

# The Limits of Limited Liability: Evidence from Industrial Pollution \*

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June 1, 2018

## Abstract

We study how parent liability for subsidiary environmental cleanup costs affects industrial pollution and production. Our empirical setting exploits a Supreme Court decision that strengthened limited liability protection for parent corporations. Using a difference-in-differences framework, we find that increased liability protection for parents leads to a 5 – 9% increase in toxic emissions by subsidiaries. Evidence suggests the increase in pollution is driven by lower investment in abatement technologies rather than by increased production. Cross-sectional tests suggest a harm-shifting motivation for these effects. Overall, our results highlight moral hazard problems associated with limited liability.

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\*We thank Vineet Bhagwat, Thomas Bourveau, Naveen Daniel, Slava Fos, Erik Gilje, Denis Gromb, Xavier Giroud, Charles Hadlock, Brandon Julio, Jonathan Karpoff, Mariana Khapko, Adair Morse, Zygmunt Plater, Roberta Romano, Pablo Slutsky, Qiping Xu, Hayong Yun, and seminar participants at Boston College, Carnegie Mellon, Manchester Business School, University of Sydney, University of Toronto, American Law and Economics Association, Drexel Corporate Governance Conference, Financial Research Association (early ideas session), ITAM Finance Conference, Maryland Junior Finance Conference, Mid-Atlantic Research Conference in Finance, NBER Spring Meeting, Northeastern University Finance Conference, and SFS Cavalcade, for valuable comments and suggestions.

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# 1 Introduction

For more than 150 years, limited liability has been a defining characteristic of many business entities. This legal concept is often credited with spurring economic growth and the development of capital markets (Manne (1967)); some call it “one of mankind’s greatest inventions” (*The Economist* (9/26/2016)). Economists have long recognized, however, that limited liability for the owners of firms engenders a moral hazard problem because the assets of a firm may be insufficient to pay stakeholders’ claims. This, in turn, incentivizes behavior that is privately profitable but socially costly (Admati (2017)). In an effort to limit such effects, courts can impose liability on firm owners. Easterbrook and Fischel (1985) note that instances of owner liability are primarily confined to closely-held corporations and parent-subsidary relationships.

In this paper, we study the tradeoffs of limited liability in the parent-subsidary context. Specifically, we ask how limited liability protection for parents affects the production and pollution decisions of subsidiaries. Such decisions can impose significant costs on other stakeholders. For example, industrial facilities emit billions of pounds of toxic chemicals that have been linked to adverse health outcomes (e.g., Chay and Greenstone (2003)), decreased worker productivity (e.g., Graff Zivin and Neidell (2012)), and lower home prices (e.g., Greenstone and Gallagher (2008)). Policymakers in many countries have adopted a “polluter pays” approach to environmental regulation to encourage the internalization of such costs; Esty (2008) states the principle has “taken on a quasi-constitutional aura in international environmental law.” However, the effectiveness of this regulatory framework is, to an extent, undercut by limited liability. Specifically, if liability truly is limited, a parent will not bear the costs of environmental remediation that exceed the value of the subsidiary’s assets.

Our empirical setting uses a Supreme Court case that clarified parent company liability under the Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA), also known as Superfund. Specifically, in *United States v. Bestfoods* (here-

after *Bestfoods*) the Supreme Court narrowed the circumstances under which parents are responsible for subsidiary environmental cleanup costs under CERCLA. Prior to *Bestfoods*, some circuit courts held parent firms liable for cleanup costs under a broad range of circumstances while others used a relatively narrow standard.<sup>1</sup> Specifically, the broad standards held parents liable if they had “actual control” of or the “ability to control” the subsidiary. In *Bestfoods*, the Supreme Court invalidated these tests. We use this decision as a natural experiment in a difference-in-differences setting. The treatment group for the analysis consists of facilities of subsidiaries located in areas that had weaker liability protection prior to *Bestfoods*; the control group consists of facilities located in areas where a relatively narrow standard was already in place.

We use plant-level data on toxic emissions of different chemicals from the Environmental Protection Agency (EPA) to examine the response of subsidiaries to the strengthening of parent liability protection. Our main outcome of interest is the amount (in pounds) of toxic ground pollution (e.g., disposals in landfills or underground injection wells), as this is the focus of CERCLA enforcement efforts. In total, our sample consists of 6,953 parent corporations that on average have 2.8 subsidiary facilities emitting 3.91 chemicals. Our baseline regression specification controls for time-invariant heterogeneity at the plant level, and time-varying heterogeneity at the chemical and parent corporation level. Thus, our estimates are relative to plants of the same parent corporation that are located in districts that employed a narrow standard for parent liability.

We find that stronger parent liability protection is associated with significant changes in subsidiary environmental behavior. Specifically, treated plants increase ground emissions by approximately 5 – 9% relative to the control group in the five years following *Bestfoods*. This effect is particularly strong for plants with publicly traded parents and is driven by both the intensive and extensive margins of pollution. Moreover, we document similar magnitudes

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<sup>1</sup>In the US, circuit courts (also called courts of appeals) are intermediate-level courts. Each circuit court covers a geographic area containing multiple states.

for chemicals that are known to cause human harm (including cancer and other chronic diseases) and for other chemicals. We do not find evidence of changes to air or water emissions, which are less likely to be directly impacted by the decision. Finally, the change in liability standards has a positive effect on firm value; CARs around the oral arguments for *Bestfoods* are approximately 1% for parents with relatively high exposure to the decision.

We consider two (non-mutually exclusive) channels that potentially explain the increase in emissions. First, stronger liability protections may decrease the incentives to invest in pollution abatement because parents do not fully internalize the risk of environmental disasters. Second, such protections may decrease the cost of using pollutive technologies and therefore lead to increased economic output. Overall, we find evidence supporting the abatement channel. Specifically, using plant-chemical-level data from the EPA’s Pollution Prevention (P2) database, we find a decrease in the likelihood of process-related abatement activities (e.g., improving chemical reaction conditions, implementing better process controls) of approximately 15–17% relative to the sample mean. We do not, however, find evidence of increased production; changes in plant output (measured using EPA mandated production data) are both economically small and statistically insignificant. In addition, we do not find evidence of changes in plant employment, measured using the National Establishment Time-Series (NETS) database. This lack of a change in output and size is consistent with the notion that costs associated with cleanups and abatement for ground pollution are often fixed in nature and therefore do not affect marginal costs of production (EPA (2011)).

We perform a series of cross-sectional tests to explore heterogeneity in responses to *Bestfoods*. First, we consider the role of subsidiary solvency. The likelihood of parent liability is, in part, a function of the likelihood that the cost of an environmental cleanup would bankrupt a subsidiary. Consistent with this idea, the increase in pollution and reduction in abatement are concentrated in less solvent subsidiaries. We also find the effects are driven by facilities of parents with a higher proportion of tangible assets — those for which pollution

abatement activities are likely more costly. Finally, we document evidence of a harm-shifting motivation for the increase in pollution and decrease in abatement activities. Specifically, the effects are concentrated in plants of parents that are closer to financial distress.

Our paper contributes to the broad literature on the economics of industrial pollution. One strand of this literature studies environmental monitoring and enforcement.<sup>2</sup> The most closely related work is Alberini and Austin (2002), which studies variation in environmental rules regarding *strict* liability, a legal standard that imposes liability on polluters regardless of intent or negligence. The authors find that strict liability is associated with fewer environmental accidents at the state-level and a reallocation of economic activity. Similarly, Stafford (2002) shows that strict liability encourages compliance with environmental regulations. Shapira and Zingales (2017) argue that firms are cognizant of legal liability stemming from industrial pollution, but this does not necessarily deter socially harmful behavior. Other papers study a variety of factors that affect corporate environmental behavior, including third-party auditors (e.g., Duflo et al. (2013)), reputational penalties (e.g., Karpoff et al. (2005)), financial characteristics (e.g., Chang et al. (2016); Kim and Xu (2018)), and ownership structure (e.g., Shive and Forster (2018)). Our paper contributes to this literature by showing that limited liability protections also play an important role in incentivizing the use of pollutive technologies that potentially impose externalities on other stakeholders.

More generally, our paper provides some of the first evidence on how limited liability impacts managerial decision making. The seminal work on legal responsibility for externalities comes from Coase (1960), who argues that when transaction costs are negligible and property rights are well defined, economic agents can bargain over the use of these rights in such a way that their initial allocation is irrelevant. Subsequent authors have noted that market imperfections (e.g., information asymmetry and moral hazard) can render regulation or the demarcation of liability important (e.g., Shavell (1984), Laffont (1995)). More recent papers including Biais et al. (2010) and Chaigneau et al. (2014) have focused on the opti-

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<sup>2</sup>See Gray and Shimshack (2011) for a review of this literature.

mal compensation contract in the presence of externalities, the limited liability of agents, and moral hazard. A tradition in legal scholarship has also debated the costs, benefits and legal practicalities of limited liability (e.g., Easterbrook and Fischel (1985), Clark Jr. and Hickok (2016)). Some previous empirical work has also studied limited liability outside of the parent-subsidiary context. For example, Grossman (2001) argues that double liability for deposit holders prior to the Great Depression was associated with less risk-taking in good economic times but not in times of financial distress. Koudijs and Salisbury (2016) find that increased limited liability protection for household assets in the 1850s increased household risk-taking only if the increase in protection was modest. Finally, Weinstein (2008) argues that the adoption of limited liability by American Express in 1965 had little effect on firm value.

