruptcy. In fact, long bankruptcies are associated with a significant reduction in emissions post-bankruptcy, suggesting that for these firms, the resolution of financial distress may also have a beneficial impact on the environment.

Finally, we divide the sample into publicly traded and private firms. Private firms are known to pollute less (Shive and Forster 2020), potentially because of concentrated ownership and heightened personal responsibility of private investors. We should therefore observe more tendency to increase pollution among public firms once they approach bankruptcy. We do not observe an acute pattern of increased pollution as firms approach bankruptcy within either subsample.

Overall, our findings document that firms that end up in bankruptcy, are systematically larger, less efficient, and more polluting. At the same time, bankruptcy itself is not associated with increased environmental risk. In fact, even before bankruptcy, as firms become financially distressed, there does not seem to be a deterioration in emission levels.

Overall, this study belongs to a line of studies that examine the effect of financial constraints on environmental footprint. For example, Xu and Kim (2022) find a positive relation between financial constraints and the level of toxic release. Levine, Lin, Wang, and Xie (2021) find a negative relation between local banks' money supply shocks and toxic release of firms in the bank locality, and Cohn and

Deryugina (2019) – between firms' cash flows and firms' tendency to spill toxic waste. Relatedly, Gentet-Raskopf (2019) shows that French firms that are financially constrained tend to invest less in pollution prevention, and Dang, Wang and Wang (2022) find that spending on mandatory pollution substitutes for other types of investment for constrained firms. We complement these studies by focusing on firm pollution decisions around bankruptcy.

More specifically, this study belongs to the growing literature examining pollution decisions around bankruptcy. The two studies most closely related to ours are by Ohlrogge (2023b) and Bellon and Boualam (2024), which focus on the acute effect of financial distress on emission. Ohlrogge (2023b) investigates compliance with the Clean Water Act and finds that compliance levels increase as firms enter bankruptcy. Ohlrogge's study does not account for variations in facility production levels, so the observed increase in compliance may reflect either improvements in financial conditions due to bankruptcy or a decrease in production levels associated with firms' distress. Bellon and Boualam (2024) examine emission and financial distress in the oil and gas industry. The paper develops a structural dynamic model in which firms' pollution is captured by the intensity of gas flaring at oil wells, and also shows a positive relationship between financial distress and gas flaring intensity that reduces during bankruptcy. We extend their study to a host of additional industries and measures of pollution to examine the relation between emission decisions in firms and bankruptcy more broadly. We also assess whether high emission in bankruptcy has a chronic effect. Our findings complement the oil and gas sector findings, and highlight that the effect of financial distress and bankruptcy on pollution may differ across industries and production functions.

More generally, the paper relates to the literature that studies the impact of the side effects of corporate bankruptcy on different stakeholders. For example, Graham, Li, Si, and Qui (2023) examine the effect of bankruptcy on employee wages, finding a substantial decrease in employee compensation during bankruptcy. Bernstein, et al. (2019) examine the spillover effect of the choice of bankruptcy restructuring (Chapter 11 vs Chapter 7) on corporate employment opportunities in geographies close to the bankrupt firm and finds a strong decline associated with liquidation decisions. Phillips and Sertsios (2013) focuses on bankruptcy in the airline industry and find that product quality deteriorates prior to bankruptcy but improves during bankruptcy. Our study complements these studies by focusing on the environmental side effects of bankruptcy.

The rest of the study continues as follows. In the next section we discuss the potential effects of corporate bankruptcy on corporate emission. Section 3 describe the data and variables, section 4 describes the results, section 5 includes robustness tests and section 6 concludes.

## 2. Financial distress and corporate environmental policy: Legal background

Financial distress can have a significant impact on a company's environmental policy, influencing both the development and implementation of sustainable practices.

On the one side, several forces could lead to increased environmental costs for firms in financial distress. Limited financial resources can hinder a company's ability to invest in environmentally friendly technologies and practices. This includes renewable energy, energy-efficient equipment, and sustainable materials, which often require substantial upfront investment. Moreover, companies facing financial difficulties may prioritize immediate financial gains over long-term sustainability goals. This can lead to cost-cutting measures that compromise environmental initiatives, such as reducing funding for environmental programs or cutting corners in waste management.

Financial distress may also force companies to focus solely on meeting regulatory requirements rather than pursuing innovative, proactive environmental strategies. This reactive approach can limit the potential for significant environmental improvements and sustainability leadership.

Firms in severe financial distress might also face production inefficiencies as experienced workers might prefer moving to other firms because of the risk of losing their job. Bringing new workers could lead to inefficient production and to higher risk of environmental side effects. In addition, due to lack of financial resources, firms might not be able to have the needed inventory from suppliers or might resort to cheaper suppliers who might not adhere to strict environmental standards. This can indirectly increase the company's environmental impact through its supply chain. Constraints can lead also to reduced spending on employee training and engagement programs related to environmental sustainability. Without proper training and motivation, employees may be less likely to adopt and support green practices. Finally, creditors might pressure firms in bankruptcy to prioritize financial recovery. These stakeholders may have less interest in or patience for environmental initiatives that do not provide immediate financial returns.

In contrast, there could be several economic forces that moderate the effect of financial distress on the environment. First, regulators impose restrictions on firms regarding their environmental impact. In the United States, several regulations and laws are designed to limit the environmental impact of firms. Among the many rules, the main ones are the Clean Air Act, which regulates air emissions and authorizes the Environmental Protection Agency (EPA) to establish National Ambient Air Quality Standards (NAAQS) to protect public health and the environment; The Clean Water Act, which establishes the basic structure for regulating discharges of pollutants into the waters of the United States and regulating quality standards for surface waters; the Resource Conservation and Recovery Act (RCRA) which provides the framework for the proper management of hazardous and non-hazardous solid waste. It includes guidelines for the generation, transportation, treatment, storage, and disposal of hazardous waste.

Research shows that most firms choose to comply with environmental regulations when faced with the threat of financial penalties. Firms with substantial violations of these rules are more likely to be penalized (e.g., Habib and Bhuiyan 2017), and they are penalized with substantial fines (Karpoff et al. 2005). Karpoff et al. (2005) examines 428 publicized violations of environmental rules in the US that were facing legal consequences. They show that firms violating environmental rules face several forms of legal penalties, including fines, payments to damaged parties, compliance costs, and cleanup expenses. The amount paid in settlement of a violation frequently is often not disclosed, but for the cases disclosed, the average fine is about $13 million and the average compliance costs and cleanup expenses is about $90 million (year 2000 dollars). Such large penalties can potentially deter firms from violating rules. Interestingly, Karpoff et al. (2005) do not find stock-price reputational penalty associated with these cases. It is important to note that not all firms are deterred from the fines or change their environmental performance after they are fined. See, for example, Shevchenko (2021).

Another important mechanism that affects debtors' incentives to comply with environmental requirements is the bankruptcy code itself. Table 1 summarizes the main points of the environmental law as it applies in bankruptcy. We outline the most salient aspects here. United States involves two sets of federal laws In Chapter 11 bankruptcy law, the idea is to give the debtor a "fresh start". When a firm reorganizes under Chapter 11 of the bankruptcy code, most pre-bankruptcy obligations that were not met in full are said to be discharged, meaning that the reorganized firm will no longer be responsible for meeting them. While many of a firms' obligations are to its creditors, firms also incur obligations such as tort liability and regulatory penalties on account of harms they externalize to third parties. Sometimes US law gives low priority to many obligations stemming from externalized harms. For example, although most courts hold that government environmental actions fall within the police and regulatory power exception when applying the automatic stay exception, some courts hold that seeking costs or fines are barred by the stay. (Coordes 2021). Consistent with that, Ohlrogge (2023) and Adler and Capkun (2023) point to the fact that secured creditors frequently have a right to be paid in full before any money goes to compensate tort victims or to pay regulatory obligations. This, in itself, reduces incentives of creditors to demand from the company compliance with environmental rules.

However, there are several precedents associated with priority to environmental claims. For example, the 2009 decision by the Seventh Circuit Court of Appeals in U.S. v. Apex Oil Co., held that a firm reorganizing in bankruptcy could not discharge certain obligations to clean up pre-bankruptcy toxic chemical contamination. This meant that even after reorganization, a firm would be required to remedy its past contamination. Following the decision, creditors in many situations, even secured creditors, would receive less in the event that a borrower contributed to a significant chemical spill. Ohlrogge (2023a) and Chen, Hsieh, Hsu, and Levine (2023) show that the ruling had a significant effect on firms' contamination decisions, and the affected companies responded to the case by reducing the volume of toxic chemicals they release.

**Table 1: Intersection of bankruptcy and environmental laws**

| Bankruptcy law | Provision for environmental issues | Caveats and exceptions |
|---|---|---|
| **Automatic stay:**<br>• Bankruptcy law prohibits any attempt to collect or enforce a prepetition debt or judgment against the debtor. | • Governmental units that are seeking to enforce their "police and regulatory power" — not a money judgment — are excepted from the stay<br>• Government environmental actions fall within this police and regulatory power exception. | • Some courts have held that governmental units that are seeking costs or fines as part of their enforcement efforts are barred by the stay |
| **Financial claim vs. ongoing obligations:**<br>• Financial claims against the firm - can be discharged (that is, forgiven); ongoing obligations (actual, necessary costs and expenses of preserving the estate) – cannot. | • Environmental cleanup benefits the estate since it allows to remain in compliance with the laws<br>• Most courts tend to classify environmental claims as administrative expenses that must be paid before the debtor can exit bankruptcy. | • Some courts have held that claims for environmental cleanup costs are simply general unsecured claims.<br>  o But: government claims are more likely to receive higher priority |
| **Claim definition and priority:**<br>• The Bankruptcy Code defines a "claim" very broadly to help debtors achieve a "fresh start" by discharging as many debts as possible.<br>• Claim priority determines the order in which creditors are paid from the debtor's assets during bankruptcy proceedings, as specified in the U.S. Bankruptcy Code. | • Negative order or injunction—such as a court order requiring the debtor to stop polluting—is typically not a dischargeable claim.<br>• Environmental obligations are nondischargeable to the extent the agency is seeking "purely nonmonetary" remedial measures<br>  o U.S. v. Apex Oil Co (2009) and Mark IV test (2010) have strengthened the status of affirmative orders and injunctions. | • Monetary clean-up obligations are more likely to be discharged than clean-up actions<br>• Timing: claims that arose prepetition are more likely to be dischargeable |

**Table 1 (cont.): Intersection of bankruptcy and environmental laws**

| Bankruptcy law | Provision for environmental issues | Caveats and exceptions |
|---|---|---|
| **Abandonment of property:**<br>• The Bankruptcy Code does allow the trustee or DIP to abandon property that is burdensome or of inconsequential value to the estate. | • Bankruptcy courts cannot allow the abandonment of estate property that contravenes state statutes or regulations reasonably designed to protect the public health or safety | • Some lower courts interpret the abandonment power was "a narrow one" and permit abandonment conditioned only on "relatively minor steps to reduce imminent danger." |
| **Asset sale:**<br>• Bankruptcy law allows debtors to sell assets "free and clear" of their attendant liabilities. | • The EPA and state environmental agencies are notified of major asset sales involving potentially contaminated property and can intervene if the sale would transfer unaddressed environmental liabilities<br>• To qualify as a "bona fide prospective purchaser" (BFPP) and avoid future liability for the purchased asset, the buyer is encouraged to conduct environmental due diligence, such as Phase I Environmental Site Assessment (ESA)<br>• Bankruptcy trustees are obligated to manage assets responsibly and ensure compliance with environmental laws | • There are nuances to qualifying as a bona fide prospective purchaser: some eligible buyers may not qualify, and non-eligible buyers may qualify |

Another mechanism that reduces firms' incentives to pollute is the United States federal environmental remediation program, established by the Comprehensive Environmental Response, Compensation, and Liability Act of 1980 (CERCLA). The program is administered by the Environmental Protection Agency (EPA) and is designed to investigate and clean up sites contaminated with hazardous substances. Sites managed under this program are referred to as Superfund sites. The EPA seeks to identify parties responsible for hazardous substances released to the environment (polluters) and either compel them to clean up the sites, or undertake the cleanup on its own using the Superfund (a trust fund) and seek to recover those costs from the responsible parties through settlements or other legal means. Approximately 70% of Superfund cleanup activities historically have been paid for by the potentially responsible parties reflecting the polluter pays principle. Thus, firms found responsible for heavy pollution are required to contribute money into the fund. To the extent that firms file for bankruptcy before they contribute their money, this liability claim becomes part of the claims in bankruptcy. Several courts have positioned that CERCLA claims brought by the federal, state, or local government, fall within the police power exception of the automatic stay provision and thus have priority over other liability claims. In other cases, CERCLA claims receive the status of administrative claims, providing priority in bankruptcy over unsecured claims. (Lorch 1991, Mailman 2005). These potential effects associated with the CERCLA rule could incentivize creditors to push firms into stronger cleanup incentives during bankruptcy and even before bankruptcy.

Bankruptcy, often viewed as a mechanism for financial rehabilitation, holds the potential to influence firms' environmental impact through additional channels: First, financing options available during bankruptcy proceedings, such as Debtor-in-Possession (DIP) financing, can alleviate firms' financial constraints, thereby reducing their incentives to cut costs associated with environmental abatement. Moreover, throughout bankruptcy, firm activities are closely monitored by creditors and by the court. Given the higher legal risks creditors face if the firm becomes less environmentally conscious, they are less likely to agree to measures that increase the corporation's environmental risk. In contrast, firms in bankruptcy might deprioritize environmental oversight, as they focus on resolving their financial condition. In addition, to the extent that bankruptcy procedures are lengthy and complex, they could take away management attention from day-to-day production decisions, which could lead to less efficient production and more environmental harm. Costly bankruptcy negotiations could further hamper necessary investments that could improve environmental footprint.

To summarize, financial distress can impact a company's environmental policies by limiting resources for sustainable practices, such as pollution control and renewable energy. Creditors in bankruptcy may also prioritize financial recovery over sustainability. However, regulatory frameworks like the Clean Air Act, Clean Water Act, and RCRA impose strict environmental requirements, with significant penalties deterring non-compliance. In addition, CERCLA's Superfund program requires polluters to cover cleanup costs, and its stringency has become stricter after the 2009 U.S. v. Apex Oil Co. decision. On the financial side, Debtor-in-Possession financing can further reduce financial strain, helping firms sustain environmental standards despite distress.

## 3. Data and Variables

### 3.1 Bankruptcy events

We compile the list of bankruptcies from Capital IQ. Although Capital IQ's coverage begins in the late 1990s, the data on bankruptcies filed before 2007 is sporadic. Therefore, following the existing literature (e.g., Adler and Capkun 2023), we start our sample in 2007. This results in an initial sample of approximately 7,600 bankruptcies from the period 2007–2019.

To focus on firms with significant environmental impact, we (1) focus on economically meaningful bankruptcies by requiring that they have total liabilities of at least $50 million at the time of bankruptcy and (2) require that the bankrupt firm operates in a polluting industry.[2] We define polluting industries by downloading all onsite emission information from the Toxic Release Inventory (TRI) database and summing the amounts of all toxic chemicals emitted onsite at the NAICS 4-digit level annually over the 2007–2019 period. We then rank the industries based on the average annual standardized emissions (see section 3.2 for definition) in descending order and select the 20 most polluting industries (listed in Table A.1). Combined, these industries account for over 99% of nationwide standardized onsite emissions (over 91% of total onsite emissions).

[2] One potential concern is that a facility of a small operational size could still cause a very significant environmental damage due to an accident or extremely toxic production practices. To investigate this, we review all the cases of the large environmental damages discussed in Blair (2011). We find only one instance of a company (Hercules Chemical Co) with liabilities under $50 million on the list of firms with the largest initial environmental claims by the EPA. We also note that this claim was related to the problematic use of asbestos in the 1970s. As the use of asbestos declined dramatically in the 1980s and 1990s, it is not a relevant environmental concern for production processes employed after 2000.

Since Capital IQ classifies industries using SIC or GICS codes, we first convert the list of NAICS codes to SIC codes using the NAICS-SIC conversion bridge and limit our Capital IQ sample to firms in these polluting industries. This process yields 350 firms filing for bankruptcy between 2007–2019 with SIC codes matching the TRI SIC codes. Given that a large fraction of Capital IQ bankruptcies does not have SIC codes but reports GICS codes, we use Compustat's last 10 years mapping of GICS to NAICS and identify firms that belong to highly polluting industries on the TRI. This matching process results in additional 380 bankruptcies.

### 3.2 Emissions data

Our emissions data come from the Toxic Release Inventory (TRI) database, which contains information on toxic releases from US facilities participating in the TRI program. Established in 1985, this program mandates that US facilities in industries with significant toxic releases report data on TRI chemicals, including releases, waste management (e.g., recycling), and pollution prevention activities at a facility-chemical-year level. Since its inception, the database has accumulated data from approximately 56,000 different facilities. The TRI program currently covers 767 individually listed chemicals and 33 chemical categories. For our analysis, we focus on data from 2004 to 2019. We begin in 2004 to ensure we have three years of data before the earliest bankruptcy event in 2007. For these years, we obtain information on facility toxic releases, waste management practices, and the production ratio, which indicates the ratio of current year production to production in the previous year. This ratio effectively captures the output growth of the facility.

Our next step is to determine facility parent firm and track changes in ownership over time. Although TRI mandates that facility-managers report the name of the parent firm, this information is often incomplete or inaccurate. Reports may sometimes indicate only the name of a higher division level instead of the ultimate parent, and changes in ownership often take several years to get updated in the TRI forms. To ensure accurate matching of each facility with its corresponding firm every year, we match the TRI sample with the National Establishment Time-Series (NETS) Database. Created through a collaboration between Dun and Bradstreet and Walls and Associates, the NETS database tracks all US establishments over time and provides annual information on the ultimate parent company of each facility. NETS has also developed a bridge to match facility IDs between NETS and TRI and used it to construct the Toxics Release Inventory (TRI) Establishments Database – facility-year database of all the firms that have ever reported to TRI. Along with the bridge information, NETS also provide facility-level SIC 4-digit code, as well as several corporate-level indicators such as corporate-level sales, and credit scores. We use these indicators in some of our analysis. We merge this database with emissions data from TRI to obtain emissions information for facilities that were operational and generated sales in a given year.

### 3.3 Final sample

To construct the final sample of bankrupt facilities, we match the names of bankrupt firms between Capital IQ sample and NETS. We begin with fuzzy matching of the names and use the generalized edit distance method to identify cases with high levels of similarity and then manually verify the accuracy of each match. This step identifies 207 NETS firms that have experienced at least one bankruptcy event and have ever reported emissions in TRI.

Next, we perform several data cleaning steps. First, we consolidate instances where a firm has multiple bankruptcy filings within a one-week period into a single case. Second, we address cases of multiple bankruptcies throughout our sample period by retaining only the earliest bankruptcy event. Third, we exclude bankrupt firms that only have TRI data reports outside of the 2004–2019 period. This reduces the number of bankruptcy cases to 161. For each bankruptcy case, we then manually review all bankruptcy-related documents in the Public Access to Court Electronic Records (PACER) to identify the bankruptcy exit date. We could find all but one case, resulting in a final sample of 160 bankrupt firms.