Finally, our cross-sectional tests highlight the role of firms' financial strength on the response to the increase in limited liability protections, a finding that is similar in spirit to the risk-shifting incentives first described by Jensen and Meckling (1976). Evidence consistent with the risk-shifting hypothesis has been documented in a variety of settings including banking (e.g., Esty (1997), Landier et al. (2015)), venture capital (e.g., Denes (2016)), and investments by distressed firms (Eisdorfer (2008)). However, evidence inconsistent with the hypothesis has also been reported by Andrade and Kaplan (1998), Gilje (2016), and Gormley and Matsa (2011), among others. A related strand of literature examines how firms' financial conditions impact non-financial stakeholders. For example, previous papers show that distress affects worker safety (Cohn and Wardlaw (2016)) as well as product quality and pricing (e.g., Dionne et al. (1997), Phillips and Sertsios (2013)). Similar to these lines of literature, we find that the increase in pollution and decrease in abatement activities are concentrated in the subsidiaries of parents that are likely to be financially distressed. One interpretation of this finding is that such firms forgo investment in costly pollution abatement in order to free up funds for more immediate financing needs, thus shifting risk,

and potentially harm, to other stakeholders.

## 2 Background

### 2.1 CERCLA

Congress passed CERCLA in 1980 in response to the Love Canal disaster in Niagara Falls, NY (Greenstone and Gallagher, 2008).<sup>3</sup> Rather than implement ex ante restrictions on polluters, the legislation was designed to address the ex post remediation of toxic sites. Specifically, under CERCLA, the EPA maintains a National Priorities List (NPL) of toxic facilities that are eligible for cleanup based on previous emissions. The list currently consists of over 1,300 facilities. Once assigned to the NPL, facilities are further scrutinized by the Agency to determine their levels of environmental and health risks as well as appropriate remedial actions. CERCLA grants the federal government “extraordinary” unilateral power in this regard — the EPA can either undertake a cleanup itself or compel the polluter to do so (Gaba, 2015).

The costs associated with the remediation of NPL sites are substantial, averaging \$43 million per cleanup (Greenstone and Gallagher, 2008). However, cleanups of larger and more complex sites can entail significantly higher costs and take decades to complete. For example, Love Canal was removed from the NPL following a cleanup effort that lasted 21 years and cost \$400 million (DePalma, 2004). More recently, the EPA has initiated CERCLA claims in excess of a billion dollars against a number of companies including Lyondell Chemical Corp. (\$4.8 billion), Assarco LLC (\$3.6 billion), Chemtura Corp. (\$2.1 billion), and Smurfit-Stone Container Corp. (\$1.1 billion) (Blair (2011), Appendix A). However, in each of these cases the firms filed for bankruptcy, and the EPAs recovery was a fraction of the initial claim.

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<sup>3</sup>Love Canal was used as an industrial waste landfill used by Hooker Chemical Corporation. In 1978, the site gained national prominence after chemicals seeped out, and President Carter ordered the evacuation of 900 local residents.

Congress intended the “polluter pays” principle to play a key role in CERCLA. To this end, the legislation imposes two statutory mechanisms to pay for cleanups: Superfund and liability rules. Superfund is a trust fund used by the EPA to pay for site cleanups in instances when the polluter either cannot pay (e.g., due to bankruptcy) or be identified (e.g., “midnight dumping”) (Plater et al., 2016). Revenue for the fund initially came from excise taxes on crude oil and imports that use hazardous substances as well as a corporate income tax. However, these taxes expired in 1995, and today the US Treasury funds the program.

CERCLA also funds cleanups by imposing liability on the “owners or operators” of toxic sites. Courts have ruled that parents are liable for cleanup costs as “owners” if the corporate veil separating the parent and subsidiary can be pierced (i.e., indirect liability). Generally speaking, the owners of corporations have limited liability for the acts of the corporation. However, in limited circumstances, courts allow creditors to pierce the corporate veil and impose liability on firm owners. Under the common law veil piercing doctrine, this may occur in limited circumstances involving an abuse of the corporate form (e.g., failing to maintain corporate formalities, fraud) (Plater et al., 2016). Normal behaviors in a parent-subsidiary relationship (e.g., appointing directors and officers, approving capital expenditures) are generally not grounds for parent liability.

CERCLA also expands parent liability beyond the veil piercing context and holds parents liable as “operators” (i.e., direct liability). However, the legislation does not specify a specific legal standard for operator liability (Cook, 1998).<sup>4</sup> Lacking such a directive, individual federal judges had discretion to impose legal standards for operator liability of parents under CERCLA. The nature of these standards varied across federal circuit courts.<sup>5</sup> Specifically, each of the circuit courts adopted one of the following tests for parent liability:<sup>6</sup>

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<sup>4</sup>CERCLA defines an “owner or operator” as “any person owning or operating such a facility” (Chay and Greenstone, 2003). The lack of clarity perhaps stems from the Act being “a last minute compromise” that was “hastily and inadequately drafted” (Bartley (2005), quoting *United States v. A. & F. Materials Co.*).

<sup>5</sup>When there is a lack of Supreme Court jurisprudence, individual circuit courts can arrive at different conclusions when presented with an ambiguous legal statute (i.e., a “circuit split”).

<sup>6</sup>See Cook (1998), Silecchia (1998), and Stovall (1998) for further discussion on these standards.



- **Ability-to-Control (ATC)** (also called Authority-to-Control) is the broadest standard that defines an “operator” as any person who has the power to control the activities of the polluter. This standard was adopted by the Fourth, Eight, and Ninth Circuits.
- **Actual-Control (AC)** imposes liability on the parent if the subsidiary does not act independently. This may be the case, for example, if the parent corporation is involved in the day-to-day operations of its subsidiary. This standard for parent corporation liability was adopted by the First, Second, Third, and Eleventh Circuits
- **Veil Piercing** is the narrowest standard. This test effectively “read out the ‘operator’ part of the statute” and imposed liability only if the corporate veil can be pierced (Cook, 1998). Courts that used this standard argued that the legislative intent of CERCLA was not to “alter so substantially a basic tenant of corporate law” (*Joslyn Manufacturing Co. v. T.L. James & Co., Inc.*). The veil piercing standard was adopted by the remaining circuits.

Figure 2 shows the geographic areas that employed each of the three standards. Liability standards are based on the location of a plant, not the parent headquarters or state of incorporation. This fact is critical for our empirical strategy.<sup>7</sup>

## 2.2 *United States v. Bestfoods*

In 1998, the Supreme Court resolved the ambiguity surrounding parent liability under CERCLA in *Unites States v. Bestfoods*. This unanimous opinion rejected the Ability-to-Control and Actual Control standards that broadened parent liability relative to traditional corporate law standards. Specifically, the Court ruled that parents were liable for environmental

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<sup>7</sup>There are not significant forum shopping concerns in this setting. CERCLA claims name, on average, nearly a dozen parties as defendants (e.g., parents, subsidiaries, other firms polluting the site, previous owners, arrangers and transporters, etc.) (GAO, 2009). Connors (1987) notes that “in a dispute with multiple defendants, the only forum practically available to the EPA may be the site of the toxic waste spill, especially if the multiple defendants have diverse home jurisdictions.”

remediation costs under two circumstances. First, parents can be held liable under the traditional veil piercing standard. Satisfying this standard requires showing an abuse of the corporate form. Second, parents are responsible if they, themselves, operated the facility responsible for the pollution. Satisfying this condition requires showing involvement that is “eccentric under the accepted norms of parental oversight of a subsidiary’s facility” (*U.S. v. Bestfoods*). Such actions may include the parent leasing the site from a subsidiary, a joint-venture with a subsidiary, or direct control of facility operations by an employee of the parent (Plater et al., 2016). Normal oversight of a subsidiary and its operations that would not give rise to CERCLA parent liability include “appointing a subsidiary’s officers and directors, monitoring its performance, supervising the subsidiary’s finances, approving budgets and capital expenditures, and even articulating general policies and procedures for the subsidiary” (Plater et al., 2016).

Thus, relative to the weaker ATC and AC standards, *Bestfoods* significantly increased the difficulty of holding parent corporations liable under CERCLA (Plater et al., 2016). In courts that had adopted the weaker standards, plaintiffs often argued that shared officers/directors or parent oversight of a subsidiary gave rise to parent liability; under *Bestfoods*, such actions are “viewed as indicative of normal parent-subsidiary relationships” and not grounds to impose liability (Plater et al., 2016). By reducing the liability of parents for cleanup costs that exceed the value of the subsidiary, the *Bestfoods* decision incentivizes behaviors that make such liabilities more likely. For example, decreasing investment in pollution abatement may increase short-term profitability or free up cash flows while increasing the probability of a long-term environmental disaster.

However, alternative regulatory mechanism may, at least in part, undercut such incentives. Specifically, while *Bestfoods* may hinder efforts to remediate toxic sites, ex ante regulations potentially substitute for the deterrence function of CERCLA. In the case of ground pollution, the Resource Conservation and Recovery Act (RCRA) governs the disposal of haz-

ardous and non-hazardous waste. In theory, this ex ante regulation may serve as a substitute for ex post liability. However, there are shortcomings of both ex ante and ex post approaches that potentially render them imperfect substitutes. For example, regulators have imperfect information about market participants, potentially leading to sub-optimal oversight, while bankruptcy undercuts the effectiveness of ex post lawsuits (Kolstad et al. (1990)). Thus, there are potentially important complementarities between ex ante regulation and ex post liability, and their joint use may be important for efficient regulation (e.g., Kolstad et al. (1990), Shavell (1984)). Some legal scholars have echoed the importance of both CERCLA and RCRA for deterring certain behaviors.<sup>8</sup>

It is also important to note the change in parent liability standards may have affected the behavior of the EPA. Enforcement actions and litigation are costly events for both the defendant and plaintiff. While *Bestfoods* likely had little effect on the EPA’s incentive to initiate claims against solvent subsidiaries able to cover the cost of cleanups, the agency may have been reluctant to initiate claims against subsidiaries close to insolvency because of a higher probability of a limited recovery.

## 3 Data and Methodology

### 3.1 Data

Our main sample consists of plants in the EPA’s Toxic Release Inventory (TRI) database from 1994 – 2003. Since 1987, the EPA has reported chemical-level emissions data in TRI for plants (associated with both public and private firms) that exceed a minimum number of employees, operate in certain industries, and emit specific hazardous pollutants. The current standard requires reporting if a facility contains at least 10 full-time employees,

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<sup>8</sup>Rallison (1987) argues “CERCLA aims to clean up existing hazardous waste sites. CERCLA’s effect, however, is not merely remedial. Its liability provisions, in conjunction with those of RCRA, provide significant incentives to current and future waste producers, transporters, and disposal site owners and operators to control the hazardous wastes they produce, transport, dispose of, or store.”

operates in one of roughly 400 industries defined at the six-digit NAICS level, and uses one of nearly 600 chemicals.<sup>9</sup> Appendix A.6 lists the industries that currently report at the three-digit NAICS; the most common include chemical manufacturing (25.1% of sample), fabricated metal product manufacturing (11.0%), primary metal manufacturing (9.1%), and transportation equipment manufacturing (6.9%). For most chemicals, disclosure is triggered if more than 25 thousand pounds of a chemical are manufactured or processed or 10 thousand pounds are otherwise used during a year, though some substances (known as Persistent Bioaccumulative Toxic (PBT) chemicals) have more stringent requirements. While TRI data are self-reported by facilities, the EPA audits the data and can initiate civil enforcement actions for non-compliance. For example, P4 Production LLC, a wholly owned subsidiary of Monsanto, was fined \$600 thousand for violating chemical reporting laws in 2015.<sup>10</sup>

For each chemical subject to TRI reporting, plants are required to provide the number of pounds released into the ground, air, and water.<sup>11</sup> Ground emissions consist of waste disposed in underground injection wells, landfills, surface impoundments, or spills and leaks released to land. Air emissions consist of stack or point releases (e.g., through a vent or duct) and fugitive emissions (e.g., evaporative losses). Water emissions consist of releases to streams and other surface bodies of water. Figure 1 plots the time series of aggregate emissions for the three categories over our sample period. Consistent with previous findings (e.g., Shapiro and Walker (2015)), emissions fell through the 1990s, primarily driven by a decrease in air pollution.

We obtain information on the toxicity of chemical emissions using the EPA’s Integrated Risk Information System (IRIS). IRIS provides information on potential human health effects from exposure to over 400 chemicals. The database includes both carcinogenic and

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<sup>9</sup>Some requirements (e.g., the industries subject to reporting) have changed over the course of our sample. We show in the appendix that such changes do not materially affect our findings.

<sup>10</sup>See [https://19january2017snapshot.epa.gov/newsreleases/epa-us-department-justice-settle-p4-production-llc-over-hazardous-chemical-reporting\\_.html](https://19january2017snapshot.epa.gov/newsreleases/epa-us-department-justice-settle-p4-production-llc-over-hazardous-chemical-reporting_.html)

<sup>11</sup>We drop observations for plants with zero total emissions. This does not have a material effect on our results.

non-carcinogenic chemicals, which are chosen for inclusion in the database according to potential effects on public health, regulatory implementation needs, and availability of scientific assessment of chemicals. IRIS also includes information on the primary system affected or tumor site for the chemicals (e.g., nervous, respiratory, developmental). We match the IRIS database to TRI using chemical identifiers (i.e., Chemical Abstract Services (CAS) numbers) and use the database to construct an indicator for whether a chemical in TRI poses potential harm to humans as well as indicators for whether particular bodily systems are affected.

We use the EPA’s Pollution Prevention (P2) database to analyze abatement activities and changes in production. Plants reporting to the TRI database are required to document source reduction activities at the chemical level that reduce the amount of hazardous substances entering the waste stream. The most common abatement activity is “good operating practices,” which comprises actions such as improved maintenance scheduling, record keeping, or procedures. For example, a soap manufacturer changing “production schedules to allow for longer run times for similar products to reduce the need for diethanolamine feedstock changeovers” is an abatement activity related to operating practices.<sup>12</sup> The second most common abatement activity is “process modifications,” which include actions such as modifying equipment, layout, or piping. For example, the EPA highlights a battery manufacturer that “upgraded its conveyor system to prevent blockage and loss of cobalt material due to contamination” as an abatement activity related to production. The list of activities included in both types of abatement are provided in Table A.5. We use these classifications to construct indicators for process-related abatement and operating-related abatement activities. While we cannot precisely classify fixed and variable costs using the P2 database, anecdotal evidence suggests changes in operating practices include significant variable costs while process modifications may include a significant fixed cost component.

The P2 database also includes a production or activity ratio that measures changes in the

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<sup>12</sup>See <https://www.epa.gov/toxics-release-inventory-tri-program/pollution-prevention-p2-and-tri>

output or outcome of processes in which a chemical is involved. For example, if a chemical is used in the manufacturing of refrigerators, the production ratio for year  $t$  is given by  $\frac{\# \text{Refrigerators Produced}_t}{\# \text{Refrigerators Produced}_{t-1}}$ . If a chemical is used in a capacity not directly related to production (e.g., cleaning), the EPA alternatively requires facilities to report the ratio reflecting changes in this activity. For example, if a chemical is used to clean molds, the activity ratio for year  $t$  is given by  $\frac{\# \text{Molds Cleaned}_t}{\# \text{Molds Cleaned}_{t-1}}$ . If a particular chemical is used in multiple production processes/activities, firms are required to report a weighted average. Due to errors in the data, we exclude production ratios that are not between zero and three (inclusive), though our findings are qualitatively similar using narrower or wider bounds (e.g.,  $[0, 2]$  or  $[0, 5]$ ).

Plant-level data are from the National Establishment Time-Series (NETS) database, which is constructed by Walls & Associates using archival data from Dun & Bradstreet. We use plant Paydex score and number of employees from NETS. Paydex score, which ranges from 0 to 100, is a business credit score based on trade credit performance provided to Dun & Bradstreet by a large number of vendors and suppliers. The score is value-weighted according to size of obligations, and a score of 80 indicates that, typically, payments are made according to the loan terms. Our analysis focuses on the minimum score reported over the course of a year. Dun & Bradstreet determines plant employment by directly contacting entities and using statistical models to impute missing values.<sup>13</sup> We match NETS data to the TRI database using a linking file between plant D-U-N-S numbers and TRI identifiers created by Walls & Associates. Finally, we use Compustat for financial information for publicly traded parent companies. We identify public parents using a fuzzy matching algorithm and manually check all matches.

We identify subsidiaries (as opposed to stand alone firms) using the TRI database. Specif-

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<sup>13</sup>Neumark et al. (2011) find that the correlations between NETS and Current Employment Statistics (CES) and Quarterly Census of Employment and Wages (QCEW) are 0.99 and 0.95 at the county-by-industry level, respectively. However, NETS has some shortcomings relative to establishment employment determined by government statistical agencies. We take steps where possible to mitigate these shortcomings. First, we obtain similar results if we exclude estimated values. Second, Barnatchez et al. (2017) note that NETS over-samples small establishments (<10 employees). Such establishments are rare in the TRI database (<5% of observations) and excluding them does not have a material effect on our findings.

ically, for each plant, the database provides the parent company, defined as highest-level corporation that owns at least 50 percent of voting shares. For example, Chemtool Inc. is a subsidiary of Lubrizol Corp., which is owned by Berkshire Hathaway, so the ultimate parent corporation for Chemtool is Berkshire Hathaway. We match subsidiaries to court districts to form treatment and control groups. Subsidiaries located in “Ability-to-Control” and “Actual Control” districts form the treatment group, and those located in districts with the veil piercing standard comprise the control group. As noted above, treatment status is based on the location of the plant. Figure 3 depicts the fraction of observations in each of the 11 court circuits and shows the breakdown between treatment and control groups during our study (1994-2003). Approximately 22% of plants are located in districts that adopted the “Actual Control” standard (the first of our treatment groups), 28.5% are in districts with the “Ability-to-Control” standard (the second of our treatment groups), and 49.5% fall into circuits that used the veil piercing standard for parent liability (our control group). Despite there being large differences in the size of some districts (e.g., the Ninth Circuit contains nine states including California), the number of observations are fairly balanced between treatment and control groups.