Our final facility-year sample consists of 217,700 NETS-TRI observations. We have a total of 28,462 facilities that belong to 17,212 US firms, both public and private. Within this dataset, 800 TRI facilities have been owned by a bankrupt firm at some point of time. The distribution of bankruptcy events between 2007–2019 appears in Table 2 Panel A. The distribution of bankrupt facilities across SIC codes appear in Table 2 Panel B.[3] We note that although we have a relatively small number of bankruptcy events in our study, this does not pose a small sample size problem. Our method of identifying bankrupt facilities comprehensively covers all sizable bankruptcies by firms operating in industries with significant emissions output. While including smaller bankruptcies and low-emission industries might increase the sample size, it is unlikely to enhance the precision of our analysis due to the relatively low environmental

[3] The data for this panel is structured at a unique facility-SIC level. Since a facility can change its SIC classification throughout its sample period, the number of observations in this panel is greater than 800.

impact of these additions. Moreover, running an OLS regression with equally weighted observations and focusing the interpretation on the average effects could bias the results towards the behavior of environmentally insignificant firms.

### 3.4 Variables and empirical design

#### 3.4.1 Environmental impact

To measure the environmental impact associated with firm production, we use several measures. Our main variable of interest is onsite emissions—the total amount of toxic chemicals a firm releases into the air, water, and soil. In our empirical analysis, it is crucial to sum up these emissions rather than analyzing their output at a facility-chemical-year level. The reason is that financial distress and bankruptcy are likely to alter a firm's production function, leading to reduced product lines, shifts to lower-quality inputs, and substitutions among different inputs. Consequently, the analysis of emissions at the individual chemical level can miss changes significant to the environment, such as a change in the number of chemicals used. Additionally, a regression that includes chemical-fixed effects would filter out the average levels of each chemical, potentially overlooking shifts from small and stable amounts of one chemical to large and stable amounts of another. By summing emissions and considering abatement activities, we can better assess the overall environmental impact of firm production.

Next, we measure the extent of abatement activities by examining the total amount of toxic chemicals managed by the facility. Chemical management practices fall into three main categories: recycling (recovering useful materials from waste), treatment (destroying or neutralizing toxic chemicals), and energy recovery (burning waste materials to generate energy, typically as heat or electricity). We sum up the amounts of chemicals managed by every facility in a given year across all chemicals.

One concern with the above measures is that some chemicals are more toxic than others, so that a simple sum across chemicals is a very imprecise measure of environmental impact. We address this concern in two ways. First, we use the Risk-Screening Environmental Indicators (RSEI), developed by the U.S. Environmental Protection Agency (EPA) to assess the potential health risks associated with chemical emissions. It combines data on toxic chemical releases, facility locations, and toxicity weights to provide a screening-level estimate of potential human health impacts. The tool integrates various factors such as the quantity of chemical releases, their toxicity, the pathway into the environment and population exposure to provide a more comprehensive risk assessment. As a result, the RSEI score scales the amount of each emitted chemical by a coefficient that measures its toxicity and the impact on the surrounding population. We use the sum of RSEI scores for every facility-year as an alternative way to measure environmental impact of a facility.

Unfortunately, the RSEI score is limited to emissions and does not account for the overall toxicity reduction achieved through activities aimed at managing toxic waste. To capture this, we construct a standardized measure of emissions using the thresholds established by the Emergency Planning and Community Right-to-Know Act (EPCRA) for reporting hazardous and toxic chemicals to the EPA. EPCRA specifies different thresholds based on the nature and quantity of chemicals: 10 or 100 pounds for extremely hazardous substances, and 25,000 pounds for other hazardous chemicals.[4] To create our standardized measure, we assume that a chemical reported at a 10-pound threshold is 10 times more toxic than one reported at a 100-pound threshold. Using the 100-pound reporting threshold as a baseline, we scale each chemical accordingly: chemicals with a 10-pound threshold are scaled by a factor of 10, those with a 25,000-pound threshold are scaled by a factor of 1/250, and chemicals with a 100-pound threshold remain unchanged. This standardization allows us to obtain a normalized amount of chemicals, which we then use to calculate total emissions and total chemical management for each facility annually.

### 3.4.2 Bankruptcy indicators

Our main independent variable is a vector of indicator variables that flags the years before, during, and after bankruptcy. To construct this vector, we start by identifying the entry and exit dates of bankruptcy.

For the bankruptcy entry, we use the filing date as listed in Capital IQ, and in cases with multiple filings, we take the earliest date. To determine the bankruptcy exit, we search for every case docket in PACER and track all related documents. Overall, the bankruptcy exit date is defined as the date in which the plan of reorganization was confirmed by the bankruptcy court. In cases where there is no confirmation date because the case was dismissed, we use the dismissal date as the date of exit. In cases where there is neither confirmation nor dismiss date, we use the date in which bankruptcy case was terminated as the

[4] For a small number of chemicals, the thresholds are reported in grams. Since this threshold applies to extremely toxic, potentially radioactive, materials, with a very different methods of treatment and disposal, we exclude these chemicals from our analysis.

exit date. In cases where the filing was under Chapter 11 that then moved to chapter 7, we use the date when it moved to Chapter 7 as bankruptcy exit date (14 cases). Finally, in cases where bankruptcy was filed under Chapter 7 (10 cases) we define the date of bankruptcy exit as the same date as the bankruptcy date. The goal is to capture the fact that, upon liquidation, facilities are transferred to new ownership through selloffs.

Using these dates, we establish each firm's bankruptcy status for each year within the bankruptcy window. For any year in which the status changes, we assign the status that had the longest duration. For example, a firm that filed for bankruptcy before July 1 (and remained in bankruptcy until the end of the year) is classified as bankrupt for that year. Based on the identified bankruptcy year, we then construct indicators for one, two, and three years prior to bankruptcy. In a similar manner, based on the identified bankruptcy exit year, we construct indicators for one, two, and three years after bankruptcy.

According to our classification, a firm can remain in bankruptcy for more than a year, or it may exit bankruptcy within a few months, resulting in no single year being classified as a majority-bankruptcy year (e.g., a firm that has filed for bankruptcy in Nov 2008 and exited in Feb 2009). In some cases, both entry into and exit from bankruptcy occur within the same calendar year; in these instances, we assign the status with the highest number of days to that year. Analysis of long and short bankruptcy cases is discussed in the robustness section.

### 3.4.3 Size

We construct facility size based on the cumulative production ratios reported by the TRI. The TRI also reports which source of operations the production ratio is based on: production or activity. Production includes manufacturing, processing, or other production-related activities involving TRI-listed chemicals. In contrast, activity encompasses the handling of TRI-listed chemicals beyond their production, which is only indirectly related to firm production and may also include emissions. To avoid potential inaccuracies, we exclude production ratios derived from activity source.

Next, we average the production ratios across all chemicals for a given facility-NAICS year. This aggregation is justified, as nearly 80% of the facilities in our sample either report one chemical or use the same production ratio for all reported chemicals. We therefore conclude that emissions reported at the chemical level are generally the result of the same production processes used by the facility.

After aggregating production ratios for each facility-year, we cumulate these ratios starting from the earliest year the facility enters the sample, or from 2004, whichever is earlier. To prevent data loss due to missing values, we substitute a production value of one for any missing year. Finally, to mitigate the impact of outliers, we winsorize the final size variable at the 1% and 99% levels.

We note that an alternative method for constructing size variables is to use data from NETS, which reports sales and the number of employees at the facility level. Although these variables provide a reasonable indicator of facility size in cross-sectional analysis, they tend to be very static over time, often remaining unchanged for 5–10 years for a given facility. To support this argument, we regress emissions as a function of the log of size from TRI and the log of sales from NETS using specification, described in Section 4.2. We find that while both size and sales have a positive and highly significant impact on facility emissions and waste management in regressions with SIC- or NAICS-year fixed effects, the significance of sales disappears once facility fixed effects are also included (unreported). This further reinforces our argument that NETS size variables are primarily useful for cross-sectional analysis but not for capturing changes over time.

### 3.4.4 Descriptive Statistics

Table 3 presents the distribution of variables for bankrupt versus control facilities. Overall, bankruptcy-related firms and facilities tend to be slightly larger, as reflected by higher facility-level sales and a greater likelihood of association with a publicly traded firm. At the same time, they have lower cumulative growth ratios (measured by *Size*), lower credit score, and higher personnel turnover rates, consistent with being associated with financial distress. Notably, these firms have more than double the annual pollution levels of control firms (124,898 lbs vs 56,169lbs). Altogether, the summary statistics suggest that our sample bankrupt firms are larger, polluting more, growing less and have worse financial conditions than non-bankrupt firms. These statistics are consistent with characteristics of bankrupt firms noted in prior literature, and also suggest that these facilities have chronic problems.

## 4. Results

### 4.1 Empirical methodology validation

In our main empirical tests, we estimate the emissions of the facilities that belong to firms that have filed for bankruptcy as a function of the time dummy variables within a three-year window before and after the bankruptcy event, as well as production size and fixed effects.

Before turning to the analysis of emission in bankruptcy we validate our empirical design. If our methodology accurately captures the differences between treated and control firms, we should be able to confirm previously established facts regarding the characteristics of bankrupt firms and their behavior during the bankruptcy process.

#### 4.1.1 Production around bankruptcy

We begin the validation test by examining facility production decisions around the time of bankruptcy. Factors such as shifting consumer preferences, technological advancements, and intensified competition make firms more vulnerable to bankruptcy. In response to these challenges, firms frequently adopt strategic measures such as reducing production capacities and divesting facilities. During the bankruptcy process, production is typically further reduced as the firm works on a reorganization plan, which often involves streamlining operations and closing peripheral production lines. Consequently, we expect to observe a decline in the overall production of affected facilities both before and during bankruptcy.

To test this prediction, we start our analysis by comparing bankrupt facilities to non-bankrupt ones using the following regression:

$$\log\left(Q_{ikjt}\right) = \sum_{t=\tau-3}^{\tau+3} \delta_{kt} + \theta_{jt} + \varepsilon_{ikjt} \qquad (1)$$

where $\delta_{kt}$ represents a vector of indicator variables that equal 1 if facility *i* belongs to firm *k* that entered bankruptcy during the sample period. The year $\tau$ is the first year of bankruptcy, $Q_{ikjt}$ represents facility size in year *t*. $\theta_{jt}$ are industry-by-year fixed effects where industry is defined at each facility's SIC 4-digit level. Standard errors are double-clustered at the facility and year levels.

To capture the dynamic effect of financial distress on bankrupt facilities, we include facility fixed effects and year fixed-effects instead of industry-year fixed effects $\theta_{jt}$. We use the alternative specification to capture changes in firms' behavior relative to its own average levels.

The resulting coefficients for the vector $\delta_{j\tau-3}..\delta_{j\tau+3}$ along with their 5% confidence level appear in Figure 1-A. The results show that firms entering bankruptcy experience a decrease in their cumulative growth compared to other firms in the sample. The decrease is significant a year before bankruptcy and also during bankruptcy years. Firms that exit bankruptcy experience still a lower overall growth than other firms in the sample, but the overall cumulative growth levels become similar to other firms two years after bankruptcy.

In Figure 1-B we present the results of estimation where we use facility and year dummies to account for the overall facility size as well as other time-invariant characteristics that may affect production growth, such as fixed assets. The results are similar to those in the previous figure and suggest that the decline in production during bankruptcy is not only relative to other firms in the industry but also relative to the average production levels of the facility over time. We also repeat the regression after including both facility and industry-year effects. Figure 1-C shows a similar pattern of decrease in production before bankruptcy and rebound after bankruptcy when controlling for both industry-year effects and facility fixed effects.

To summarize, facilities around bankruptcy experience a significant decrease in production compared to otherwise similar facilities. This result also emphasizes the importance of controlling for production patterns when examining environmental impact of production. To the extent that production decreases before and during bankruptcy, one will likely observe a decrease in pollution by the mere fact that facilities produce less. Omission of production levels from the equation will likely lead to wrong inferences.

As another check for the changes in production levels around bankruptcy we also examine whether facilities file TRI reports around bankruptcy. To the extent that production levels decrease, pollution levels are also bound to decrease and it is more likely that some facilities will reach the pollution disclosure threshold and will not be required to file. We therefore run a linear regression model similar to regression (1) except that the dependent variable is a dummy variable for whether the facility filed a report in year

t. The results are presented in the Appendix in figure A1. Consistent with our original results we find a decrease in the probability of filing as the firm approaches bankruptcy and during bankruptcy.

### 4.1.2 Managerial changes around bankruptcy

In addition to reduced production, the onset of bankruptcy often triggers personnel shifts. This happens for two reasons. First, employees of firms heading towards bankruptcy are more likely to seek new job opportunities due to job insecurity. Second, firm executives may try to avoid the deepening of the economic distress by bringing in new managers with fresh perspectives to revamp the existing production strategies.

Although we do not have data on the entire facility personnel, we can track the identity of the individuals who sign the TRI forms for the Environmental Protection Agency (EPA) at each facility. Note that the certifying official is always an individual in a senior management position. In most cases, this is the plant manager, but in large enough facilities it can also be the Environmental Health and Safety (EHS) manager. To account for potential inconsistencies in name reporting, such as the use of short names or abbreviations, we employ fuzzy matching to determine whether the name is the same across years for the same facility. We define a dummy variable *Replaced* that equals one if the name of the person signing the TRI report in year *t* is different from the person that has signed it in *t*-1. We then run the following linear probability regression:

$$Replaced_{ijkt} = \sum_{t=\tau-3}^{\tau+3} \delta_{ijkt} + \theta_{jt} + \varepsilon_{ijkt} \qquad (2)$$

The coefficient results for the dummy variables $\delta_{j\tau-3}..\delta_{j\tau+3}$ along with their 5% confidence level appear in Figure 2-A. The results show that firms entering bankruptcy experience an increase in manager replacement a year before bankruptcy compared to other firms in the sample. We get similar result when we control for differences across facility characteristics by adding firm-fixed effects. The results, reported in Figure 2-B, show a significant increase during bankruptcy years.

To summarize, facilities around bankruptcy experience a significant increase in personnel replacements compared to otherwise similar facilities. This result is consistent with the effect of financial distress both on employee interest in working with the firm and with firms' struggle to keep existing personnel.

### 4.1.3 Attrition of facilities

Another potential effect of bankruptcy is the closure and sale of facilities. Theory suggests that when firms face economic distress, they often respond by closing or selling off facilities to become more focused and productive. Relatedly, Duchin, Gao, and Xu (2024) show that in response to environmental pressure firms tend to divest facilities. To examine the relationship between bankruptcy and the number of facilities, we analyze the number of facilities associated with each firm in any given year. For this purpose, we calculate the total number of operating NETS facilities for each firm-year, regardless of whether they reported to the TRI in that year or not.

We then run the following Poisson regression:

$$Number\ of\ facilities_{kjt} = \sum_{t=\tau-3}^{\tau+3} \delta_{kjt} + \theta_{jt} + \varepsilon_{kjt} \qquad (3)$$

where $\theta_{jt}$ are a firm's industry by year dummy. To identify firm industry, for every firm-year, we aggregate sales across all the facilities in the same SIC 4-digit code and assign the SIC code corresponding to SIC with the largest sales volume as the firm's SIC code in that year. We double cluster standard errors at a firm and SIC (2 digit) by year levels.

The coefficient results for the dummy variables $\delta_{j\tau-3}..\delta_{j\tau+3}$ along with their 5% confidence level appear in Figure 3-A. On average, firms that end up in bankruptcy tend to have significantly more facilities than their peers in the same industry and year. This pattern aligns with previous bankruptcy studies, which indicate that bankrupt firms are often larger due to past acquisitions or rapid expansion strategies that turned unsuccessful, leaving the firm too big and inefficient. When examining the time trend, we do not observe a significant pattern before bankruptcy. However, when we add also firm fixed effects (Figure 3-B) we observe a significant decline in the number of facilities during bankruptcy year. This pattern persists also after bankruptcy. A potential reason for the differences in the results once we control for firm effects is that there are firm-level differences in the number of facilities that each firm has, likely driven by production requirements or other reasons. Once we control for these differences using firm-fixed effect we detect a declining pattern in the number of facilities before bankruptcy.

### 4.1.3 Validation – summary

Taken together, the results confirm the validity of our empirical design and data. Our setting reliably captures both changes in production and turnover in facility management, as one would anticipate happening in firms around bankruptcy. It also points to facility closures as part of the reorganization plan. The validity tests address several potential concerns, including the relatively small ratio of affected to control facilities, the possibility that annual TRI reporting may not precisely capture the timing of bankruptcy entries and exits, and the self-reported nature of TRI data, which may not precisely measure a facility's actual production. With these concerns alleviated, we can now proceed to analyze the environmental footprint of bankrupt firms.

## 4.2 Emission-level decisions around bankruptcy

In this section, we turn to our main tests and examine whether bankrupt firms increase their emission levels before bankruptcy and whether filing for bankruptcy improves or worsens a firm's environmental impact. Our empirical design allows us to differentiate between chronic emission levels and acute levels associated with financial distress. To the extent that firms increase their emission levels as they become more financially distressed, we should observe larger coefficients for the indicator variables as the firm becomes more financially distressed.

### 4.2.1 On-site emission

We start our analysis of environmental impact by examining facility-level on-site emissions.[5] We estimate the following Poisson regression:

$$E_{ikjt} = \sum_{t=\tau-3}^{\tau+3} \delta_{kt} + \log\left(Q_{ikjt}\right) + \theta_{jt} + \varepsilon_{ikjt} \qquad (4)$$

[5] The TRI also requires facilities to report the amount of toxic chemicals transported and emitted off-site. This amount is relatively small compared to on-site emissions, and the vast majority of firms do not transport emissions off-site. Therefore, we do not focus on off-site emissions in our analysis. However, our results remain consistent when analyzing total emissions, including both on-site and off-site.

where $E_{ikjt}$ is total emissions of a facility *i* in year *t*, and the rest of the variables are as indicated in the previous equations. Notably, we include industry-years fixed effects to examine the relative level of emission of our facilities relative to other facilities. Our first measure of emissions is a simple sum of all toxic waste chemicals reported by the facility to the TRI. We present the results in Table 4 Panel A columns 1 and 2 and plot the coefficients of the bankruptcy fixed effects in Figure 4.

Table 4-A column 1 shows that the indicator variables from three years before bankruptcy the year of bankruptcy range between 0.529 and 0.732. They are all statistically significant from zero but not statistically different from one another. These results indicate that the bankrupt facilities pollute more than other firms in their industry, but these pollution levels are not increasing as the firm approaches bankruptcy. These findings are consistent with a chronic effect of higher pollution of these firms, regardless of whether they were approaching bankruptcy or were further away from bankruptcy. Interestingly, upon exiting bankruptcy, these facilities' pollution levels become similar to the industry.