In total, our sample consists of 6,953 parent corporations which have an average 2.80 plants of subsidiaries. Each of these plants report emissions for, on average, 3.91 toxic chemicals. Table 1 reports summary statistics for our main outcomes of interest. The first four columns of the table report statistics for all subsidiaries, and the second four limit the sample to subsidiaries with public parent corporations. Unless otherwise noted, all summary statistics are at the chemical-plant-year level. For the full sample, plants average 43 thousand pounds of ground pollution for each chemical reported in TRI, though nearly 85% do not report ground emissions. Air and water emissions average about 30 thousand and 4 thousand, respectively. Abatement activities are fairly common: operating and process related actions are taken for 8% and 5% of the sample, respectively. The production ratio averages 0.96 and

has a median of 1.0, and the average plant employs 334 workers.

### 3.2 Regression Specification

We use the *Bestfoods* decision as a natural experiment in a difference-in-differences framework. We define an indicator *Bestfoods* that takes a value of one starting in 1999, the first full calendar year following the decision, for plants located in a district that previously adopted relatively weaker standards for parent liability (i.e., the AC or ATC legal tests).<sup>14</sup>

For our initial analysis, the main outcome variable is the natural logarithm of 1 plus the pounds of emissions (chemical-level) for each plant.<sup>15</sup> Our main specification takes the following form:

$$\log(1 + Lbs\ Ground\ Pollution_{c,p,f,i,t}) = \beta Bestfoods_{f,t} + \alpha_p + \alpha_{i,t} + \alpha_{c,t} + \epsilon_{c,p,f,i,t},$$

where  $c$  indexes a chemical emitted by a plant  $p$  located in federal circuit  $f$  and belonging to parent firm  $i$  at time  $t$ . We include plant fixed effects ( $\alpha_p$ ) to control for time-invariant heterogeneity at the facility level (e.g., industry). In addition, we include parent-year fixed effects ( $\alpha_{i,t}$ ) to control for time-varying heterogeneity at the parent level. The coefficient estimates for the main specification are therefore relative to plants with the same parent located in areas with stronger liability protections already in place. We also include chemical-year fixed effects ( $\alpha_{c,t}$ ) to control for time-varying heterogeneity at the chemical-year. As Chatterji et al. (2009) and DiGiuli (2013) note, there is not a clear way of aggregating pollutants or easily comparing their environmental impact; chemical-year fixed effects allow us to exploit within-chemical-time variation. In some specifications, we also include industry-year fixed effects, defined using the primary 4-digit SIC code for each plant to control for time-varying heterogeneity at the industry level. We cluster robust standard errors at the

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<sup>14</sup>The court decision was in June of 1998. We obtain similar results if we exclude 1998 from the sample.

<sup>15</sup>In unreported analysis, we rescale pollution levels by adding 1000 instead of 1 as in Chatterji et al. (2009). This does not have a material effect on the results.



circuit level.

We also conduct analysis on outcomes related to abatement and production (both at the facility-chemical level) using the above specification. We analyze employment at the plant level using a similar specification but excluding chemical-year fixed effects. Finally, we use 1997 values (prior to *Bestfoods*) to analyze subsets of the main sample based on plant characteristics (e.g., Paydex) or parent characteristics (e.g., Z-score). The specifications used for these tests is the same as above.

## 4 Results

### 4.1 Effect of Parent Liability on Emissions

We first analyze the effect of *Bestfoods* on toxic emissions by subsidiaries. The main outcome of interest is ground pollution, as this is the focus of CERCLA enforcement efforts. In this section, we ask whether the relative increase in parent liability protection affected the quantity and toxicity of ground emissions and whether the decision was associated with changes to other types of pollution.

#### 4.1.1 Facility Ground Emissions

Table 2 examines the effect of the *Bestfoods* on facility ground emissions. The dependent variable is the natural logarithm of one plus pounds of ground pollution. Columns (1) – (4) indicate *Bestfoods* is associated with an increase in ground emissions for treated plants that experienced a relative increase in parent liability protection. In addition to the baseline specifications (columns (3) and (4)), we also report coefficients for relatively parsimonious specifications with plant and year (column (1)) or plant and chemical-year fixed effects (column (2)). The point estimates range from 0.047 to 0.086 and are statistically significant at the 1% level in each of the specifications. The increase in emissions is economically large:

the average value of the dependent variable is 0.90, indicating an increase of between 5% and 9% relative to the sample average.

The remainder of Table 2 analyzes the effect of *Bestfoods* on different subsets of plants. Columns (5) and (6) separately estimate the treatment effect for plants located in districts that employed Ability-to-Control and Actual Control tests. The indicators *ATC* and *AC* are defined analogously to *Bestfoods* in the baseline specification, but only take a value of one for plants located districts that used the respective standards. The results indicate similar effects across both types of jurisdictions. Specifically, the coefficients for both *ATC* and *AC* are statistically significant at the 5% level or lower, and the points estimates for both are of similar magnitude to the baseline specification.

Next, we restrict the sample to subsidiaries with publicly traded parents. Shive and Forster (2018) argue public status is positively associated with emissions, potentially as a consequence of pressure from short-term investors.<sup>16</sup> The effects of *Bestfoods* may be particularly strong for this set of facilities because larger emissions potentially lead to larger future liabilities. Our findings are consistent with this intuition. Specifically, the point estimates in columns (7) and (8) are nearly triple those of the main sample, corresponding to an increase of approximately 17% relative to the subsample mean.

Finally, columns (9) and (10) restrict analysis to plants that do not have a parent listed in the TRI database. Consistent with the idea that a change in parent liability should only affect plants with a parent corporation, we find no evidence of an increase in emissions for this set of plants. The point estimates are both economically small (ranging from -0.006 to -0.018) and statistically indistinguishable from zero. This analysis serves as a useful falsification test as it suggests there was not a confounding shock (e.g., local economic conditions or public attitudes towards pollution) that broadly affected emissions by all plants (both with and without parent corporations) in districts that previously adopted weaker liability standards.

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<sup>16</sup>Consistent with this finding, the median ground emission (at the chemical level) for all facilities is approximately one quarter (2,050 pounds) the median of facilities with public parents (8,472 pounds) in our sample of chemicals with positive ground emissions.

Figure 4 plots the coefficient dynamics around the *Bestfoods* decision. We construct this figure by replacing the pooled treatment variable in the baseline specification with indicators for each year before and after the decision. The coefficient trend is relatively flat prior to the decision, but begins to increase once liability standard changed for the treated group. While the “parallel trends” assumption necessary for empirical identification in our setting is untestable, this figure provides evidence that is consistent with the assumption.

We verify that the main result on ground emissions is not driven by any individual court circuit by iteratively removing one circuit and rerunning our main analysis. This analysis further mitigates concerns that contemporaneous geographical shocks that are unrelated to the *Bestfoods* decision may confound the analysis. We plot the point estimates and confidence intervals in Figure A.1. The estimate for each iteration remains positive and statistically significant at the 5% level or lower.

#### 4.1.2 Intensive and Extensive Margins

Table 3 examines whether the increase in emissions is driven by the intensive or extensive margins of pollution. To analyze the intensive margin, columns (1) – (4) restrict the sample to plants that reported positive ground pollution in 1997, the year before the *Bestfoods* decision. Because we exclude plants with zero (or missing) ground pollution in 1997, the sample size is considerably smaller than the main test reported in Table 2. Thus, this test also mitigates concerns that the primary effect is driven by the presence of firms with zero ground emissions. We find the change in parent liability protection is associated with an increase in ground emissions along this margin for both the full sample of subsidiaries (columns (1) and (2)) as well as the sample with public parents (columns (3) and (4)). As in Table 2, the point estimates for the sample with public parents are approximately three times larger than those for the full sample of subsidiaries. The economic magnitude of this effect is sizable, corresponding to an increase of 7.5% to 9.6% relative to the sample mean

of the dependent variable for the full sample.

We next examine the intensive margin of pollution. The dependent variable in columns (5) – (8) is an indicator for ground emissions at the chemical level. For the sample of all subsidiaries (columns (5) – (6)), the likelihood of ground pollution increases by approximately 0.8 percentage points, though this effect is statistically noisy and not significant at conventional levels when we include industry-year fixed effects. The effect is stronger both in terms of economic magnitude (approximately 3 percentage points) and statistical significance ( $p < .01$ ) for the sample of subsidiaries with public parents.

Taken together, the findings in Table 3 indicate that the increase in emissions following the strengthening of parent liability protections occurs along both the intensive and extensive margins.

#### 4.1.3 Chemical Toxicity

We next turn attention to the types of chemicals emitted by subsidiaries. By definition, the chemicals included in the TRI database are toxic, though not all have adverse effects on humans. In this section, we analyze whether there is a differential effect for chemicals that are known to be toxic to humans versus those that are not. It is possible, for example, that stronger parent liability protections afforded firms leeway to increase emissions of non-hazardous chemicals, but the presence of ex-ante regulations (e.g., RCRA) made it costly to increase hazardous emissions. To this end, we match the chemicals from the TRI database with the EPA’s Integrated Risk Information System (IRIS), which classifies chemicals based on evidence of harm to humans. We define chemicals as either harmful or non-classified based off of the IRIS definitions. Approximately 62% of the chemical observations in the full sample have known adverse effects on humans.