We next capture changes in pollution levels around bankruptcy, controlling for facility fixed effects. This specification allows isolating fluctuations in firm pollution levels after controlling for both industry fluctuations and long-term facility-level average pollution. The results, shown in Table 4 column 2 show no significantly different changes in pollution levels before, during and after the bankruptcy. In fact, three years before the bankruptcy the coefficient is significantly different than zero but becomes insignificant across all other years.

Our pollution measure aggregates various toxins, assuming a homogenous effect across pollutants on the environment and on human health. We next relax the homogeneity assumption but examining a more refined pollution measure - the RSEI score. This score was developed by the EPA and it measures emission, adjusting for chemical toxicity, exposure route-specific toxicity weight (i.e., whether the release is into air, water, or soil), and the effect on potentially exposed nearby population. We present the results with this refined measure in Table 4 Panel A columns 3 and 4 and plot the time dummy coefficients in Figure 5. Column 3 in Table 4 shows no clear relation between the firm approaching bankruptcy and emission levels. Moreover, most coefficients are not statistically different from zero. Column 4 presents the results with the facility effects, where most coefficients are also statistically insignificant.

As a final method to verify the robustness of our results, we use toxicity-adjusted total emissions, weighting the chemicals by their hazard levels. Although potentially less precise than the RSEI, this measure avoids the skewness that the RSEI model can introduce by scaling the amount of toxic chemicals by an extremely large coefficient due to a very dense nearby population – a scope of dissemination estimate that may not always be accurate. At the same time, it is more precise than our first measure because it accounts for varying toxicity levels across different toxic wastes. The results, presented in Table 4 Panel A columns 5 show emission levels of bankrupt firms that are significantly higher than their industry counterparts, similar to the results in Column 1. These findings are consistent with chronic emission levels as far as three years before bankruptcy. Column 6 shows no significant differences in pollution levels relative to average facility-levels, detecting no acute effect of financial distress and bankruptcy.

Overall, we find evidence consistent with heightened pollution levels for firms in the bankrupt sample relative to the non-bankrupt sample. These high pollution levels persist from three years before the bankruptcy to the bankruptcy event itself, and they are consistent with a chronic effect of pollution levels for firms in the sample. In contrast, we do not find an acute effect as firms approach bankruptcy.

*4.2.1.A On-site emission - robustness*

We perform several additional robustness checks to examine the sensitivity of the above results to different empirical specifications and controls and report the results in the appendix.

We first examine the sensitivity of our results to the level of production. In Figure A.1A we plot the coefficients of regression (4) without controlling for changes in production levels. We can see that without controlling for production, the pattern shown is decrease in pollution before bankruptcy, consistent with a declining production pattern. In Figure A.1B we include the less-accurate corporate-level sales controls in regression 4 (rather than the facility-level change-in-production controls). The results, shown in Figure A.1B show a similar pattern to the ones in Figure 4.

Next, we examine whether the non-result is driven by the existence of strategic bankruptcies that do not necessarily represent firms in deep financial distress. To that end, we separate bankruptcy firms into firms with low MinPayDex score and firms with high MinPayDex score. The PayDex Score is a dollar-weighted indicator intended to reflect a business's past payment performance. Companies receive a score between 1 and 100, where a higher number represents a greater likelihood that a business will pay its debts on time. This proprietary score is calculated based upon all records of payment experiences submitted to Dun & Bradstreet by suppliers and vendors, and are subject to Dun & Bradstreet's review, verification, and approval process. Following Akey and Appel (2021), we use MinPayDex – the lowest PayDex score a company received during the year. In Figure A.1C we show the results for firms with below sample-median MinPayDex score (score below 70), and in Figure A.1D we show the results for firms with above sample-median PayDex. The pattern in both cases is rather similar. In fact, in the case of the more financially distressed firms, the decrease in emission levels before bankruptcy is more pronounced, suggesting no acute effect of emission levels for financial distressed firms as they move towards bankruptcy. Cutting the sample at the bottom 25 percentile of the PayDex score – (score below 64) yields similar results (unreported for brevity).

Finally, in Table A.2 we test the sensitivity of our results to alternative industry definitions and repeat the baseline analysis of emissions using the more granular, 6-digit NAICS classification instead of the 4-digit SIC classification. The pattern remains the same under the alternative industry classification.

### 4.2.2 Emission management

In this subsection we focus on the emission management levels of bankrupt firms. Note that if there is an acute effect of financial distress on emission abatement, we should observe that bankrupt firms avoid treating toxic wastes to cut costs. To examine this hypothesis, we run the following regression:

$$TWM_{ikjt} = \sum_{t=\tau-3}^{\tau+3} \delta_{kt} + \log\left(Q_{ikjt}\right) + \theta_{jt} + \varepsilon_{ikjt} \qquad (5)$$

where *TWM* stands for the total amount of toxic waste managed onsite. We present the results in Table 5 Panel A in columns 1 and 2. The time coefficients are also plotted in Figure 7. Table 5 column A shows positively significant coefficients from three years before bankruptcy to the year of bankruptcy. However, these coefficients are not statistically different from one another, consistent with these facilities polluting chronically more. Once we include the facility fixed effect in column 2, we observe no significant pattern in emission management, consistent with no acute effect of financial distress on emission levels.

Next, we examine an alternative measure of abatement using standardized chemical abatement levels, which we construct in the same way as standardized toxic emissions - by weighting its chemical by its toxicity threshold. We present the results in Table 5 Panel A columns 3 and 4. The plot of time coefficients appear in Figure 8. The results are similar to those in columns 1 and 2.

To conclude, our results indicate a chronic effect of higher pollution among the bankrupt sample facilities, but no acute effect of pollution as these firms approach bankruptcy.

**4.2.3 Extensive margins**

So far, our results have focused on the intensive margins – the amount of pollution a facility reports to the TRI conditional on having to file a report. However, it is possible that the number of reporting facilities changes when firms enter bankruptcy. This could happen for one of the two reasons: Either the facility's operations have become significantly greener, or the facility size and operation volume have dropped below the TRI reporting requirement threshold. Since we are interested in the effect of financial distress and bankruptcy on total emission, we switch to a firm-level analysis and calculate the fraction of TRI-reporting facilities out of the total number of facilities a firm operates in a given year. We then estimate the following regression at the firm-year level:

$$Ratio\ of\ emitting\ facilities_{kjt} = \sum_{t=\tau-3}^{\tau+3} \delta_{kt} + \beta_{kt} + \theta_{jt} + \varepsilon_{kjt} \qquad (6)$$

where $\beta_{kt}$ is the natural log of one plus the total number of facilities that the firm operates in year *t*, and the rest of the variables and fixed effects are the same as in equation (3).

Figure 9-A presents the results with firm-level SIC by year fixed effects. The fraction of reporting facilities is on average 0.1 higher in the three years and two years before bankruptcy compared to other firms in the same industry. This suggests that bankrupt firms, on average, have more facilities that emit under the TRI program, potentially indicating that their plants are larger and therefore more likely to be subject to reporting requirements. We also find a decrease in the number of reporting facilities to about industry

levels starting a year before bankruptcy and continuing during bankruptcy year. Following bankruptcy, the fraction of reporting facilities drops and two years after bankruptcy it becomes in line with the peer average. We find similar results when we include firm-fixed effects (Figure 9-B and Figure 9-C). Keeping the firm time-invariant level of reporting constant, there is a significant drop in the fraction of reporting facilities.

To better understand whether the bankruptcy procedure has an overall positive impact on the environment, we re-estimate the regression of onsite emissions and management at a firm level, using the log of the total number of facilities as a control for firm size. The results are presented in Figures 10-A and 10-B.

The results in Figure 10-A are consistent with higher level of emissions in bankrupt firms, after controlling for size. These levels are in the order of magnitude of 1.4 across all years and they are statistically significant. Yet, there is no statistically significant change from year to year. Emission management at the firm level is also higher once controlling for size as shown in Figure 10C, but there are not significant changes from year to year once we control for firm fixed effects (Figure 10D).
Overall, these firm-level results corroborate the facility-level results and further suggest that the bankruptcy sample includes firms who are chronically emitting more pollution. Yet there is no acute increase in pollution as the firm approaches bankruptcy.

## 5. Mechanism and cross-sectional tests

The results of the previous section robustly indicate that bankrupt firms are inherently more polluting but there is no acute effect of financial distress and bankruptcy on their level of pollution. In this section, we aim to explore heterogeneity in the acute effect among bankrupt firms.

### 5.1 Financial crisis

In this section, we divide our sample of bankruptcies into those driven by financial distress and those driven by economic distress. Approximately 40% of the bankruptcies in our sample occurred during the financial crisis of 2008-2009. Since our sample consists of manufacturing firms, the financial crisis is more likely to impact them through the financial channel rather than the operational channel.

Consequently, firms that declared bankruptcy during the crisis likely faced unexpected financial constraints due to difficulties to raise capital and suffered from a short-term drop in sales. These firms are potentially less likely to alter their pollution profile over a short period of time and therefore would not be subject to an acute pollution affect. In contrast, firms that filed for bankruptcy outside the financial crisis period usually cite a combination of financial and economic factors for their entry into bankruptcy. They therefore have potentially more time and flexibility to address their financial distress by changing their emission strategy.

To test whether the pattern of no significant changes in the emission output during the bankruptcy window is due to firms that filed during the financial crisis, we repeat our key tests separately for each bankruptcy type (our control group for each type is the same as in the main test and includes all the facilities which parent firms have never gone bankrupt). We note that from an econometric standpoint, splitting the sample into financial crisis-driven versus non-financial crisis-driven bankruptcies also helps address concerns related to staggered bankruptcy design (Baker, Larcker, and Wang, 2022). Averaging the treatment effect across bankruptcies that span a long period and including bankrupt facilities outside of their bankruptcy windows as controls for other bankruptcy events could potentially bias our findings towards a non-result. By focusing on the sample of financial crisis facilities, the vast majority of which declared bankruptcy in the same year, we mitigate the first concern. Additionally, in the analysis of financial crisis bankruptcies, we only use control facilities that either belonged to financial crisis bankruptcies or have never experienced bankruptcy, thus addressing the second concern. As a result, our financial sample analysis is essentially a staggered-design analysis, only with one treatment event.

In Figure 11 we present the main results using the facility and industry-year fixed effects. Additional specifications based on alternative ways to measure emission and management are relegated to the appendix Figure A.2.

First, we confirm the validity of the empirical setting by estimating the regression of facility size within each group. The results, shown in Figure 11-A show similar pattern regardless of whether bankruptcy occurred during the financial crisis or outside the crisis. We also find an increased managerial replacement before bankruptcy in both subsamples (Figure 11-B). The increased likelihood of replacement starts in the year before bankruptcy in the noncrisis sample and in the bankruptcy year in the crisis sample. This is further consistent with the idea that the financial crisis was unexpected.

We then estimate the emission level as a function of bankruptcy dummies. We find that the sample levels during the financial crisis and outside the financial crisis are not statistically different from zero across all year (Figure 11-C). In particular, there is no increase in emission levels as the firm approaches bankruptcy for the noncrisis sample. We repeat the analysis for onsite management. Figure 11-D shows that onsite management in the noncrisis sample bankruptcies remains stable and does not decline as the facility approaches bankruptcy.

Overall, the results from the subsample split tests indicate that leaving out the facilities that went into bankruptcy during the financial crisis from the sample does not alter any of our original results.

### 5.2 Bankruptcy duration

One possible reason for the fact that we do not find an acute effect of financial distress on emission is that there is heterogeneity in the extent of financial distress firms experience before bankruptcy. Since filing for bankruptcy is a choice decision by firms (e.g., White 1989, Carapeto 2005, Hotchkiss, John, Mooradian and Thorburn 2008), firms might opt to file for bankruptcy strategically, even if they are not severely distressed. At the same time, we expect firms that are less profitable, firms with lower quality, and firms that are in declining industries to spend longer time in bankruptcy (Denis and Rodgers, 2009). It is possible that these firms are more susceptible to finding ways to cut costs and increase emissions because of their relative disadvantage.

The first category includes firms that spent less than a year in bankruptcy; these firms have no single year where the $\tau = 0$ indicator is equal to one, meaning that year $\tau + 1$ follows right after year $\tau - 1$. The second category consists of firms where there is only one time indicator where $\tau = 0$ is equal to one, so that these firms spent one year in bankruptcy. The third category comprises firms that spent two years or more in bankruptcy. We refer to these categories as short bankruptcies, regular bankruptcies, and long bankruptcies, respectively. Among all the bankruptcy events in our sample, 38% are short bankruptcies, 23% are long, and the rest are regular. For each subsample we run the regression (3) of emissions on firm industry-year effects, facility and time dummies for bankrupt firms. For the sake of brevity, we present the only results using the facility and industry-year fixed effects.

We begin by verifying the validity of our classification. Figure 12-A, illustrates the changes in facility production for each bankruptcy types. As expected, firms undergoing short bankruptcies experience the smallest decrease, while those involved in long bankruptcy cases face the steepest production decline. This pattern remains consistent when we repeat the estimation with facility fixed effects, as shown in Figure 12-B. These findings confirm not only the validity of our bankruptcy type classification but also the robustness of our empirical setting in general. The TRI data effectively distinguishes between simple and complex bankruptcy cases and accurately captures the timing of bankruptcy events.

We then turn to the analysis of emissions. We do not find any substantial increase in emission prior or during the bankruptcy for short, regular, and long bankruptcies (Figure 12-B). We also examine changes in abatement practices and repeat our analysis of onsite management of toxic waste and find no significant pattern in abatement levels in short, regular, or long bankruptcies (Figure 12-C). In the appendix Figure A.3 we provide additional analysis, including alternative specifications. All the results are consistent with the results in Figure 12.

Overall, our cross-sectional analysis across bankruptcy types does not identify an acute effect of increased pollution levels as a response to financial distress. These findings further corroborate our initial results of a chronic, rather than acute, pollution effect of bankrupt firms.

### 5.3 Public versus private firms

Lastly, we investigate whether emission patterns leading to bankruptcy differ between public and private firms. Private firms tend to emit less compared to public firms (Shive and Forster 2020), likely because of owners' stronger personal responsibility and concentrated ownership. We should therefore expect public firms rather than private firms to be more prone to acute increases in pollution as they approach bankruptcy.

We define public firms as those that were publicly traded at any point during the sample period.[6] Around quarter of the facility-years in our sample are flagged as public. Once again, we verify that the decline in production exists among both public and private firms (Figure 13-A). When we examine emissions, we do not find an increase in emission in public firms as they approach bankruptcy. In fact, we find a decrease in emissions over time. Facilities of firms that were never public do not show any significant pattern prior to bankruptcy or within bankruptcy (Figure 13-B). These results are robust to the use of alternative emission levels (see Appendix). Consistent with the above results we also do not observe any decrease in abatement expenses among public firms as they approach bankruptcy. (Figure 13-C).

## 6. Conclusion

Our study reveals that high pollution levels among bankrupt firms are due to heighten chronic pollution levels of firm facilities rather than due to acute increase in pollution because of financial distress. By analyzing bankruptcy cases in the US from 2007 to 2019, particularly in industries known for pollution, we found no significant increase in emissions or toxic waste management activities as firms approach bankruptcy.

There could be several reasons for this result. We highlight the potential importance of regulatory frameworks that effectively mitigate potential environmental risks associated with financial distress. But it is also possible that production processes these days do not allow for strong deviations from emission standards, either because production equipment already embed regulatory requirements (such as, for example, catalytic converters), or because the processes themselves cannot be easily altered.

From investors' perspective, these results highlight the causes of environmental risks and their relation to financial risk. Our findings are more consistent with environmental risks being a chronic problem in

[6] This classification method is dictated by our data source for identifying public firms. We use Mergent Intellect, which assigns a "publicly traded" flag to firms based on their DUNS numbers. As Mergent's data is primarily header-level, we can only determine if a firm was ever publicly traded. We believe this approach is still valid, as many publicly traded firms go private during bankruptcy or are involuntarily delisted due to low stock prices and trading volumes.

firms that enter bankruptcy. To mitigate their risk, investors should put more emphasis on analyzing firms' environmental risks at the outset.

These findings have also important regulatory implications. From a policy perspective, existing disclosure requirements and enforcement mechanisms appear to curb the risky behavior associated with emissions before and during bankruptcy. It also appears that creditor covenants and monitoring processes mitigate risky emission behaviors, which aligns with Gilje (2016), who finds that financially distressed firms in the oil industry tend to reduce risk. Thus, contractual arrangements can be effectively managed to avoid environmental risks. This suggests that additional regulatory measures to limit emissions among financially distressed firms may not be necessary.

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**Table 2: Sample description – the number of bankruptcy cases and impacted facilities**

The table shows the distribution of bankrupt firms and their facilities over time and across industries. Bankrupt firms are firms that operate in polluting industries, have at least $50 million in liabilities at the time of bankruptcy and appear in Capital IQ, NETS, and TRI. Bankrupt facilities are facilities that have belonged to a bankrupt firm at any point of the sample period. See Section 3 for further details of the bankrupt firms' sample construction. Panel A shows the distribution of bankruptcy events over time, based on the year of bankruptcy filing. Panel B shows the distribution of facilities across industries, where industry is defined at a facility's SIC 2-digit level. If a facility changes SIC classification throughout its life, it appears as a separate record for each new classification.