Table 4 reports the results. Panel A shows the impact of *Bestfoods* on ground pollution split by chemical type. The sample consists of chemicals that have known adverse health

outcomes in columns (1) – (4) and unclassified chemicals in columns (5) – (8). For both samples we report results for both all subsidiaries as well as subsidiaries with public parents. Overall, estimates for both samples are similar and comparable to the baseline results in Table 2. Panel B further categorizes harmful chemicals based on biological impact to humans. We document an increase in ground emissions of chemicals that harm a variety of biological systems, especially the nervous, respiratory, urinary, and developmental. Overall, our analysis indicates the increase in ground emissions is not driven by inert substances. Rather, we find little evidence of differences in the estimates for harmful and non-classified chemicals.

#### 4.1.4 Other Types of Emissions

We next analyze the effect of *Bestfoods* on air and water pollution. It is unlikely that parent liability under CERCLA would directly affect these types of emissions. Specifically, courts have ruled the CERCLA does not apply to air emissions, even if chemicals pollute land or water after being released into the air (see *Pakootas v. Teck Cominco Metals*). In addition, while CERCLA technically does cover disposals into waterways, the EPA only recently began cleanups of such sites on a large scale (DePalma, 2012). The reason for this lax enforcement stems from the fact that it is often difficult to identify the polluters of waterways and cleaning up such sites often comes at considerable expense and questionable efficacy.<sup>17</sup> Thus, the focus of CERCLA cleanups is “on upland sites, with rivers all but forgotten.” (DePalma, 2012). However, *Bestfoods* may still have an indirect effect on water or air pollution if they serve as complements or substitutes for ground pollution. It is unclear if this is the case as plant production functions are unobservable to the econometrician.

Table 5 reports the effect of *Bestfoods* on water and air emissions. The dependent variable

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<sup>17</sup>DePalma (2012) notes “Under the Superfund’s ‘polluter pays’ approach, companies that are responsible for the pollution can be forced to pay for the cleanup. But with rivers like the Passaic, which has been used by hundreds of businesses to dump industrial wastes for more than two centuries, identifying those responsible can be a legal nightmare. According to the E.P.A., more than 70 businesses will have to pay for the Passaic cleanup, which could cost more than \$3 billion.”

in columns (1) – (4) is  $\log(1 + Lbs\ Water\ Pollution)$ , and the dependent variable in columns (5) – (8) is  $\log(1 + Lbs\ Air\ Pollution)$ . As before, we report results both for the full sample of subsidiaries as well as for subsidiaries with public parents. Overall, we find little evidence that the decision affected other types of emissions. Specifically, the point estimates are positive across different specifications for both variables, but they are not significant at conventional levels. The lack of evidence of a change in other types of emissions is consistent with Greenstone (2003), who finds no change in non-regulated emissions following the adoption of the Clean Air Act.

## 4.2 Effect of Parent Liability on Firm Value

We next test the effect of *Bestfoods* on the value of parent corporations. Stronger limited liability protections make it less likely that a parent incurs costs associated with subsidiary environmental cleanups. This may, in turn, have a positive effect on firm value. Moreover, a reduced threat of environmental liability may lead to cost savings (e.g., via lower investment in abatement technologies) or increased production for subsidiaries, both of which may also increase the value of the parent corporation.

For this analysis, we focus on cumulative abnormal returns (CARs) around two important events for the *Bestfoods* case: oral arguments (March 24, 1998) and the Supreme Courts decision (June 8, 1998). These dates represent important milestones in the resolution of uncertainty for a case before the Supreme Court. During oral arguments, justices often ask attorneys questions that indicate their level of skepticism towards a given side of the case. It is plausible that market participants update their beliefs regarding the outcome of a case during such arguments before any residual uncertainty is resolved by the final ruling. This is particularly likely for unanimous decisions, such as *Bestfoods*, where the final outcome did not hinge on the decision of one or two justices.

In order to estimate the effect on shareholder value, we compute daily CARs adjusted for

the Fama-French three-factor model around both the date of oral arguments and the decision. Results are qualitatively similar using a four-factor model. We estimate each model in the 100 days prior to each event for the publicly traded firms in our sample. Because such firms often have plants located in both the treatment and control districts, we define an indicator, *High Exposure*, that takes the value of one if a parent has relatively more plants (i.e., above median) in the treatment districts. This allows us to compare the CARs of firms in our sample for which the event was relatively more important.

Table 6 reports the results of this analysis. Panel A analyzes CARs for the entire sample of firms in our sample, while Panel B restricts the sample to multi-plant firms for which the effects of *Bestfoods* may be more salient. Columns (1) – (3) report results the oral arguments date, and columns (4) – (6) report results for the decision date. Overall, we find evidence of higher abnormal returns for high exposure firms around the date of oral arguments but no effect around the actual decision date. Specifically, for the (-1, 5) and (-1, 10) windows, firms with relatively high exposure experienced higher abnormal returns ranging from 82 to 148 basis points. The effect is economically smaller and indistinguishable from zero for the (-1, 1) window. However, CARs are somewhat stronger in terms of magnitude and statistical significance for the multi-plant firms in Panel B, with effects of 109 and 160 basis points for the (-1, 5) and (-1, 10) windows, respectively. In unreported results, we find similar results for the (-1, 30) window, suggesting this effect is not short-lived. We do not, however find evidence of differences in abnormal returns around the decisions date; the coefficients in columns (4) – (6) are both economically small and statistically indistinguishable from zero for both samples. This finding is consistent with the idea that market participants anticipated the unanimous decision.

### 4.3 The Channel

In this section we investigate the channel linking liability protections to increased emissions. We specifically consider whether higher emissions result from an increase in economic activity or a decrease in firms efforts to reduce pollution output.

#### 4.3.1 Pollution Abatement

We first examine subsidiary pollution abatement activities. Investment in abatement is a considerable expense for industrial firms, ranging from 5–7% of new capital expenditures (EPA, 2005). Such investments are undertaken, at least in part, to reduce the costs associated with emissions (e.g., fines for violating regulations, remediation costs, etc.). By reducing parent liability for future cleanups, *Bestfoods* may have effectively reduced the cost of polluting. Because parents control subsidiaries (as majority owners), this reduction in costs may have reduced the incentives to undertake abatement activities.

We test this hypothesis using data from the EPA’s Pollution Prevention (P2) database, which provides information on abatement activities at the plant-chemical-year level. Our specific focus is on the two most common abatement categories: changes in operating practices and process improvements. According to P2 guidelines, good operating practices include activities like improving maintenance or quality control, while process improvement include activities such as improving chemical reaction conditions or implementing better process controls. Table A.5 provides the full list of activities classified under these types of abatement.

Table 7 reports the results of our analysis. The dependent variable in columns (1) – (4) is an indicator for abatement related to operating practices, and the dependent variable for columns (5) – (8) is an indicator for abatement related to process improvements. Overall, we find that plants decrease abatement activities for actions related to the production process but not for activities related to plant operations. Specifically, the magnitudes of the



estimated coefficients for operating practices are both economically small and statistically indistinguishable from zero. However, for abatement related to the manufacturing process, estimates are both larger (ranging from -0.008 to -0.018) and statistically significant at conventional levels. The effects for process-related abatement are sizable relative to the sample mean, implying a drop of 16–35%. As with the emissions results, our findings are particularly strong for facilities that have a publicly traded parent. This reduction in abatement activities is consistent with the idea that lower investment in abatement leads to a larger increase in emissions. In unreported analysis we examine less common types of abatement. We find evidence of a decrease in efforts to improve inventory management, but estimates for other types of abatement are statistically indistinguishable from zero, though such actions are relatively uncommon to begin with.

#### **4.3.2 Plant Production and Employment**

As noted above, the expansion of parent liability protection resulting from *Bestfoods* can be viewed as a decrease in the expected cost of polluting. A natural question is whether this change in costs leads to increased production. The answer to this question depends on the nature of costs impacted by the change in parent liability standards. If, for example, *Bestfoods* lowered current fixed costs (e.g., those pertaining to pollution abatement) or expected future fixed cleanup costs, the change in parent liability protection would not lead to a change in current production. However, if the decision instead impacted variable costs borne by firms, standard economic theory predicts increased production.

We examine this question using two measures of economic activity — the production ratio (i.e., the ratio of current year to previous year output at the chemical-level) from the TRI database and facility employment data from NETS. Table 8 reports the results of this analysis. Columns (1) – (4) indicate little evidence of changes to output as measured by the production ratio. Specifically, coefficients for the full sample of subsidiaries (columns

(1) and (2)) are positive but economically small (less than 1 percentage point) and not statistically significant at conventional levels. Point estimates for subsidiaries with public parents (columns (3) and (4)), which have relatively large changes in ground pollution, are of similar magnitude to the full sample and also indistinguishable from zero.