**Panel A: Bankruptcy events by year**

| Year | Number of bankruptcies |
|---|---|
| 2007 | 3 |
| 2008 | 26 |
| 2009 | 40 |
| 2010 | 13 |
| 2011 | 12 |
| 2012 | 13 |
| 2013 | 9 |
| 2014 | 8 |
| 2015 | 6 |
| 2016 | 8 |
| 2017 | 7 |
| 2018 | 8 |
| 2019 | 7 |
| **Total** | **160** |

**Panel B: The distribution of bankrupt facilities across industries**

| SIC 2-digit | Description | Number of Facilities |
|---|---|---|
| 33 | Primary Metal Industries | 112 |
| 26 | Paper and Allied Products | 95 |
| 37 | Transportation Equipment | 93 |
| 28 | Chemicals and Allied Products | 70 |
| 24 | Lumber and Wood Products, Except Furniture | 69 |
| 34 | Fabricated Metal Products | 56 |
| 30 | Rubber and Miscellaneous Plastic Products | 55 |
| 20 | Food and Kindred Products | 43 |
| 36 | Electronic & Other Electrical Equipment & Components | 41 |
| 35 | Industrial and Commercial Machinery and Computer Equipment | 37 |
| 50 | Wholesale Trade - Durable Goods | 29 |
| 27 | Printing, Publishing and Allied Industries | 28 |
| 51 | Wholesale Trade - Nondurable Goods | 19 |
| 52 | Building Materials, Hardware, Garden Supplies & Mobile Homes | 16 |
| 22 | Textile Mill Products | 15 |
| 87 | Engineering, Accounting, Research, and Management Services | 14 |
| 25 | Furniture and Fixtures | 13 |
| 12 | Coal Mining | 12 |
| 49 | Electric, Gas and Sanitary Services | 12 |
| 39 | Miscellaneous Manufacturing Industries | 10 |
| 59 | Miscellaneous Retail | 9 |
| 29 | Petroleum Refining and Related Industries | 8 |
| 38 | Measuring, Photographic, Medical, & Optical Goods, & Clocks | 8 |
| 55 | Automotive Dealers and Gasoline Service Stations | 8 |
| 73 | Business Services | 8 |
| 42 | Motor Freight Transportation | 6 |
| 32 | Stone, Clay, Glass, and Concrete Products | 5 |
| 15 | Construction - General Contractors & Operative Builders | 4 |
| 17 | Construction - Special Trade Contractors | 4 |
| 10 | Metal Mining | 2 |
| Other | | 18 |
| **Total** | | **919** |

**Table 3: Descriptive Statistics**

The table shows the distribution of bankrupt and non-bankrupt facility-year observations within our sample. The sample period is 2004 – 2019. Bankrupt facilities are facilities that at some point during the sample period belonged to firm that has filed for bankruptcy. *Sale* is total sales, in $million. *MinPayDex* is the lowest PayDex business credit score a company received during the year. *Indicator (Public)* takes on a value of one if the facility belongs to a firm that was ever publicly traded. *Size* is the cumulative production ratios, starting from 2004 or the first year the facility appears in the TRI database, whichever comes first. *Indicator (New manager)* takes on a value of one if the manager filing the TRI firm in year t is different from the previous year. *Onsite emissions* [*Onsite management*] is the total amount of toxic chemicals emitted by [managed by] a facility onsite. *Onsite emissions RSEI* are the total amount of toxic chemicals emitted by a facility, where the amount of every emitted chemical is scaled by a coefficient of its toxicity, its path to the environment, and the breadth of the chemical impact on the surrounding population. *Onside emission – std.* [*Onside management – std.*] are the total amount of chemicals emitted onsite [chemicals managed onsite] where the amount of chemical is adjusted based on it toxicity threshold, using a 100-pound chemical reporting threshold as the benchmark. See Section 3 for more details.

## Table 3: Descriptive Statistics (continued)

### Panel A: Bankrupt facilities

| | Nobs. | Mean | Median | P25 | P75 | Std. Dev. |
|---|---|---|---|---|---|---|
| *NETS variables* | | | | | | |
| Sales ($Million) | 9,349 | 60.0 | 25.5 | 8.4 | 57.4 | 104.4 |
| MinPayDex | 8,231 | 65.3 | 67.0 | 60.0 | 73.0 | 10.8 |
| Indicator (Public) | 9,349 | 0.41 | 0.0 | 0.0 | 1.0 | 0.5 |
| | | | | | | |
| *TRI variables* | | | | | | |
| Size | 4,146 | 1.0 | 1.0 | 0.7 | 1.2 | 0.7 |
| Indicator (New manager) | 4,230 | 0.3 | 0.0 | 0.0 | 1.0 | 0.5 |
| Onsite emissions | 5,008 | 124,898 | 1,770.5 | 1.2 | 35,304 | 375,324 |
| Onsite emissions RSEI | 4,388 | 15,317 | 83.0 | 1.5 | 1,447 | 62,767 |
| Onsite emission - std. | 5,008 | 1,365 | 19.4 | 0.1 | 272 | 4,926 |
| Onsite management | 5,008 | 922,873 | 0.0 | 0.0 | 73,750 | 2,858,360 |
| Onsite management - std. | 5,008 | 5,310 | 0.0 | 0.0 | 329 | 17,207 |

### Panel B: Control facilities

| | Nobs. | Mean | Median | P25 | P75 | Std. Dev. |
|---|---|---|---|---|---|---|
| *NETS variables* | | | | | | |
| Sales ($Million) | 492,100 | 39.4 | 12.7 | 4.1 | 37.2 | 80.0 |
| MinPayDex | 433,578 | 68.0 | 70.0 | 63.0 | 76.0 | 10.5 |
| Indicator (Public) | 493,592 | 0.26 | 0.0 | 0.0 | 1.0 | 0.4 |
| | | | | | | |
| *TRI variables* | | | | | | |
| Size | 211,142 | 1.2 | 1.0 | 0.7 | 1.3 | 1.0 |
| Indicator (New manager) | 225,243 | 0.2 | 0.0 | 0.0 | 0.0 | 0.4 |
| Onsite emissions | 258,359 | 56,169 | 101.4 | 0.0 | 6,526 | 259,100 |
| Onsite emissions RSEI | 223,906 | 10,459 | 9.7 | 0.2 | 470 | 50,532 |
| Onsite emission - std. | 258,359 | 618 | 1.4 | 0.0 | 42 | 3,400 |
| Onsite management | 258,359 | 347,460 | 0.0 | 0.0 | 510 | 1,770,142 |
| Onsite management - std. | 258,359 | 2,010 | 0.0 | 0.0 | 4 | 10,486 |

## Table 4: Onsite emissions

This table reports the results of Poisson regressions where the dependent variables are measures of onsite emissions. The sample period is 2004 – 2019. *Onsite emissions* is the total amount of toxic chemicals emitted by a facility onsite. *Onsite emissions RSEI* are the total amount of toxic chemicals emitted by a facility, where the amount of every emitted chemical is scaled by a coefficient of its toxicity, its path to the environment, and the breadth of the chemical impact on the surrounding population. *Onsite emission – std.* are the total amount of chemicals emitted onsite where the amount of chemical is adjusted based on it toxicity threshold, using a 100-pound chemical reporting threshold as the benchmark. Facility *Size* is the cumulative production ratios, starting from 2004 or the first year the facility appears in the TRI database, whichever comes first. See Section 3 for more details of sample and variable construction. Standard errors are double clustered by facility and year levels. Standard errors are reported in parentheses. The symbols *, * *, and * * * denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: SIC industry classification

| | (1) Onsite emiss | (2) Onsite emiss | (3) Onsite emiss RSEI | (4) Onsite emiss RSEI | (5) Onsite emiss - std. | (6) Onsite emiss - std. |
|---|---|---|---|---|---|---|
| Log(size) | 0.173*** | 0.221*** | 0.095*** | 0.127*** | 0.187*** | 0.216*** |
| | (0.023) | (0.023) | (0.028) | (0.025) | (0.028) | (0.027) |
| -3 | 0.603** | 0.159*** | 0.009 | -0.145 | 0.663*** | 0.086 |
| | (0.261) | (0.053) | (0.186) | (0.107) | (0.226) | (0.127) |
| -2 | 0.732*** | 0.104 | 0.565** | 0.254* | 0.988*** | 0.143 |
| | (0.194) | (0.080) | (0.243) | (0.142) | (0.216) | (0.133) |
| -1 | 0.529*** | 0.003 | 0.386 | 0.159 | 1.018*** | 0.117 |
| | (0.186) | (0.066) | (0.275) | (0.146) | (0.283) | (0.149) |
| Bank. Year | 0.623*** | -0.140 | -0.293 | -0.235 | 1.051*** | -0.039 |
| | (0.211) | (0.100) | (0.457) | (0.434) | (0.375) | (0.172) |
| 1 | 0.160 | -0.013 | 0.058 | -0.681** | 0.433 | 0.027 |
| | (0.207) | (0.181) | (0.631) | (0.325) | (0.330) | (0.151) |
| 2 | 0.189 | 0.028 | -0.371 | -0.351 | 0.348 | 0.074 |
| | (0.232) | (0.144) | (0.694) | (0.291) | (0.344) | (0.121) |
| 3 | 0.323 | 0.135* | 0.209 | 0.220 | 0.273 | 0.086 |
| | (0.310) | (0.078) | (0.702) | (0.514) | (0.545) | (0.122) |
| SIC x Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Facility FE | No | Yes | No | Yes | No | Yes |
| Nobs | 215291 | 215205 | 200450 | 200450 | 215291 | 215205 |
| Pseudo R-sq. | 0.508 | 0.959 | 0.244 | v0.902 | 0.565 | 0.963 |

## Table 5: Emission management

This table reports the results of Poisson regressions where the dependent variables are emission management. The sample period is 2004 – 2019. *Onsite mgmt* is the total amount of toxic chemicals emitted by a facility onsite. *Onsite mgmt – std.* are the total amount of chemicals emitted onsite where the amount of chemical is adjusted based on it toxicity threshold, using a 100-pound chemical reporting threshold as the benchmark. *Size* is the cumulative production ratios, starting from 2004 or the first year the facility appears in the TRI database, whichever comes first. See Section 3 for more details of sample and variable construction. Standard errors are double clustered by facility and year levels. Standard errors are reported in parentheses. The symbols *, * *, and * * * denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: SIC industry classification

| | (1) Onsite mgmt | (2) Onsite mgmt | (3) Onsite mgmt - std. | (4) Onsite mgmt - std. |
|---|---|---|---|---|
| Log(size) | 0.185*** | 0.098*** | 0.181*** | 0.087*** |
| | (0.028) | (0.027) | (0.029) | (0.026) |
| -3 | 0.769*** | -0.011 | 0.834*** | 0.044 |
| | (0.203) | (0.100) | (0.223) | (0.082) |
| -2 | 0.759*** | 0.096 | 0.758*** | 0.032 |
| | (0.215) | (0.127) | (0.214) | (0.162) |
| -1 | 0.784*** | 0.103 | 0.803*** | 0.021 |
| | (0.217) | (0.147) | (0.222) | (0.154) |
| Bank. Year | 0.833** | 0.042 | 0.731** | -0.149 |
| | (0.414) | (0.174) | (0.351) | (0.192) |
| 1 | 0.619** | 0.000 | 0.456 | -0.271 |
| | (0.303) | (0.181) | (0.293) | (0.210) |
| 2 | 0.418 | -0.009 | 0.231 | -0.270 |
| | (0.359) | (0.162) | (0.402) | (0.189) |
| 3 | 0.353 | -0.105 | -0.059 | -0.539** |
| | (0.413) | (0.172) | (0.466) | (0.265) |
| SIC x Year FE | Yes | Yes | Yes | Yes |
| Facility FE | No | Yes | No | Yes |
| Nobs | 215291 | 215291 | 215291 | 215291 |
| Pseudo R-sq. | 0.38 | 0.94 | 0.35 | 0.93 |

**Table 6: Bankruptcy and environmental violations**

This table reports the results of OLS regressions where the dependent variable is an indicator that takes on a value of one if the facility's parent has filed for bankruptcy in year *t*, and zero otherwise. The sample period is 2004 – 2019. In column (1) Δ*Nonattainment* is a dummy variable that takes on a value of one if the facility's county attainment status in year *t* has changed from "attainment" across all chemicals to "non-attainment" in at least one chemical, and zero otherwise. In column (2) Δ*Nonattainment* is a dummy variable that takes on a value of one if the number of non-attained chemicals in facility's county has increased in year *t*, and zero otherwise. In column (3) ICIS penalty is the natural log of one plus the total dollar amount of ICIS penalty imposed on a facility in year *t*, and zero otherwise. In column (4) ICIS penalty is a dummy variable that takes on a value of one if the penalty was $80,000 or higher, and zero otherwise. See Section 3 for more details of sample and other variable construction. Standard errors are double clustered by facility and year levels. Standard errors are reported in parentheses. All the coefficients and their standard errors are multiplied by a factor of 100 for tractability. The symbols *, * *, and * * * denote statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| ΔNonattainment (t) | 0.015 | -0.030 | | |
| | (0.072) | (0.049) | | |
| ΔNonattainment (t-1) | 0.018 | -0.005 | | |
| | (0.066) | (0.023) | | |
| ΔNonattainment (t-2) | 0.098 | 0.054 | | |
| | (0.219) | (0.062) | | |
| ICIS penalty (t) | | | 0.005 | 0.100 |
| | | | (0.005) | (0.107) |
| ICIS penalty (t-1) | | | -0.001 | 0.092 |
| | | | (0.005) | (0.126) |
| ICIS penalty (t-2) | | | 0.003 | -0.142*** |
| | | | (0.003) | (0.045) |
| Ln(Size) | -0.008 | -0.008 | -0.010 | -0.010 |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| SIC x Year FE | Yes | Yes | Yes | Yes |
| Nobs | 158750 | 158750 | 162046 | 162046 |
| Pseudo R-sq. | 0.01 | 0.01 | 0.01 | 0.01 |

**Figure 1: Production output levels of bankrupt facilities around bankruptcy**

The figure shows coefficients of the time dummy variables in regression (1), from 3 years before the bankruptcy to three years after the bankruptcy, as well as their 95% confidence intervals. The explanatory variable is *Log(size)*, where size is the cumulation of production growth ratios from TRI. *Bank. Year* equals one for every year the firm is in bankruptcy, and zero otherwise. The sample is based on all NETS facilities over the 2004 to 2019 period that report to the TRI in a given year. See Section 3 for more details of sample and variable construction. Standard errors are double clustered by facility and year levels.

**Figure 1-A: Log size, with SIC x Year FE**

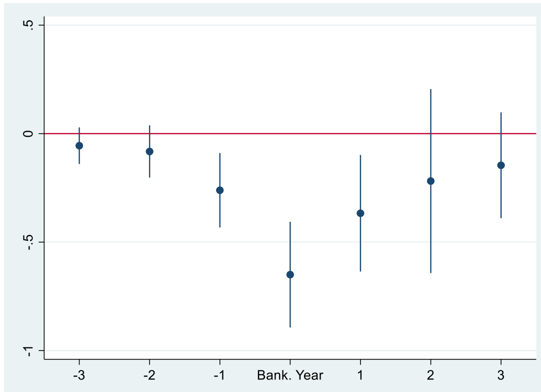



**Figure 1-B: Log size, with Facility & Year FE**

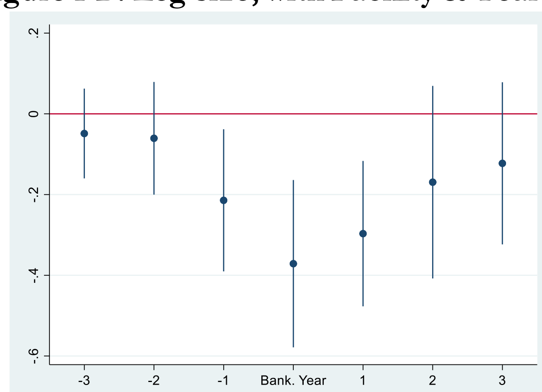



**Figure 1-C: Log size, with Facility & SIC x Year FE**

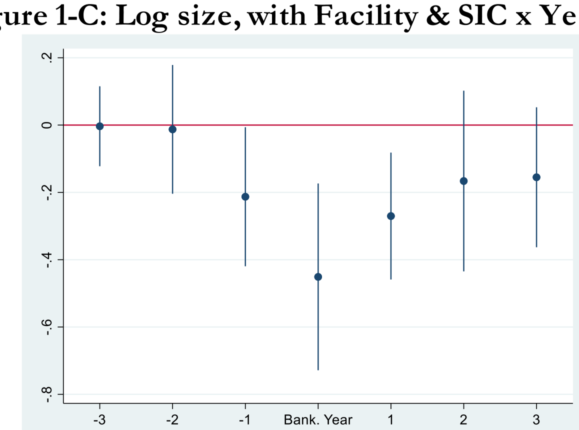


**Figure 2: Replacements of facility managers around bankruptcy**

The figure shows coefficients of the time dummy variables in regression (2), from 3 years before the bankruptcy to three years after the bankruptcy, as well as their 95% confidence intervals. The dependent variable is an indicator that takes on a value of one if the name of the manager that submits the report to TRI is different from the previous year. *Bank. Year* equals 1 for every year the firm is in bankruptcy, and zero otherwise. The sample is based on all NETS facilities over the 2004 to 2019 period that report to the TRI in a given year. See Section 3 for more details of sample and variable construction. Standard errors are double clustered by facility and year levels.

**Figure 2-A: New manager, with SIC x Year FE**

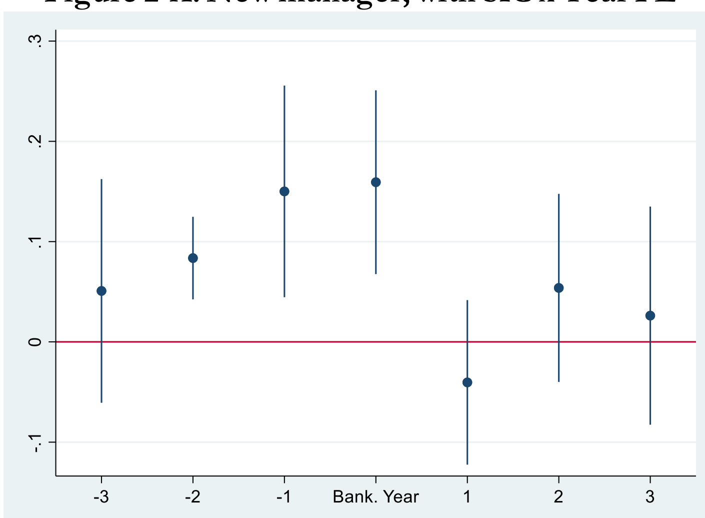



**Figure 2-B: New manager, with Facility & SIC x Year FE**

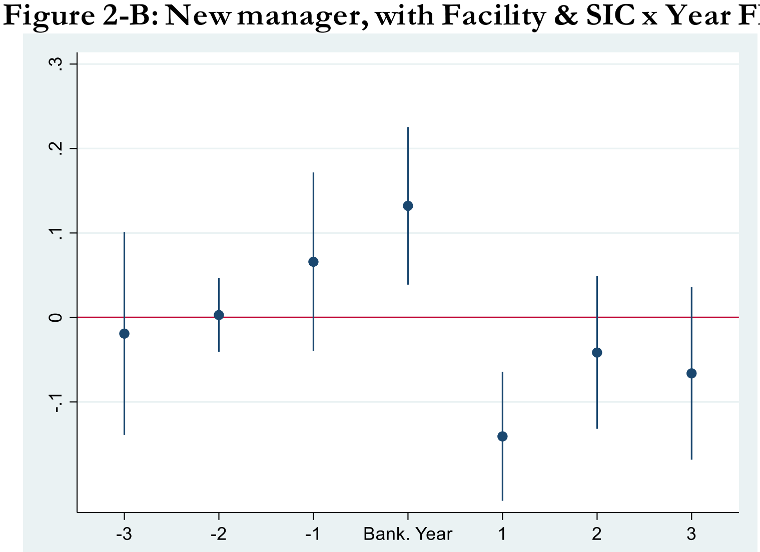


**Figure 3: Number of facilities around bankruptcy**

The figure shows coefficients of the time dummy variables in regression (3), from 3 years before the bankruptcy to three years after the bankruptcy, as well as their 95% confidence intervals. The dependent variable is the total number of operating facilities, as reported in NETS. *Bank. Year* equals one for every year the firm is in bankruptcy, and zero otherwise. The sample is based on all NETS firms over the 2004 to 2019 period. See Section 3 for more details of sample and variable construction. Standard errors are double clustered by facility and year levels.

**Figure 3-A: Number of facilities for a firm, with SIC x Year FE**

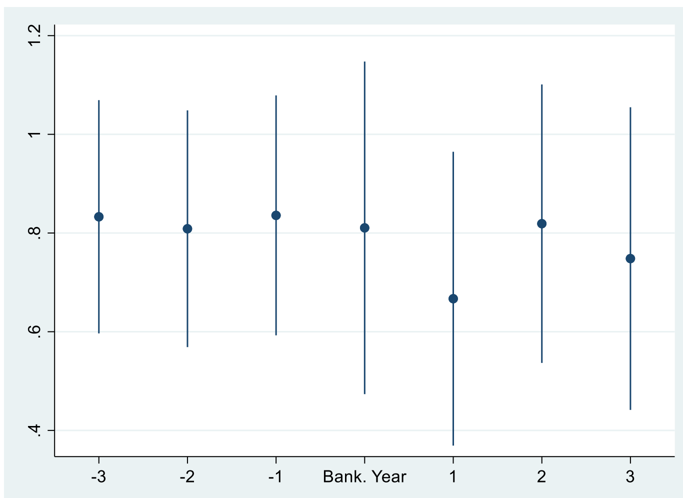



**Figure 3-B: Number of facilities for a firm, with Firm & SIC x Year FE**

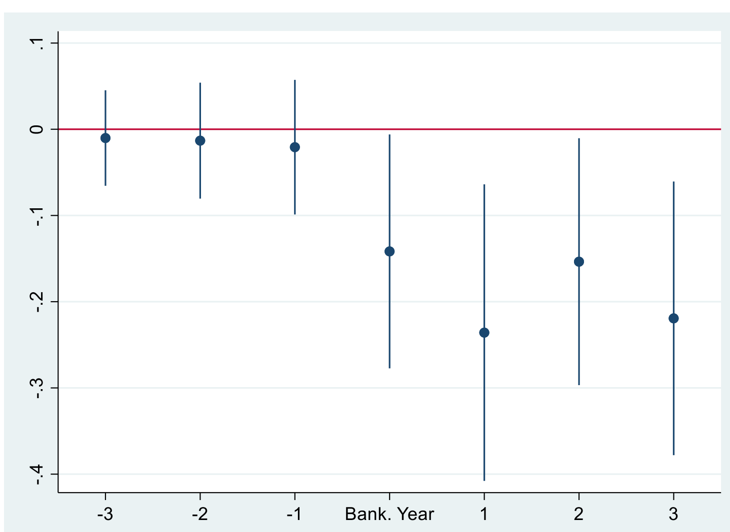


**Figure 4: Emission levels of reporting facilities in the TRI database**

The figure shows coefficients of the time dummy variables in regression (4), from 3 years before the bankruptcy to three years after the bankruptcy, as well as their 95% confidence intervals. The dependent variable is the total amount of toxic chemicals (in pound) emitted by a facility in a given year. *Bank. Year* equals one for every year the firm is in bankruptcy, and zero otherwise. The sample is based on all NETS facilities over the 2004 to 2019 period that report to the TRI in a given year. See Section 3 for more details of sample and variable construction. Standard errors are double clustered by facility and year levels.

**Figure 4-A: Onsite emissions, SIC x Year FE**

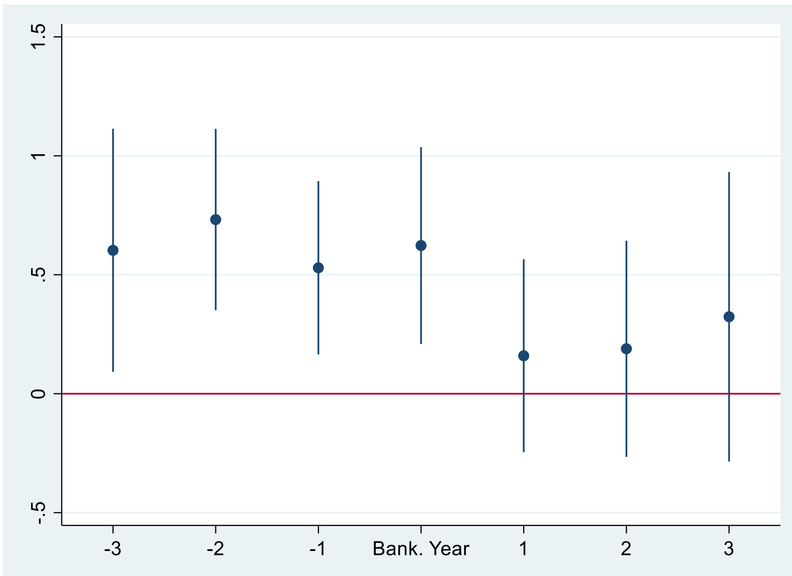



**Figure 4-B: Onsite emissions, Facility & SIC x Year FE**

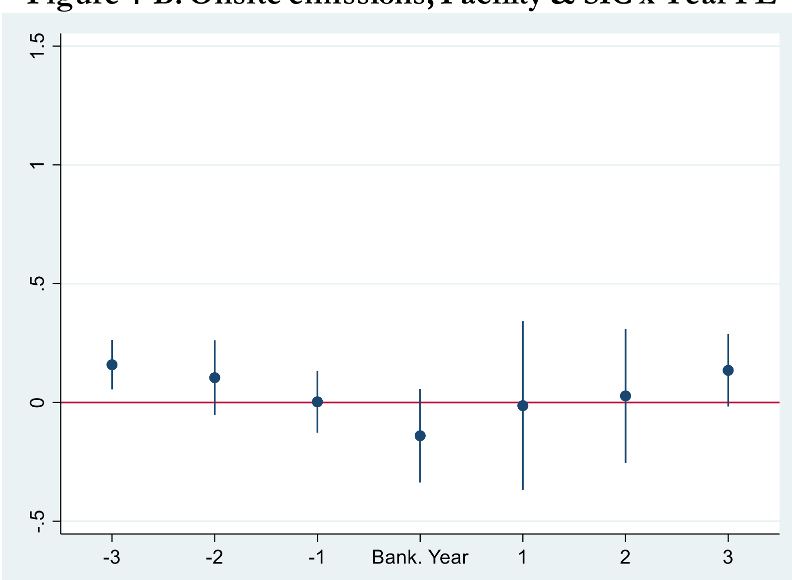


**Figure 5: Emission levels of reporting facilities in the TRI database – RSEI score**

The figure shows coefficients of the time dummy variables in regression 4, from 3 years before the bankruptcy to three years after the bankruptcy, as well as their 95% confidence intervals. The dependent variable is the total amount of emitted chemicals, weighted by their toxicity and population proximity, at a facility-year level. *Bank. Year* equals one for every year the firm is in bankruptcy, and zero otherwise. The sample is based on all NETS facilities over the 2004 to 2019 period that report to the TRI in a given year. See Section 3 for more details of sample and variable construction. Standard errors are double clustered by facility and year levels.

**Figure 5-A: RSEI score, SIC x Year FE**

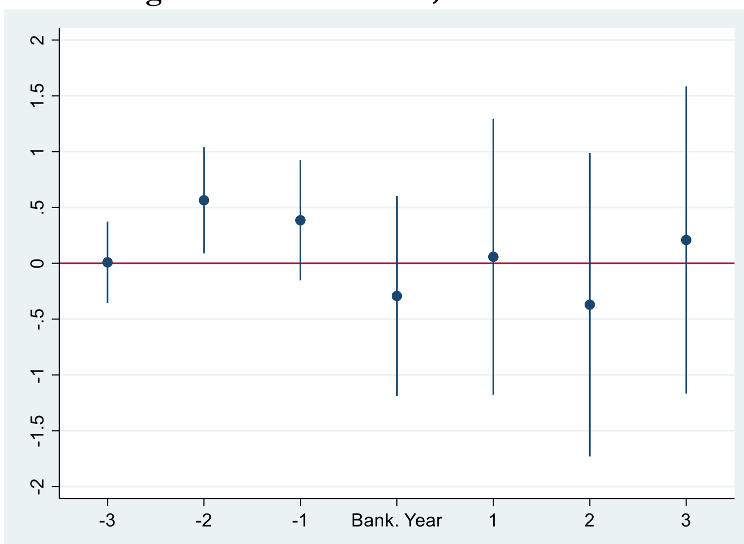



**Figure 5-B: RSEI score, Facility & SIC x Year FE**

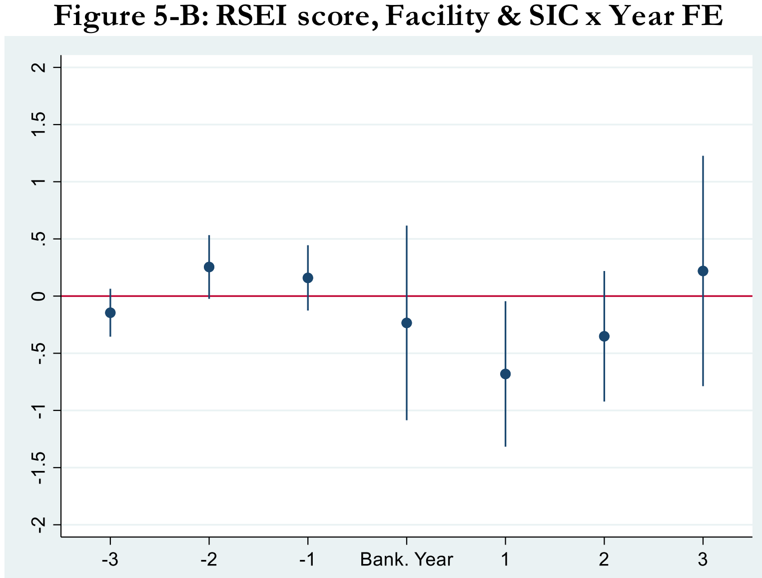


**Figure 6: Emission levels (standardized) of reporting facilities in the TRI database**

The figure shows coefficients of the time dummy variables in regression (4), from 3 years before the bankruptcy to three years after the bankruptcy, as well as their 95% confidence intervals. The dependent variable is the standardized emission - total amount of emitted chemicals, weighted by their toxicity, at a facility-year level. *Bank. Year* equals one for every year the firm is in bankruptcy, and zero otherwise. The sample is based on all NETS facilities over the 2004 to 2019 period that report to the TRI in a given year. See Section 3 for more details of sample and variable construction. Standard errors are double clustered by facility and year levels.

**Figure 6-A: Onsite std. emissions, SIC x Year FE**

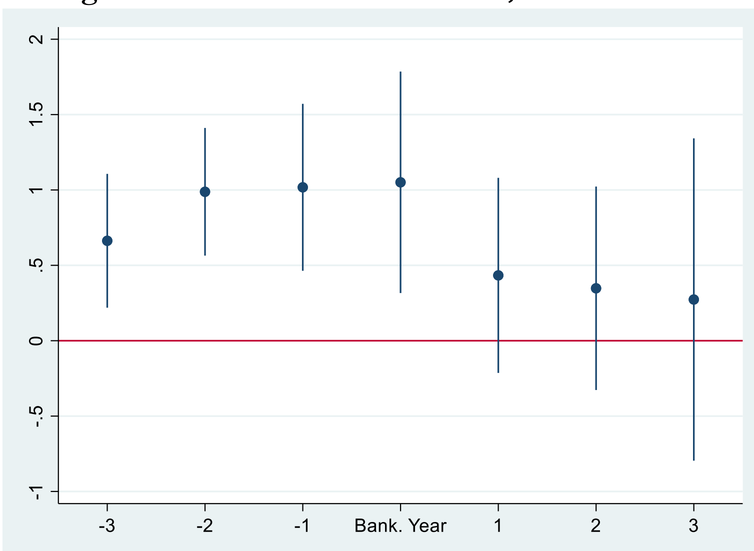



**Figure 6-B: Onsite std. emissions, facility & SIC x Year FE**

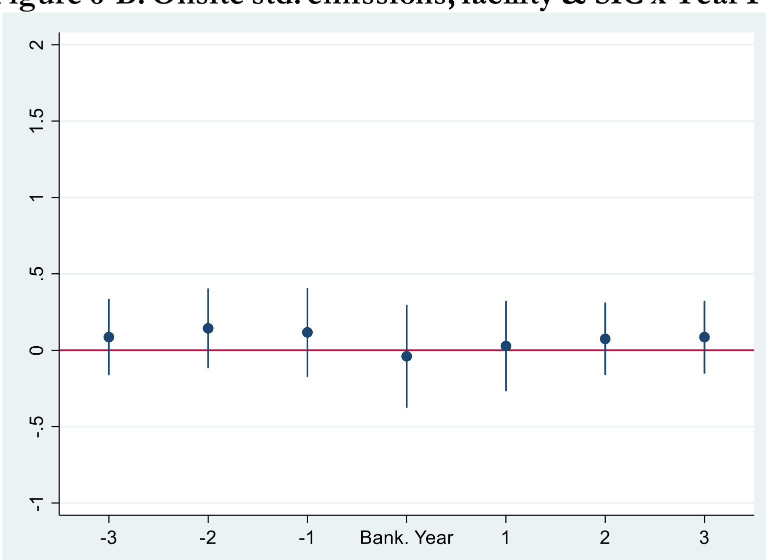


**Figure 7: Onsite emission management as a function of bankruptcy dummies**

The figure shows coefficients of the time dummy variables in regression 5, from 3 years before the bankruptcy to three years after the bankruptcy, as well as their 95% confidence intervals. The dependent variable is the total amount of toxic chemicals (in pound) managed onsite (that is, recycled, energy recovered, or treated) by a facility in a given year. *Bank. Year* equals one for every year the firm is in bankruptcy, and zero otherwise. The sample is based on all NETS facilities over the 2004 to 2019 period that report to the TRI in a given year. See Section 3 for more details of sample and variable construction. Standard errors are double clustered by facility and year levels.

**Figure 7-A: Onsite management, SIC x Year FE**

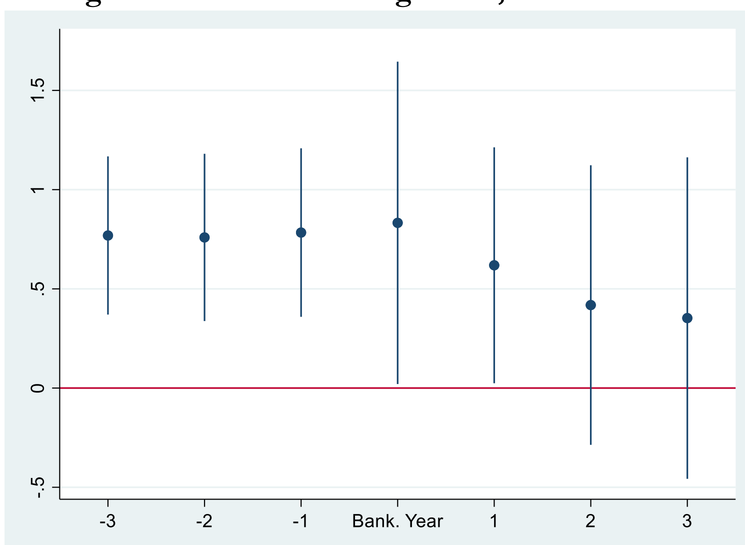



**Figure 7-B: Onsite management, facility & SIC x Year FE**

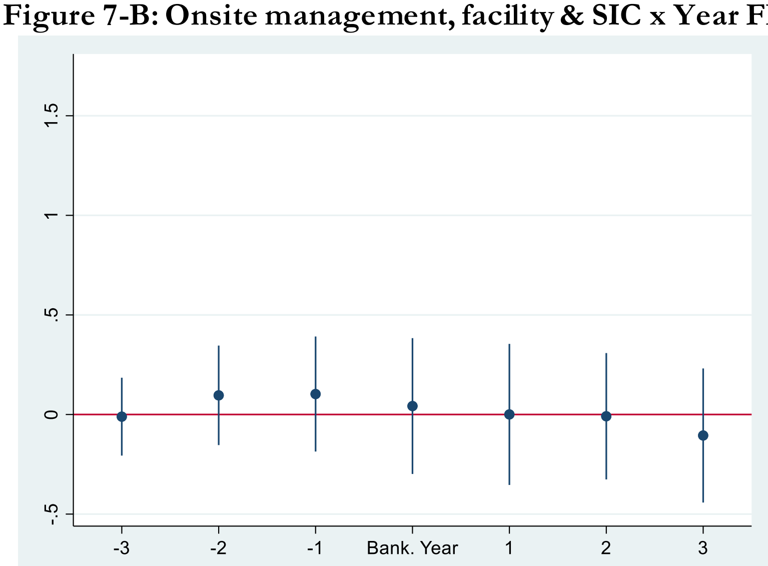


**Figure 8: Emission management (standardized) as a function of bankruptcy dummies**

The figure shows coefficients of the time dummy variables in regression 5, from 3 years before the bankruptcy to three years after the bankruptcy, as well as their 95% confidence intervals. The dependent variable is the total amount of toxic chemicals (in pound) managed onsite (that is, recycled, energy recovered, or treated), weighted its toxicity, by a facility in a given year. *Bank. Year* equals one for every year the firm is in bankruptcy, and zero otherwise. The sample is based on all NETS facilities over the 2004 to 2019 period that report to the TRI in a given year. See Section 3 for more details of sample and variable construction. Standard errors are double clustered by facility and year levels.