Columns (5) – (8) report the results for estimated employment, a proxy for plant size. The dependent variable in these columns is the natural logarithm of facility employment. We omit chemical-year fixed effects from the regression specifications because employment is defined at the plant, rather than chemical, level. Overall, we find little evidence of changes to employment. If anything, the estimates for this analysis are *negative*, though only significant at the 10% level for one specification (column (7)).

Taken together, we find little evidence that *Bestfoods* was associated with changes in production or employment despite there being an increase in emissions. This finding is consistent with the idea that costs associated with abatement and remediation of ground pollution are often fixed in nature and therefore do not affect marginal production decisions. Indeed, environmental remediation costs for ground pollution “often involves upfront expenditures on costly equipment. Such sunk costs are unrelated to current production decisions, unlike variable costs that firms often incur when complying with air and water regulations” (EPA (2011)). In addition, abatement efforts related to process modifications often include actions such as investing in new production technologies, which likely have a sizable fixed-cost component.

## 4.4 Cross-Sectional Heterogeneity in Responses

In this section we test for heterogeneity in responses to the *Bestfoods* decision based on subsidiary and parent characteristics. Specifically, we consider the effect of subsidiary solvency, parent tangibility, and parent risk of distress. We find the results are driven by less solvent subsidiaries that have the largest impact (all else equal) on their parents’ expected liabilities.

Moreover, the results are stronger for plants of parents with a higher fraction of tangible assets that may disproportionately benefit from reduced investment in production-related abatement technologies. Finally, the results are driven by parents that are closer to distress. Such firms are more likely to benefit from reducing investment in abatement, thus potentially shifting harm to other stakeholders.

#### 4.4.1 Subsidiary Solvency

All else equal, less solvent subsidiaries are more likely to go bankrupt as a result of environmental liabilities. Thus, the likelihood of parent liability for cleanups depends, in part, on the solvency of subsidiaries. We conjecture the effects of strengthening parent limited liability protection are therefore concentrated in the sample of subsidiaries that are less solvent. In this section, we test this conjecture. Our analysis focuses on subsidiary solvency rather than actual bankruptcy events for two reasons. First, major environmental penalties leading to bankruptcy are relatively rare events. Rather than rely on this limited variation, we instead make use of a proxy for the relative distance from bankruptcy. Second, *Bestfoods* may have altered to behavior of the EPA in equilibrium by reducing the incentive to try to recover costs from subsidiaries that are close to bankruptcy. Thus, it is theoretically unclear whether the change in liability protection should lead to an increase in bankruptcy events.

We measure solvency at the plant level using Dun & Bradstreet’s Paydex score, which measures the creditworthiness of an establishment in a given year. For this analysis, we compare the effects on ground pollution and process-related abatement for plants with above/below median Paydex scores in 1997, the year before *Bestfoods*. The minimum 1997 Paydex score for the median firm in the sample is 69, indicating payments to suppliers of trade credit typically arrive two weeks beyond terms.

Table 9 presents the results of this analysis. The dependent variable for columns (1) and (2) is the natural logarithm of one plus pounds of ground pollution, and the dependent

variable for columns (3) and (4) is an indicator for process-related abatement. Columns (1) and (3) use the baseline specification, and columns (2) and (4) add industry-year fixed effects. We find that our previous results for both emissions and abatement are concentrated in plants with below-median Paydex scores. For example, column (1) indicates that the point estimate for the less solvent subsidiaries is 0.0859 (significant at the 5% level) whereas the point estimate for more solvent subsidiaries is -0.0503 (barely significant at the 10% level). There are similar patterns in column (3), where the point estimate for less solvent subsidiaries is -0.017 (significant at the 5% level) and 0.0083 (insignificant at conventional levels) for the subsidiaries that were more solvent. The differences between the coefficients for the high and low solvency samples are statistically significant at the 10% level or lower across the different specifications.

#### 4.4.2 Parent Tangibility

We next examine how the main results vary across parents with different levels of tangible assets. The previous analysis indicates *Bestfoods* led to a decrease in pollution abatement activities related to the production process. Such activities potentially entail significant fixed costs, especially for firms with a large amount of fixed assets. Thus, we conjecture the disincentive to invest in abatement is particularly strong for plants with a higher proportion of tangible assets (net plant, property and equipment/total assets). To the extent that a drop in abatement impacts emissions, we also expect the increase in ground emissions to be driven by this set of firms. Because we do not observe tangibility at the plant level, we use parent-level data from Compustat in 1997 (i.e., the year before *Bestfoods*) to classify plants as having above or below median tangibility.

Table 10 reports the results of this analysis. Columns (1) and (2) report results for ground pollution, and columns (3) and (4) report results for process-related abatement. Columns (1) and (3) use the baseline specification, and columns (2) and (4) add industry-year fixed effects.

Consistent with our conjecture, we find stronger results for the sample of plants with parent companies that have a higher fraction of tangible assets. For ground emissions, the coefficient for the baseline specification (column (1)) is 0.270 (significant at the 1% level) in the sample with high tangibility; the corresponding point estimate for the low-tangibility sample (.124) is less than half this magnitude and significant at the 10% level. We find a similar difference for abatement: the estimate for the baseline specification in column (3) is -0.0179 (significant at the 1% level) for the high-tangibility sample, whereas the corresponding coefficient for the low-tangibility sample is -0.0144 (significant at the 10% level). For the most part, these differences are suggestive in nature and not statistically significant at conventional levels.

#### 4.4.3 Parent Risk of Distress

We finally examine how parent financial health impacts the response to stronger liability protection. While previous research argues highly-levered firms in poor financial health have incentives to shift risk from equity holders to credit holders (e.g. Jensen and Meckling (1976)), such firms may similarly have incentives to shift economic harm to other stakeholders (e.g., to plant workers or the local community). For example, parents that are close to default may disproportionately respond to *Bestfoods* because they view investments in pollution abatement as having a higher short-term value if directed towards immediate financing needs. This would particularly be true for the low probability, high cost liabilities potentially incurred under CERCLA. The incentive to shift harm suggests parents with relatively high risk of distress may disproportionately respond to *Bestfoods*.

In Table 11 we examine whether parent risk of distress is associated with differential effects to the *Bestfoods* decision. We repeat the analysis from Table 10 but define firms as having above or below median parent unlevered Z-score in 1997. The dependent variables in columns (1) – (2) and (3) – (4) are ground pollution and process abatement, respectively. We find the increase in pollution and decrease in abatement concentrate in firms with low

Z-scores (i.e., those firms that are the least financially solvent). For ground pollution, the coefficients for the sample of facilities with low parent Z-score are more than three times larger than the sample with high Z-scores (e.g., 0.378 vs. 0.125 for column (1)). We find a similar difference for investment in process abatement. The difference between the coefficients for the samples with high/low distress risk is statistically noisy for column (4), but otherwise significant at conventional levels.

## 4.5 Robustness Tests

We report additional robustness tests in the supplementary appendix. We first show our findings are robust to using alternative measures of ground pollution. The dependent variable in Table A.1 is the proportion of ground emissions to total emissions. The regression specifications in this table are otherwise identical to Table 2. The results indicate *Bestfoods* is associated with an increase in the ratio of ground emissions to total emissions for both the full sample of facilities (Columns (1) – (6)) and the sample of facilities with a public parent (Columns (7) – (8)). As before, we find no evidence of a change in behavior for facilities that do not have a parent (Columns (9) – (10)).

Because the industries required to report emissions to the EPA has changed over time, Table A.2 removes those that were added to the TRI database after the *Bestfoods* decision. The estimated coefficients for ground pollution and process-related abatement are similar, both in terms of magnitude and statistical significance, to the main analysis.

We also conduct tests to address potential correlation in the standard errors of our estimates. First, in Table A.3 we collapse the data to contain only one pre-treatment and one post-treatment time period, as suggested by Bertrand et al. (2004). The point estimates for both ground emissions and process abatement are similar to the main analysis and remain statistically significant at conventional levels. We further verify that our results are robust to our method of computing standard errors. Panel A of Table A.4 reports our main results

with state-level clustering, which preserves much of the panel structure of our treatment unit (e.g., Circuit Courts), but has a larger number of clustering units. Panel B clusters by parent-firm in addition to by state, to account for correlation in the standard errors of subsidiaries that share a parent. The estimated coefficients remain statistically significant at conventional levels.

## 5 Conclusion

Limited liability is a ubiquitous feature of modern economic organization. However, because the owners of corporations are not responsible for obligations that exceed the value of the firm, they do not bear all costs associated with risky activities. Such risks are therefore borne by other stakeholders, including creditors, employees, the surrounding community, and society at large. Admati (2017) argues that lack of accountability for managers further exacerbates these misaligned incentives.

In this paper, we use industrial emissions as a setting to analyze the tradeoffs of limited liability in the parent-subsidary context. Our identification strategy uses a Supreme Court case (*United States v. Bestfoods*) that clarified parent liability for subsidiary environmental cleanup costs. We find stronger liability protection for parents is associated with an increase in subsidiary ground emissions of 5 – 9%. The effect operates on both the intensive and extensive margins and is partially driven by chemicals with known toxicity to humans. In addition, we document an increase in firm value for parents affected by the decision.