**Figure 8-A: Onsite std. management, SIC x Year FE**

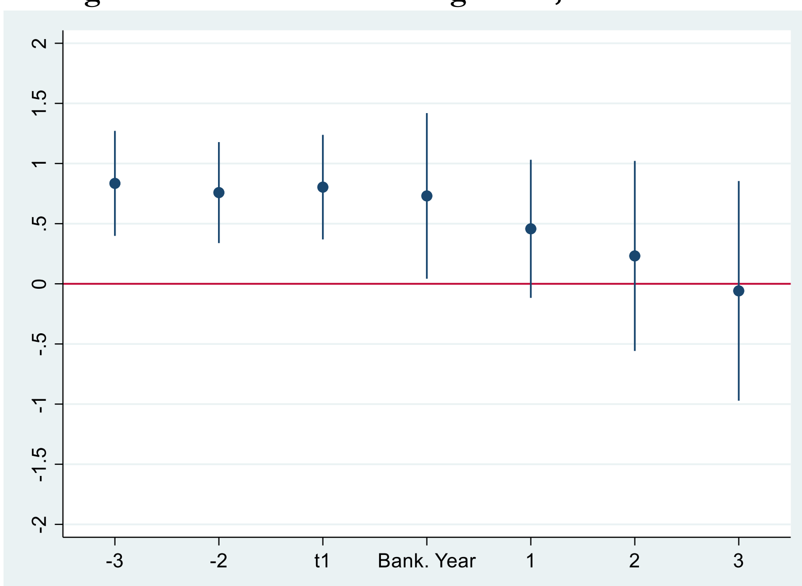



**Figure 8-B: Onsite std. management, facility & SIC x Year FE**

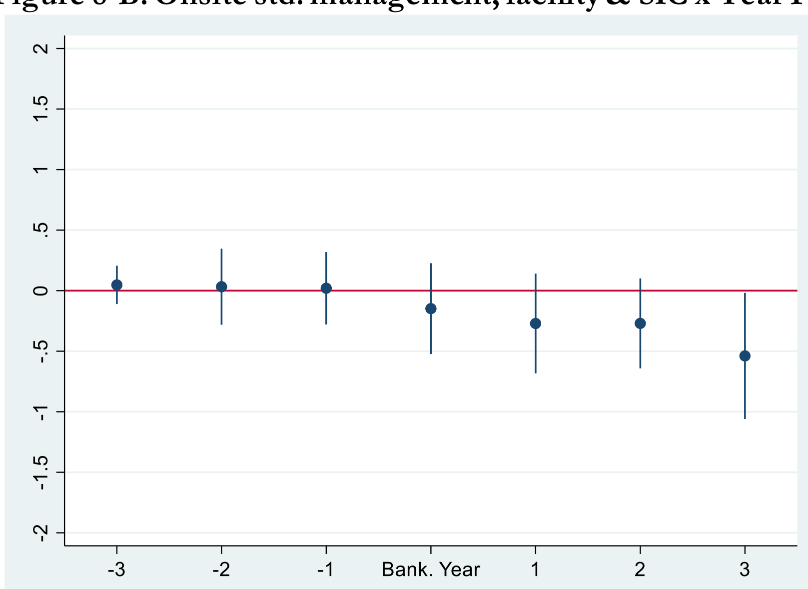


**Figure 9: Ratio of TRI-reporting facilities in the NETS database**

The figure shows coefficients of the time dummy variables in regression (6), from 3 years before the bankruptcy to three years after the bankruptcy, as well as their 95% confidence intervals. The dependent variable is the number of facilities that have file a report with TRI, scaled by the total operating facilities, as reported in NETS, of a firm in a given year. *Bank. Year* equals one for every year the firm is in bankruptcy, and zero otherwise. The sample includes all firms in the NETS database (regardless of whether they report to the TRI in a given year or not) between the years 2004 and 2019. See Section 3 for more details of sample and variable construction. Standard errors are double clustered by facility and year levels.

**Figure 9-A: Ratio of reporting facilities, SIC x Year FE**

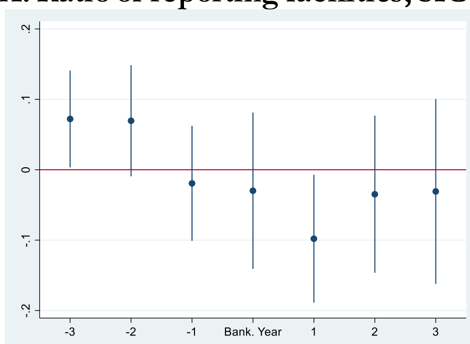



**Figure 9-B: Ratio of reporting facilities, Firm & Year FE**

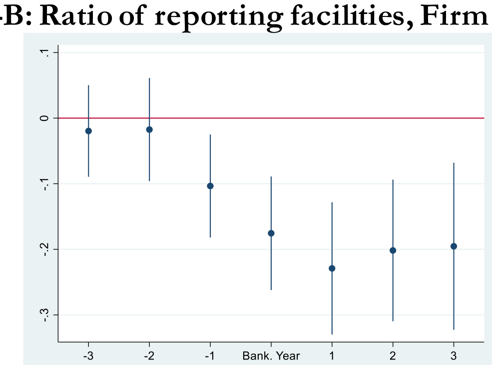



**Figure 9-C: Ratio of reporting facilities, Firm & SIC x Year FE**

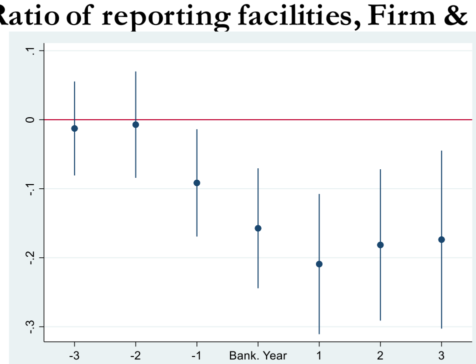


**Figure 10: Firm-level emissions and management**

The figure shows time variables coefficients of estimating the total firm-level emission (Figures A and B), or emission management (Figures C and D) as a function of indicator variables, from 3 years before the bankruptcy to three years after the bankruptcy, as well as their 95% confidence intervals. The dependent variable is the total amount of chemicals emitted [managed] summed across all the chemicals and facilities that have filed a report with TRI of a firm in a given year. If a firm has operating facilities in NETS but does not report emissions in TRI, we assign a value of zero. *Bank. Year* equals one for every year the firm is in bankruptcy, and zero otherwise. The regression is estimated using Poisson model and includes control for the number of operating facilities, in log, as well as a vector of fixed effects, as indicated in the title of each figure. The sample includes all firms in the NETS database (regardless of whether they report to the TRI in a given year or not) between the years 2004 and 2019. See Section 3 for more details of sample and variable construction. Standard errors are double clustered by facility and year levels.

**Figure 10-A: Firm-level onsite emissions, SIC x Year FE**

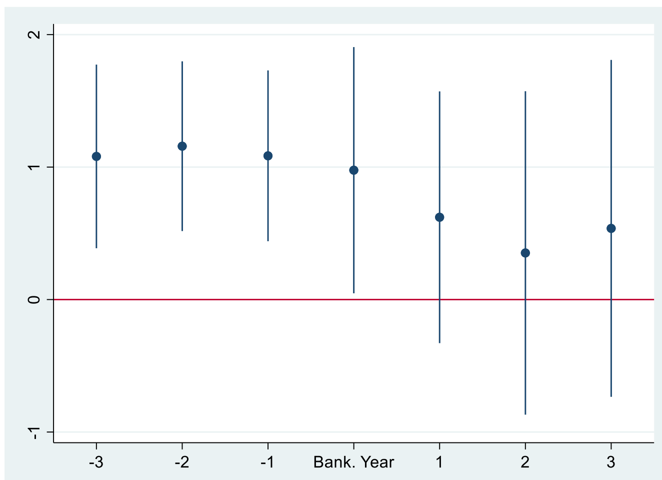
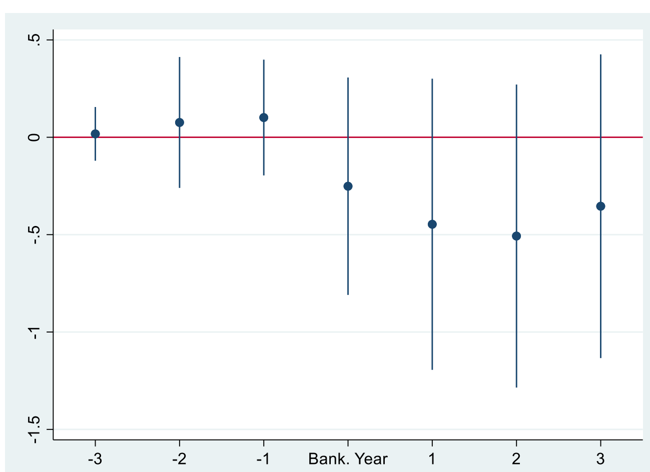
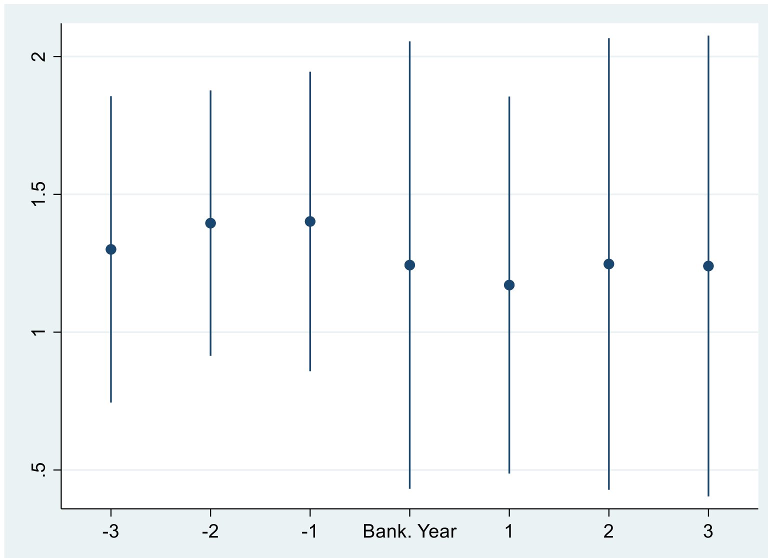



**Figure 10-B: Firm-level onsite emissions, Firm & SIC x Year FE**



### Figure 10: Firm-level emissions and management (cont.)

### Figure 10-C: Firm-level emission management, SIC x Year FE




### Figure 10-D: Firm-level emission management, Firm and SIC x Year FE

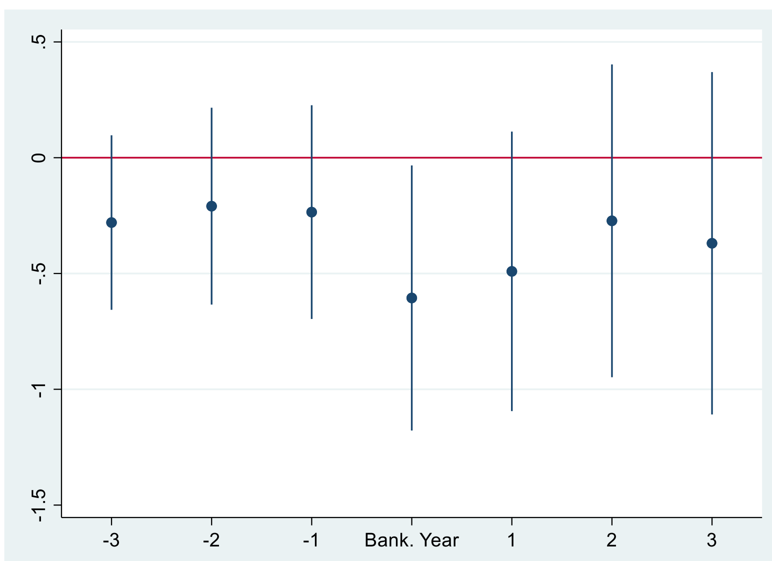


**Figure 11: Analysis of crisis- and noncrisis-related bankruptcies**

The figure shows coefficients of the time dummy variables, from 3 years before the bankruptcy to three years after the bankruptcy, as well as their 95% confidence intervals. The universe of bankruptcies is split into crisis ones (filed during the 2008-2009 period), and non-crisis ones (the rest of the cases). The dependent variable is indicated in the title of each figure. *Bank. Year* equals one for every year the firm is in bankruptcy, and zero otherwise. The sample is based on all NETS facilities over the 2004 to 2019 period that report to the TRI in a given year. See Section 3 for more details of sample and variable construction. Standard errors are double clustered by facility and year levels.

**Figure 11-A: Log size, with facility & SIC x Year FE**

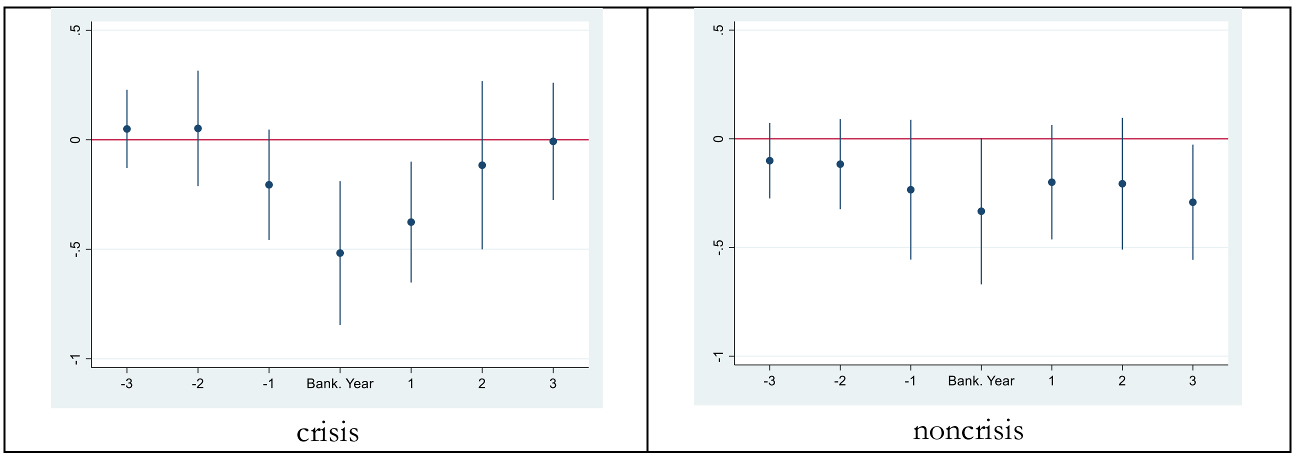
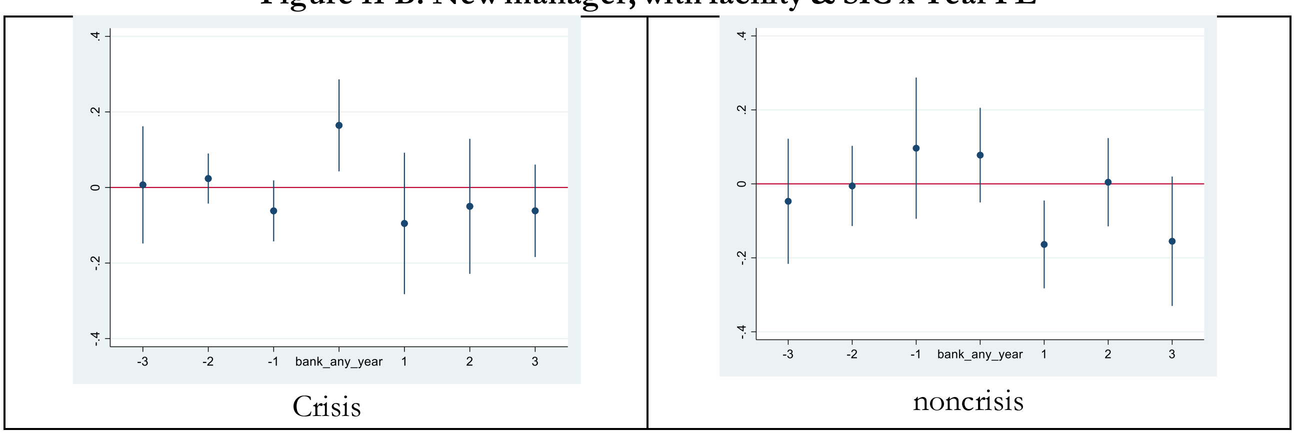
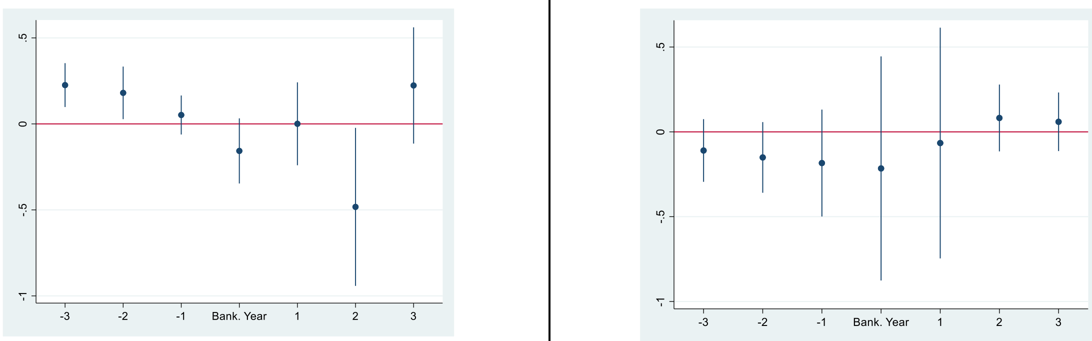



**Figure 11-B: New manager, with facility & SIC x Year FE**



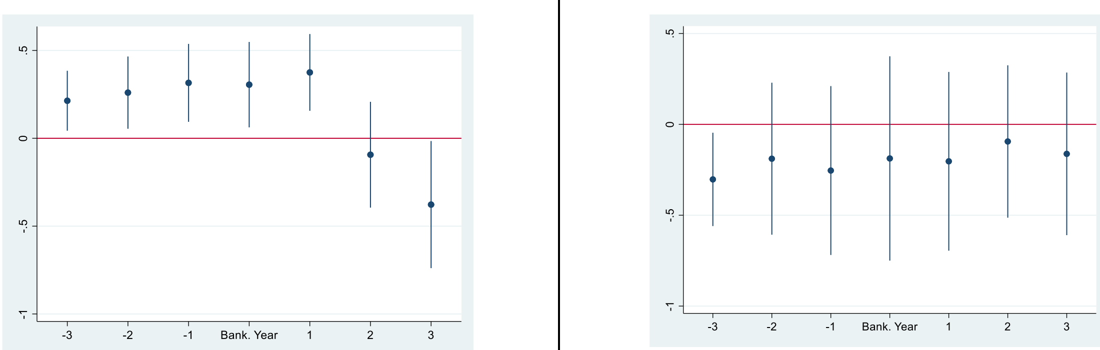
## Figure 11: Analysis of crisis- and noncrisis-related bankruptcies (continued)

### Figure 11-C: Onsite emissions, with facility & SIC x Year FE




crisis | noncrisis

### Figure 11-D: Onsite management, with facility & SIC x Year FE




crisis | noncrisis

## Figure 12: Analysis by bankruptcy duration

The figure shows coefficients of the time dummy variables, from 3 years before the bankruptcy to three years after the bankruptcy, as well as their 95% confidence intervals. The universe of bankruptcies is split into short (under one year), regular (up to two years) and long (two tears and longer) bankruptcies. The dependent variable is indicated in the title of each figure. *Bank. Year* equals one for every year the firm is in bankruptcy, and zero otherwise. The sample is based on all NETS facilities over the 2004 to 2019 period that report to the TRI in a given year. See Section 3 for more details of sample and variable construction. Standard errors are double clustered by facility and year levels.

**Figure 12-A: Log size, with facility & SIC x Year FE**

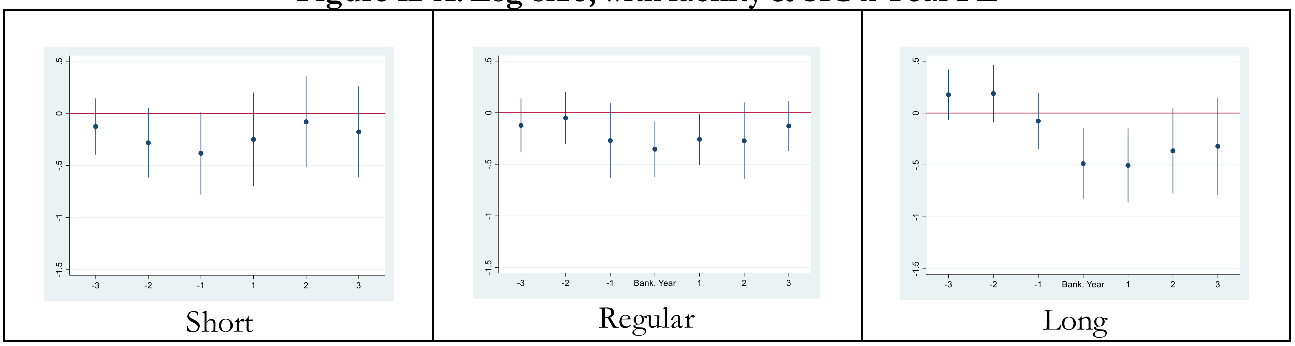



**Figure 12-B: Onsite emissions, by bankruptcy duration, with facility & SIC x Year FE**

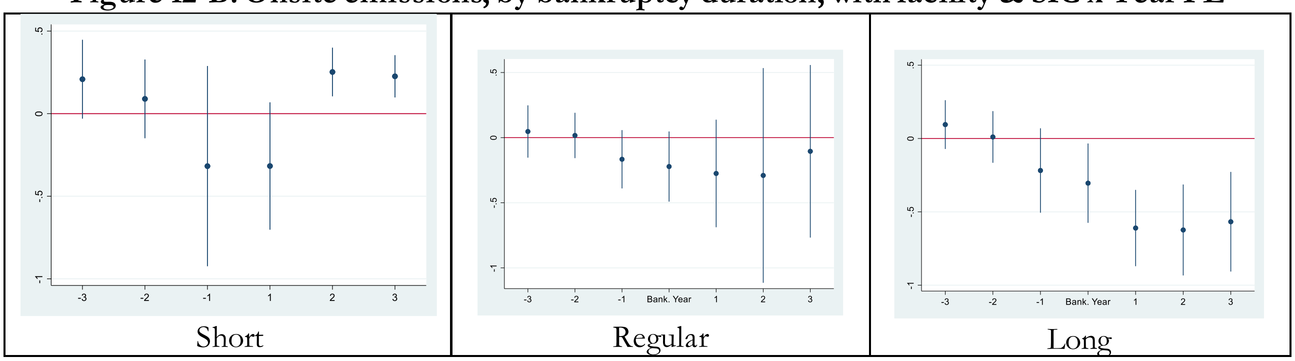



**Figure 12-C: Onsite management, by bankruptcy duration, with facility & SIC x Year FE**

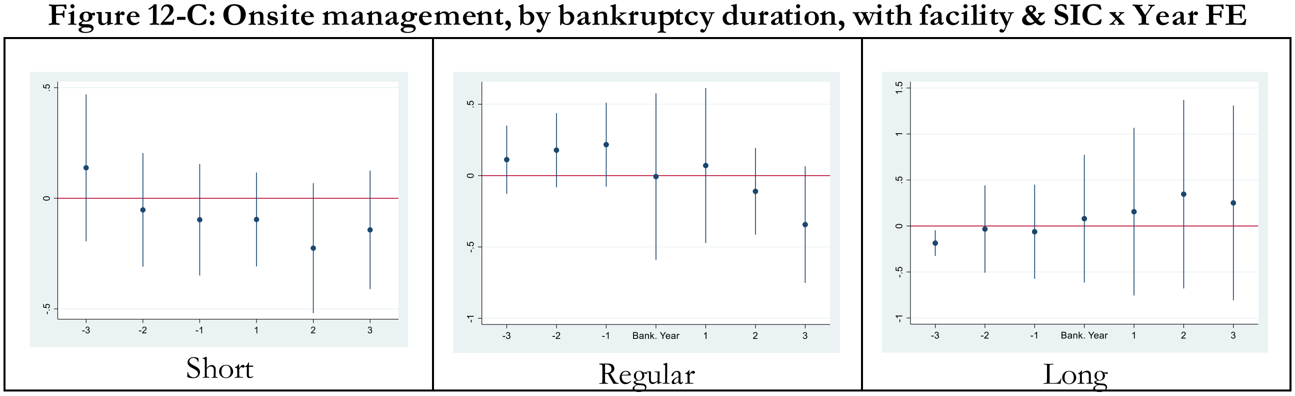
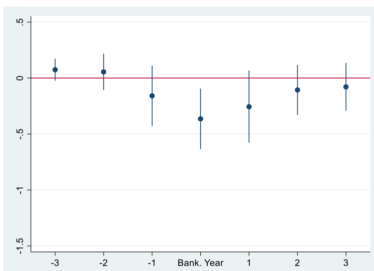


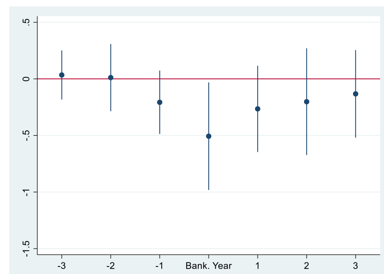
**Figure 13: Analysis by public-private status**

The figure shows coefficients of the time dummy variables, from 3 years before the bankruptcy to three years after the bankruptcy, as well as their 95% confidence intervals. The universe of bankruptcies is split into public facilities (belong to a firm that was publicly traded at some point of its history) and private facilities (belong to a firm that was never publicly traded). The dependent variable is indicated in the title of each figure. *Bank. Year* equals one for every year the firm is in bankruptcy, and zero otherwise. The sample is based on all NETS facilities over the 2004 to 2019 period that report to the TRI in a given year. See Section 3 for more details of sample and variable construction. Standard errors are double clustered by facility and year levels.

**Figure 13-A: Log(size), by public-private status, with facility & SIC x Year FE**

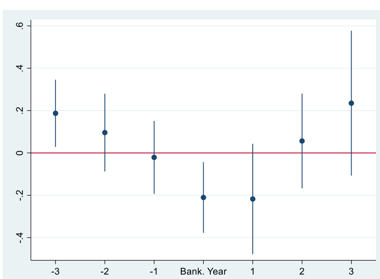



public

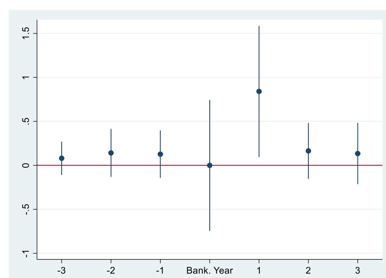



private

**Figure 13-B: Onsite emissions, by public-private status, with facility & SIC x Year FE**

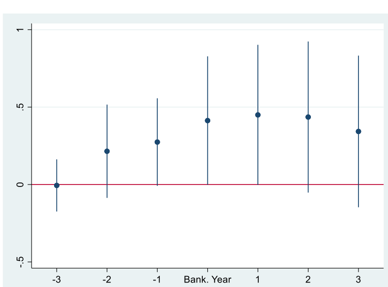



public

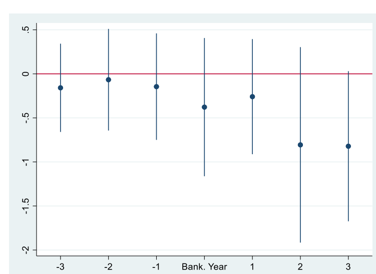



private

**Figure 13-C: Onsite management, by public-private status, with facility & SIC x Year FE**




public




private

## Appendix

**Table A.1: Most polluting industries based on annual emission**

| NAICS4 | onsite emission | onsite std. emission | onsite std. emission (% total) |
|---|---|---|---|
| 3251 | 230,199,674 | 6,503,962,080 | 42.00% |
| 3314 | 85,585,024 | 5,732,596,700 | 37.02% |
| 5622 | 115,309,393 | 1,753,126,786 | 11.32% |
| 2122 | 1,557,804,299 | 662,373,418 | 4.28% |
| 2211 | 516,713,428 | 201,005,146 | 1.30% |
| 3313 | 17,403,944 | 176,600,710 | 1.14% |
| 3221 | 164,341,199 | 171,522,696 | 1.11% |
| 3311 | 70,176,798 | 59,469,476 | 0.38% |
| 3211 | 1,852,273 | 57,984,821 | 0.37% |
| 3273 | 7,501,580 | 46,332,945 | 0.30% |
| 3252 | 65,337,373 | 39,907,245 | 0.26% |
| 3371 | 4,350,682 | 18,770,161 | 0.12% |
| 3241 | 65,091,490 | 15,837,181 | 0.10% |
| 3253 | 94,152,698 | 11,045,815 | 0.07% |
| 3112 | 30,240,785 | 6,197,099 | 0.04% |
| 3274 | 3,362,261 | 5,333,859 | 0.03% |
| 9281 | 25,094,858 | 5,167,201 | 0.03% |
| 3315 | 6,833,691 | 5,106,905 | 0.03% |
| 3212 | 6,867,504 | 3,320,173 | 0.02% |
| 9241 | 3,844,689 | 1,746,799 | 0.01% |

**Table A.2: Emissions and management using NAICS classification**

**Panel A: Emissions**

| | (1) Onsite emiss | (2) Onsite emiss | (3) Onsite emiss RSEI | (4) Onsite emiss RSEI | (5) Onsite emiss - std. | (6) Onsite emiss - std. |
|---|---|---|---|---|---|---|
| Log(size) | 0.173*** | 0.254*** | 0.094*** | 0.151*** | 0.192*** | 0.254*** |
| | (0.022) | (0.024) | (0.028) | (0.025) | (0.025) | (0.025) |
| -3 | 0.203 | 0.096 | -0.003 | -0.190* | 0.289 | 0.094 |
| | (0.225) | (0.079) | (0.161) | (0.109) | (0.181) | (0.117) |
| -2 | 0.323* | 0.033 | 0.543* | 0.094 | 0.509*** | 0.104 |
| | (0.170) | (0.080) | (0.282) | (0.151) | (0.196) | (0.117) |
| -1 | 0.154 | -0.141 | 0.375 | -0.107 | 0.563** | 0.053 |
| | (0.185) | (0.109) | (0.296) | (0.185) | (0.239) | (0.128) |
| Bank. Year | 0.168 | -0.232 | -0.302 | -0.660 | 0.512* | -0.128 |
| | (0.207) | (0.143) | (0.427) | (0.420) | (0.292) | (0.156) |
| 1 | -0.177 | -0.266 | -0.072 | -0.820* | 0.060 | -0.086 |
| | (0.171) | (0.199) | (0.633) | (0.430) | (0.307) | (0.106) |
| 2 | -0.029 | -0.133 | -0.452 | -0.895* | 0.082 | -0.051 |
| | (0.264) | (0.244) | (0.653) | (0.531) | (0.361) | (0.150) |
| 3 | 0.213 | -0.041 | 0.166 | -0.693 | 0.302 | -0.029 |
| | (0.233) | (0.207) | (0.551) | (0.714) | (0.423) | (0.167) |
| NAICS x Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Facility FE | No | Yes | No | Yes | No | Yes |
| Nobs | 215290 | 215240 | 200449 | 200449 | 215290 | 215240 |
| Pseudo R-sq. | 0.575 | 0.953 | 0.263 | 0.881 | 0.627 | 0.958 |

**Table A.2 (continued)**

**Panel B: management**

| | (1) Onsite mgmt | (2) Onsite mgmt | (3) Onsite mgmt - std. | (4) Onsite mgmt - std. |
|---|---|---|---|---|
| Log(size) | 0.150*** | 0.082*** | 0.154*** | 0.095*** |
| | (0.031) | (0.026) | (0.031) | (0.027) |
| -3 | 0.254 | -0.066 | 0.376 | -0.005 |
| | (0.249) | (0.077) | (0.322) | (0.066) |
| -2 | 0.326 | -0.119 | 0.350 | -0.147 |
| | (0.228) | (0.091) | (0.241) | (0.136) |
| -1 | 0.414* | -0.148 | 0.445* | -0.172 |
| | (0.212) | (0.152) | (0.233) | (0.164) |
| Bank. Year | 0.490 | -0.350* | 0.428 | -0.382* |
| | (0.439) | (0.205) | (0.377) | (0.197) |
| 1 | 0.270 | -0.186 | 0.182 | -0.355* |
| | (0.302) | (0.217) | (0.268) | (0.210) |
| 2 | 0.254 | -0.202 | 0.100 | -0.344** |
| | (0.317) | (0.142) | (0.327) | (0.167) |
| 3 | 0.265 | -0.297* | -0.102 | -0.611** |
| | (0.310) | (0.158) | (0.322) | (0.239) |
| NAICS x Year FE | Yes | Yes | Yes | Yes |
| Facility FE | No | Yes | No | Yes |
| Nobs | 215290 | 214990 | 215290 | 214990 |
| Pseudo R-sq. | 0.45 | 0.93 | 0.42 | 0.92 |