Evidence suggests the increase in emissions is driven by reduced investment in abatement technologies rather than an increase in economic activity. Specifically, *Bestfoods* is associated with a drop in process-related abatement activities for treated firms, but not a change in plant production or employment. The findings are driven by less solvent subsidiaries that are more likely to impose liability on parents and by firms with relatively high tangible assets that would likely most benefit from reducing expenditures on pollution abatement. Consistent

with a harm-shifting motivation, the effects concentrate in firms that are relatively close to financial distress.

Overall, the results highlight the moral hazard problem associated with limited liability. While our setting precludes a rigorous welfare analysis, the findings suggest the strengthening of liability protections for parents leads to an increase in costs borne by other stakeholders. Thus, efforts by policymakers to strengthen liability protections should carefully weigh the interests of the owners of corporations with those of other constituencies.



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Figure 1: **Total Pollution by Type, 1994 – 2003**

The figure below shows the total amount of pollution reported by facilities in the TRI database from 1994 – 2003 for industries that were required to report over the entire sample.

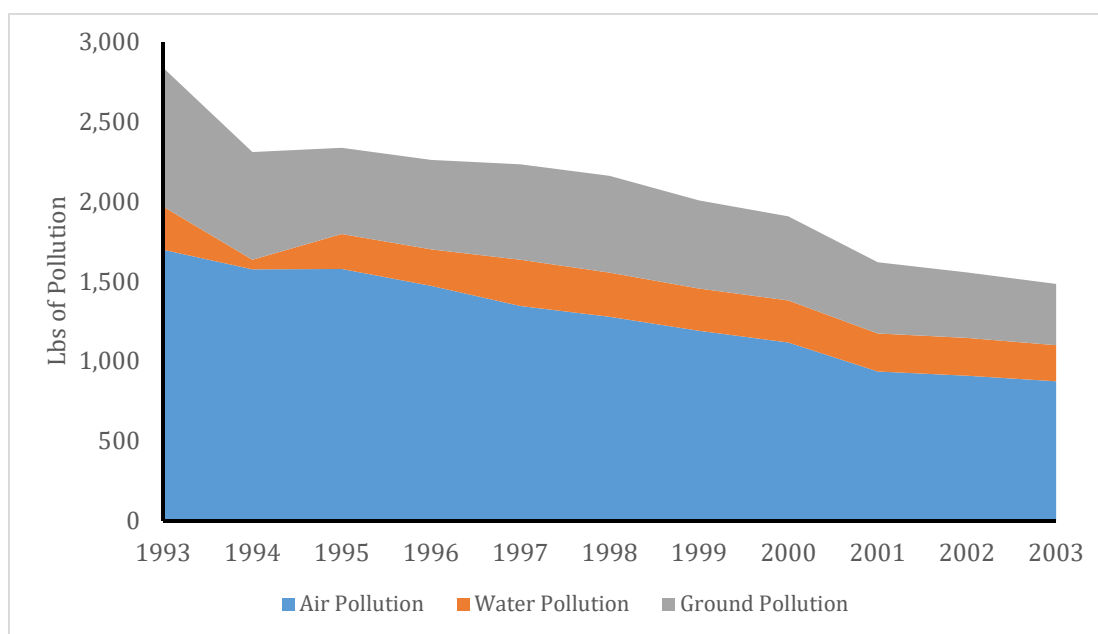


Figure 2: Treatment and Control Groups

The map below shows the states that fall into treatment and control groups.

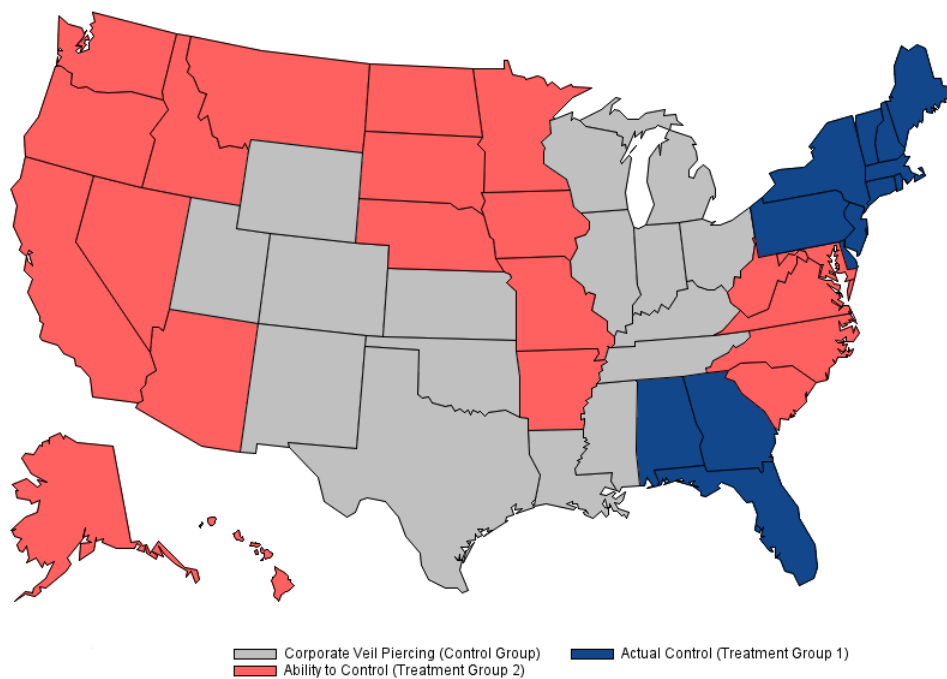


Figure 3: Distribution of Plants to Court Circuits and Treatment Groups

The figure below shows the percentage of observations in different court circuits and the distribution of observation into treatment and control groups.

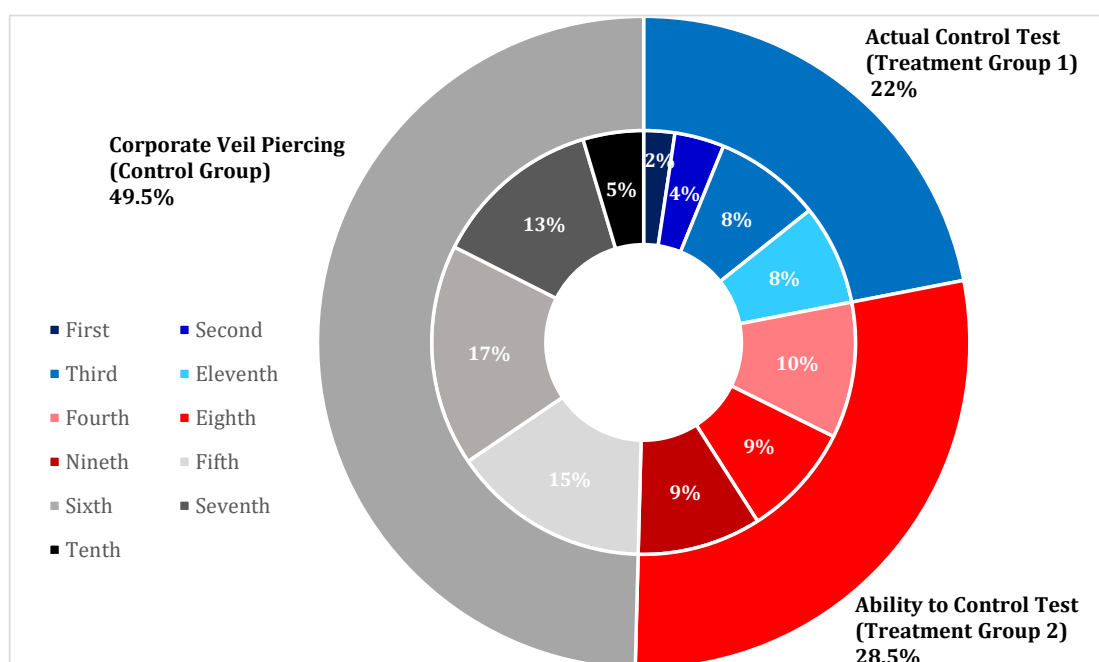


Figure 4: **Treatment Effect Dynamics – Ground Pollution**

This figure plots the coefficient dynamics for ground pollution around the *Bestfoods* decision. The dependent variable is one plus the log of pounds of ground pollution. The regression model is estimated with plant fixed effects, parent firm times year fixed effects, and chemical times year fixed effects. Standard errors are clustered by court circuit.