**Figure A.1: Onsite emissions – robustness tests**

**Figure A.1A: Onsite emissions, Facility & SIC x Year FE, no size control**

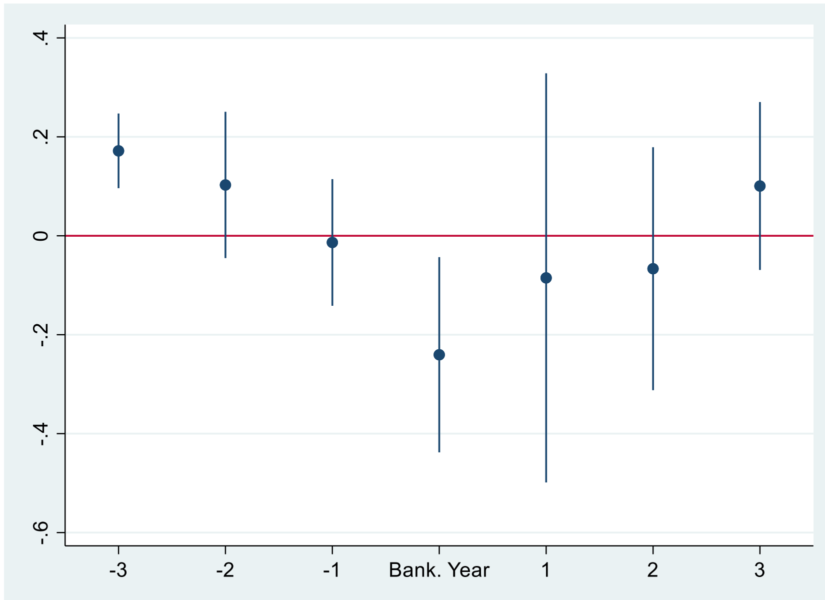



**Figure A.1B: Onsite emissions, Facility & SIC x Year FE, with sales (NETS-based) control**

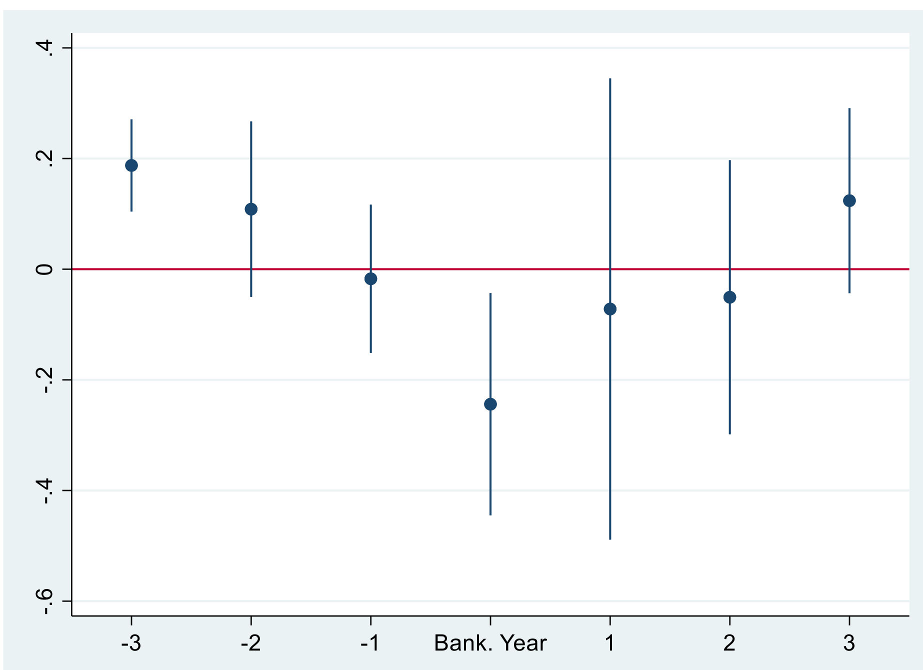


**Figure A.1: Onsite Emissions (continued)**

**Figure A.1C: Onsite emissions, Facility & SIC x Year FE, PayDex score <70**

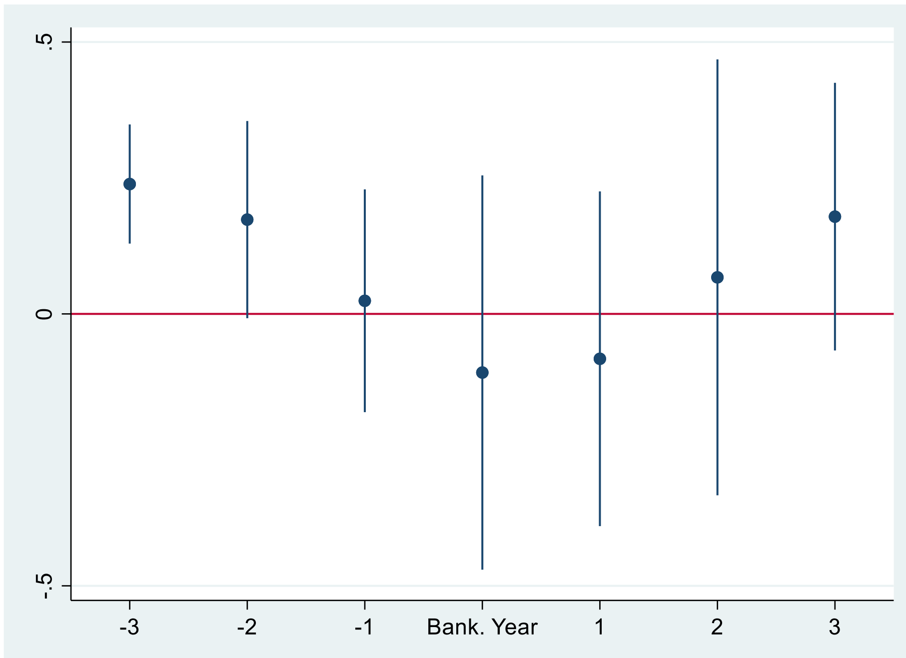



**Figure A.1D: Onsite emissions, Facility & SIC x Year FE, PayDex score >=70**

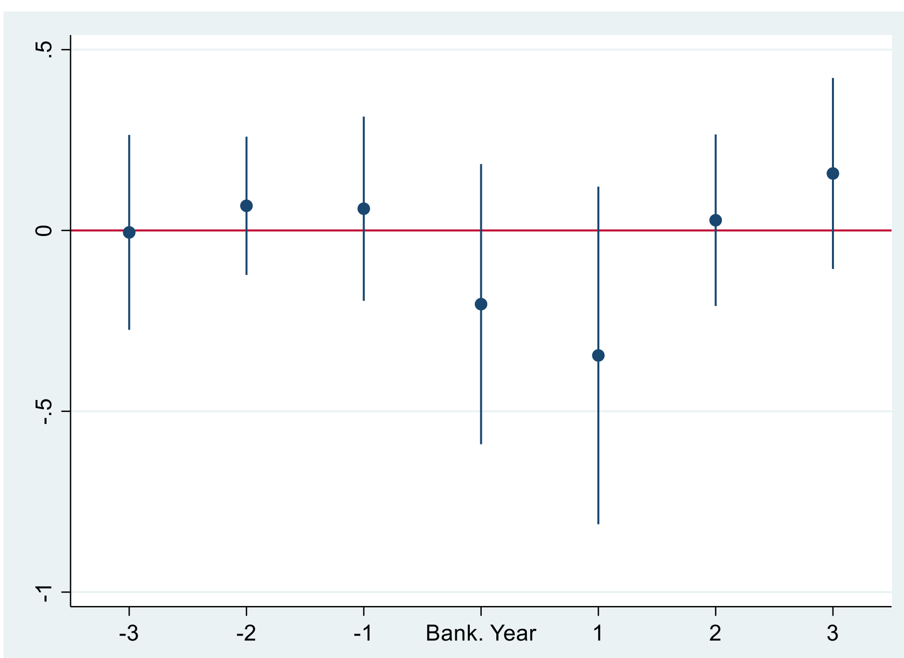
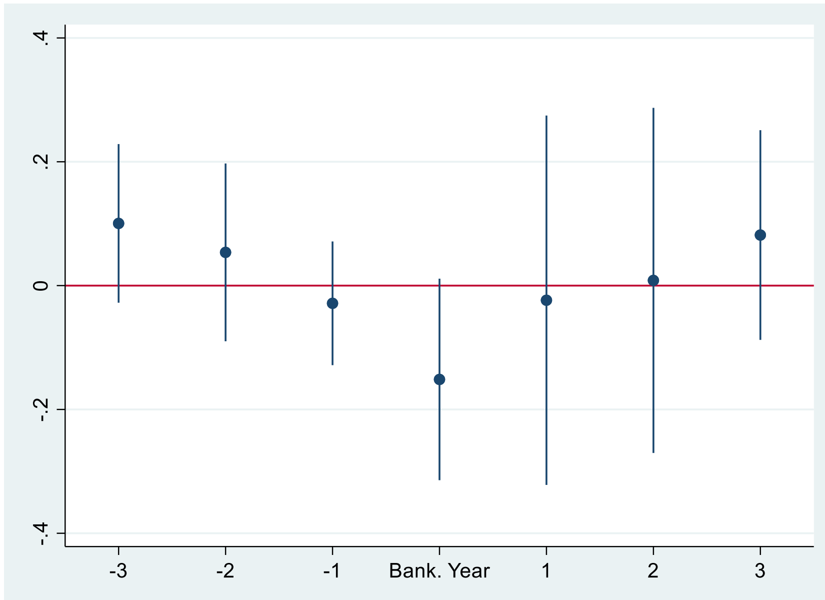


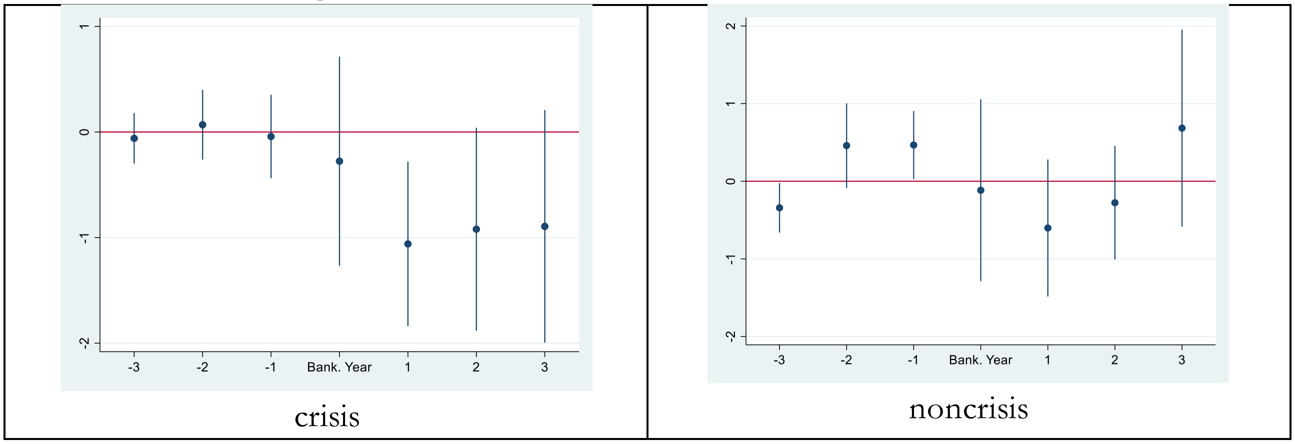
**Figure A.1: Onsite Emissions (continued)**

**Figure A.1E: Total (onsite and offsite emissions), Facility & SIC x Year FE**

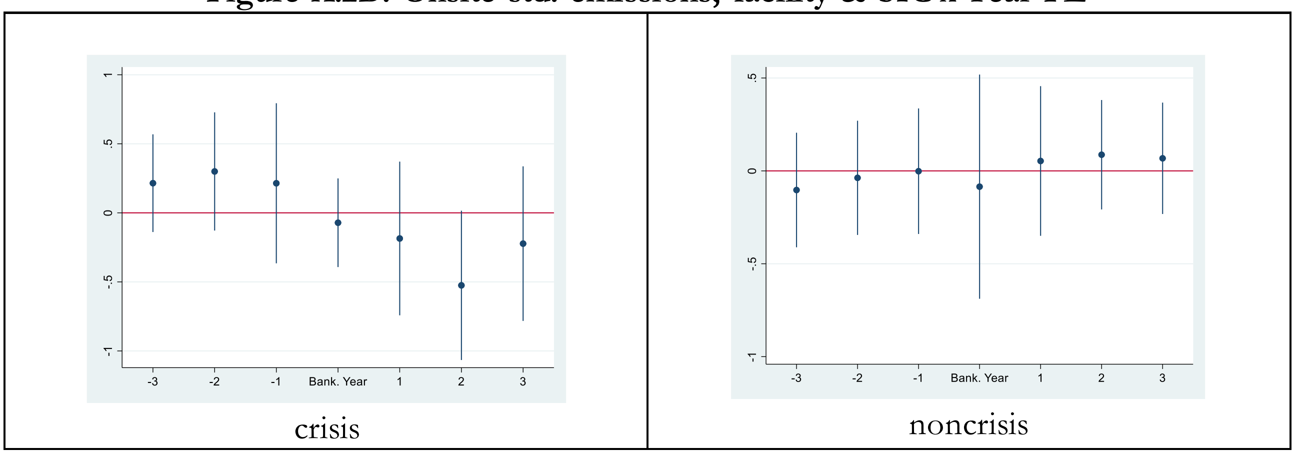


## Figure A.2: Crisis-related and noncrisis-related bankruptcies

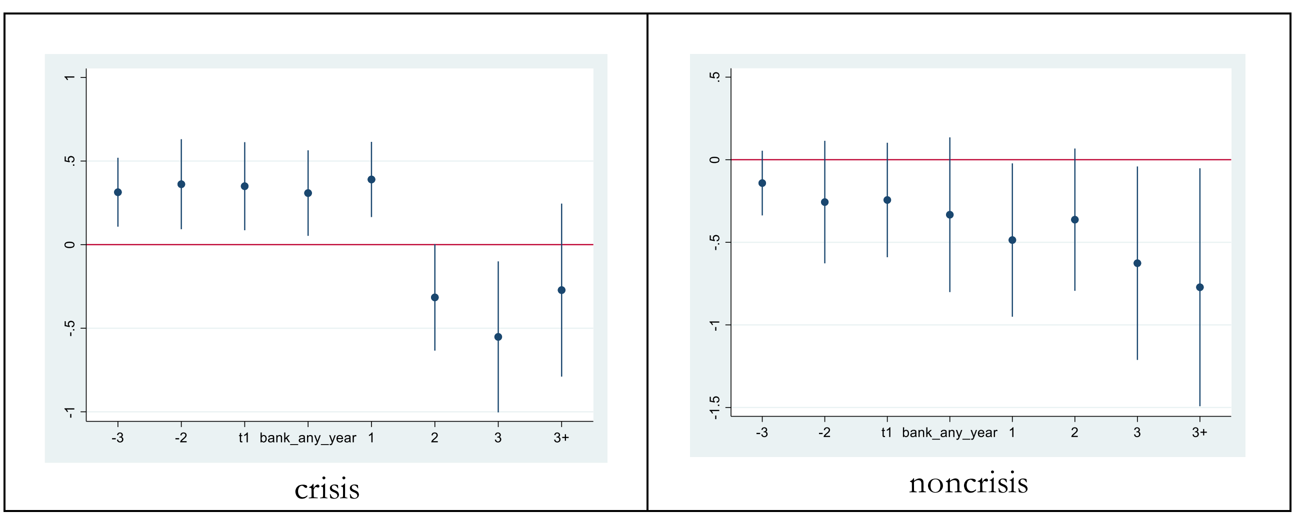
### Figure A.2A: RSEI score, facility & SIC x Year FE




### Figure A.2B: Onsite std. emissions, facility & SIC x Year FE

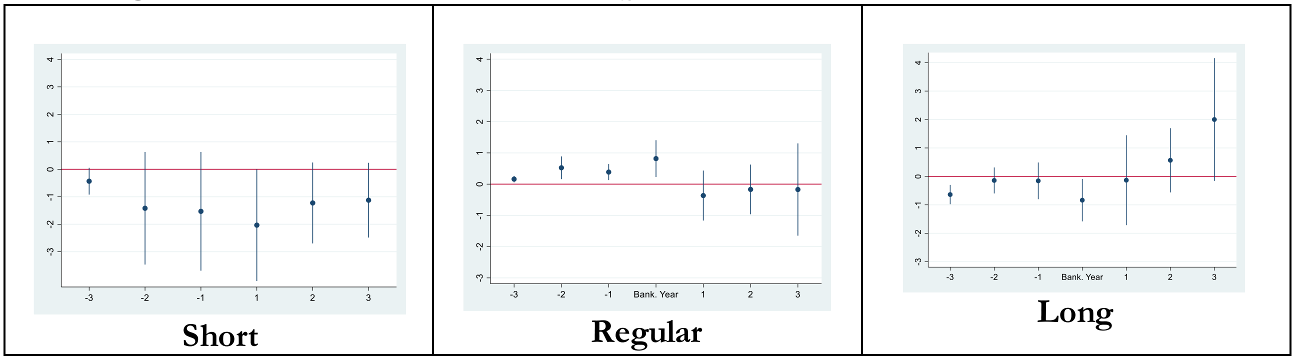



### Figure A.2C: Onsite std. management, facility & SIC x Year FE

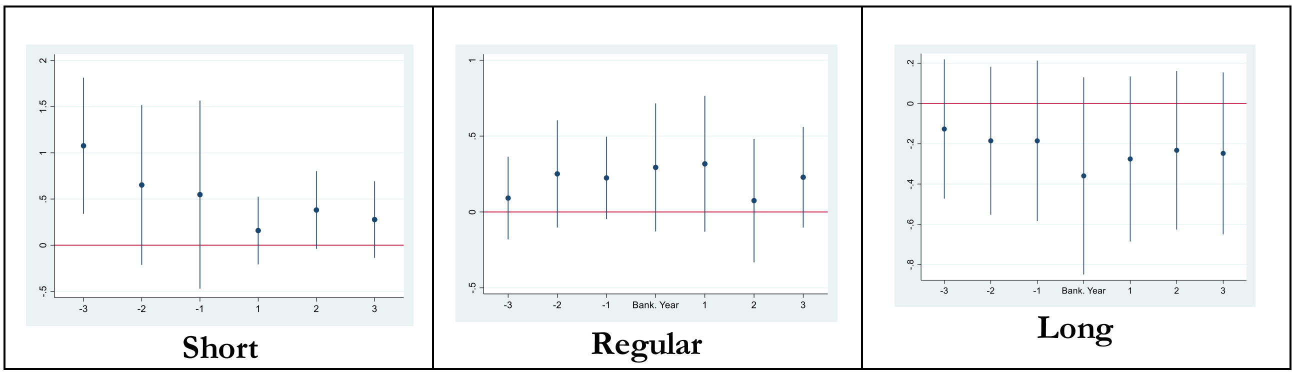


## Figure A.3: Analysis by bankruptcy duration

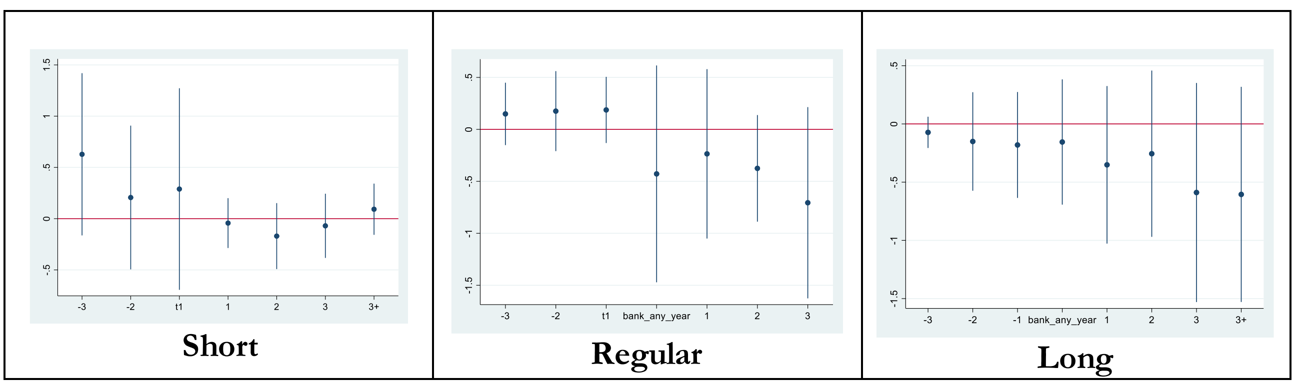
### Figure A.3A: RSEI score, by bankruptcy duration, facility & SIC x Year FE




### Figure A.5D: Onsite std. emissions, by bankruptcy duration, facility & SIC x Year FE

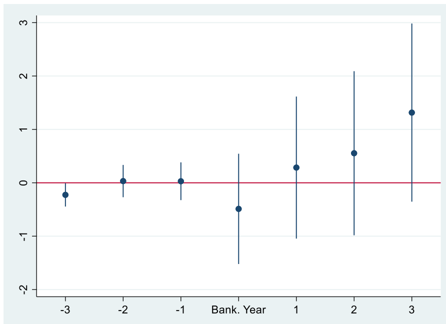



### Figure A.5I: Onsite std. management, by bankruptcy duration, facility & SIC x Year FE

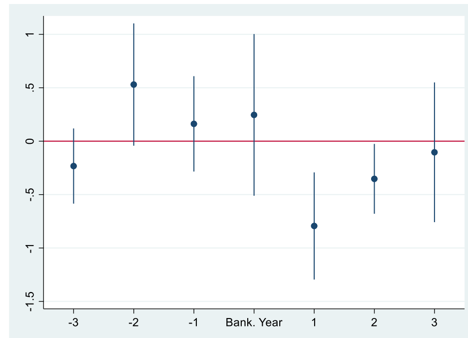


## Figure A.4: Analysis by public-private (never public) status

### Figure A.4A: RSEI score, facility & SIC x Year FE

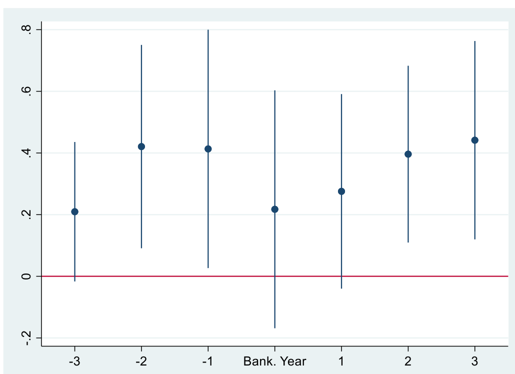



public

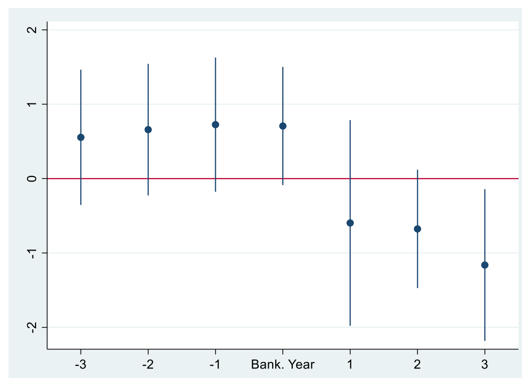



never public

### Figure A.4B: Onsite std. emissions, facility & SIC x Year FE

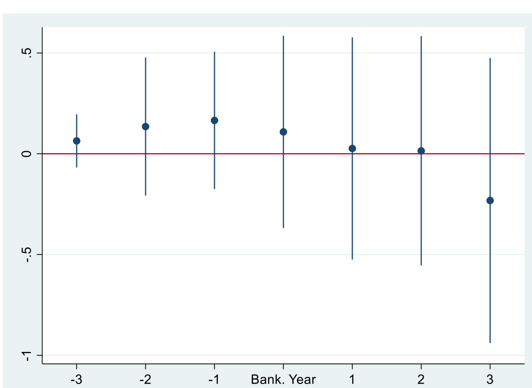



public

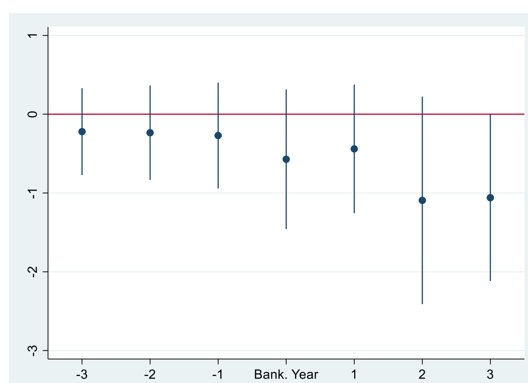



never public

### Figure A.4C: Onsite std. management, facility & SIC x Year FE




public




never public