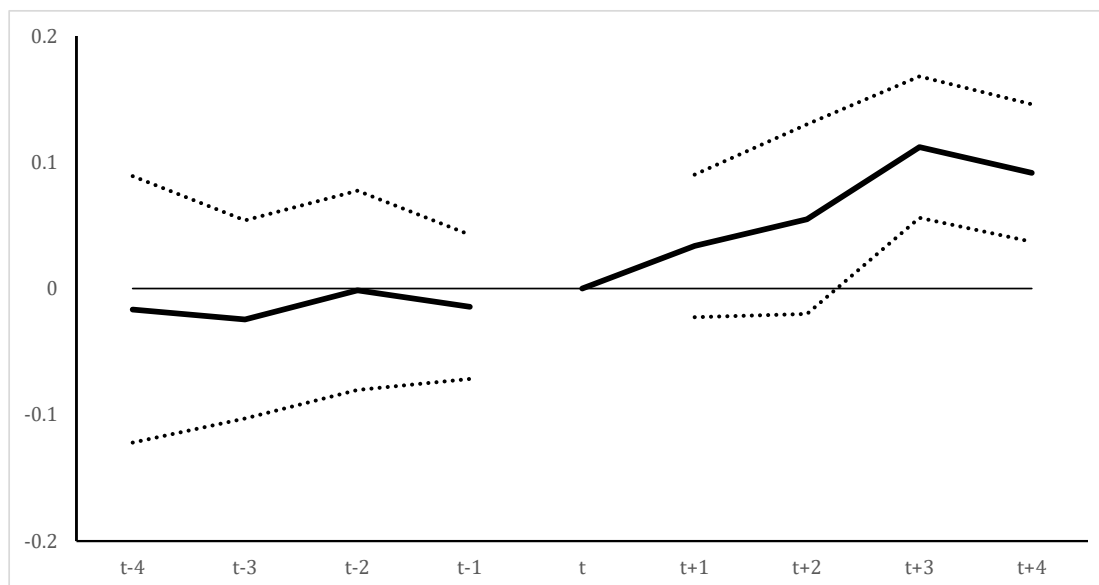




Table 1: **Summary Statistics**

The table reports summary statistics for the full sample and for the subsample with public parent companies. Emissions data are from the EPA Toxic Release Inventory, abatement and productivity data are from the EPA P2 database, and employment data are from the National Establishment Time-Series database.

	<b>All Subs</b>				<b>Subs w/ Public Parent</b>			
	Obs	Mean	Median	SD	Obs	Mean	Median	SD
Lbs Ground Pollution (1000s)	503,275	43.60	0	1,846.80	156,947	47.78	0	1,663.69
Lbs Air Pollution (1000s)	503,279	29.99	520	318.41	156,949	37.98	566	321.87
Lbs Water Pollution (1000s)	503,276	4.35	0	160.08	156,947	5.34	0	205.01
Lbs Total Pollution (1000s)	503,275	77.93	1,000	1,880.72	156,947	91.11	1,419	1,706.03
$\mathbb{1}(\text{Ground Polluter})$	503,279	0.12	0	0.33	156,949	0.16	0	0.36
$\frac{\text{Ground Pollution}}{\text{Total Pollution}}$	503,275	0.08	0	0.25	156,947	0.11	0	0.30
$\mathbb{1}(\text{Abatement - Operating})$	503,279	0.08	0	0.27	156,949	0.09	0	0.28
$\mathbb{1}(\text{Abatement - Process})$	503,279	0.05	0	0.23	156,949	0.05	0	0.23
Productivity Ratio	477,903	0.96	1	0.38	149,081	0.96	1	0.39
Employment (Plant)	93,378	334.23	140	717.85	26,842	446.36	190	971.27

Table 2: **Effect of *Bestfoods* on Subsidiary Ground Pollution**

This table uses OLS regressions to test the effect of the *Bestfoods* court decision on ground pollution. The dependent variable is the log of one plus pounds of ground pollution. *Bestfoods* is an indicator that takes the value of 1 after 1998, (the year of the *Bestfoods* decision) for plants that are located in the circuits that had previously adopted the Ability-to-Control or Actual Control standards for parent company liability. *AC* and *ATC* are indicators defined similarly to *Bestfoods*, but take the value of one after 1998 for plants located in Actual Control or Ability-to-Control circuits, respectively. Robust standard errors clustered by court circuit are reported in parentheses. The fixed effects used in each specification are noted in the table. The symbols \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Ln(1+ Lbs Ground Pollution)									
	All Subs			Subs w/ Public Parent			Non-Subs			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
<i>Bestfoods</i>	0.0469*** (0.0145)	0.0534*** (0.0162)	0.0861*** (0.0193)	0.0812*** (0.0188)			0.220*** (0.0309)	0.224*** (0.0415)	-0.0063 (0.0259)	-0.0184 (0.0324)
<i>ATC</i>					0.0925*** (0.0281)	0.0873*** (0.0239)				
<i>AC</i>					0.0773*** (0.0177)	0.0727*** (0.0220)				
Plant FE	x	x	x	x	x	x	x	x	x	x
Year FE	x									
Chem-Year FE		x	x	x	x	x	x	x	x	x
Parent-Year FE			x	x	x	x	x	x	x	x
Industry-Year FE				x		x		x		x
Observations	501,259	500,553	488,739	488,009	488,739	488,009	154,404	153,951	107,695	106,839
R-squared	0.559	0.661	0.683	0.688	0.683	0.688	0.741	0.748	0.630	0.654

Table 3: **Margin of Response to *Bestfoods***

This table uses OLS regressions to test the effects of the *Bestfoods* court decision on the intensive and extensive margins of ground pollution. The dependent variable in columns (1) – (4) is the log of one plus pounds of ground pollution for firms with positive emissions in 1997. The dependent variable in columns (5) – (8) is an indicator variable that takes the value of one if a facility pollutes with a given chemical and zero otherwise. *Bestfoods* is an indicator that takes the value of 1 after 1998, (the year of the *Bestfoods* decision) for plants that are located in the circuits that had previously adopted the Ability-to-Control or Actual Control standards for parent company liability. Robust standard errors clustered by court circuit are reported in parentheses. The fixed effects used in each specification are noted in the table. The symbols \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively.

<b>Panel A</b>								
	Ln(1+ Lbs Ground Pollution), 1997 Pollution > 0				1(Ground Pollution)			
	All Subs		Subs w/ Public Parent		All Subs		Subs w/ Public Parent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Bestfoods</i>	0.242** (0.101)	0.187 (0.119)	0.729*** (0.175)	0.960*** (0.219)	0.0084* (0.0038)	0.0070 (0.0044)	0.0289*** (0.0041)	0.0305*** (0.0056)
Plant FE	x	x	x	x	x	x	x	x
Chem-Year FE	x	x	x	x	x	x	x	x
Parent-Year FE	x	x	x	x	x	x	x	x
Industry-Year FE		x		x		x		x
Observations	83,755	83,536	24,103	23,942	488,744	488,014	154,407	153,954
R-squared	0.568	0.579	0.538	0.555	0.641	0.648	0.690	0.702

Table 4: **Differential Effects of *Bestfoods* for Harmful Chemicals**

This table uses OLS regressions to test the differential effects of the *Bestfoods* court decision on ground pollution based on the potential harm to humans. The dependent variable is the log of one plus pounds of ground pollution. *Bestfoods* is an indicator that takes the value of 1 after 1998, (the year of the *Bestfoods* decision) for plants that are located in the circuits that had previously adopted the Ability-to-Control or Actual Control standards for parent company liability. Specifications (1) – (4) in Panel A are run on the subsample of chemicals that are classified by the EPA as harmful to human health. Specifications (5) – (8) are run on the subsample of chemicals that are not classified. Panel B further breaks down known harmful chemicals by biological system. Robust standard errors clustered by court circuit are reported in parentheses. The fixed effects used in each specification are noted in the table. The symbols \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively.

<b>Panel A — Ground Pollution by Human Harm</b>								
	Ln(1 + Lbs Ground Pollution)							
	Harmful Chemicals				Non-Classified Chemicals			
	All Subs		Subs w/ Public Parent		All Subs		Subs w/ Public Parent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Bestfoods</i>	0.0721*** (0.0210)	0.0685** (0.0219)	0.188*** (0.0413)	0.174*** (0.0453)	0.0989*** (0.0270)	0.0919*** (0.0273)	0.269*** (0.0536)	0.312*** (0.0701)
Plant FE	x	x	x	x	x	x	x	x
Chem-Year FE	x	x	x	x	x	x	x	x
Parent-Year FE	x	x	x	x	x	x	x	x
Industry-Year FE		x		x		x		x
Observations	294,201	293,527	89,544	89,010	181,320	180,739	62,970	62,398
R-squared	0.699	0.706	0.759	0.767	0.721	0.726	0.764	0.771

<b>Panel B — Biological Impact of Chemicals</b>						
<i>System Affected</i> =	Ln(1 + Lbs Ground Pollution), All Subs					
	Nervous	Respiratory	Urinary	Developmental	Hematologic	Heptatic
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Bestfoods</i>	0.0701*** (0.0126)	0.0847** (0.0315)	0.116*** (0.0195)	0.0557*** (0.0123)	0.0781 (0.0455)	-0.0024 (0.0293)
Plant FE	x	x	x	x	x	x
Chem-Year FE	x	x	x	x	x	x
Parent-Year FE	x	x	x	x	x	x
Observations	122,062	77,521	60,826	60,280	47,518	38,056
R-squared	0.683	0.694	0.829	0.696	0.822	0.741

Table 5: **Effect of *Bestfoods* on Subsidiary Water and Air Pollution**

This table uses OLS regressions to test the effect of the *Bestfoods* court decision on the output of water and air pollution. The dependent variable is the log of one plus pounds of water pollution or one plus pounds of air pollution. *Bestfoods* is an indicator that takes the value of 1 after 1998, (the year of the *Bestfoods* decision) for plants that are located in the circuits that had previously adopted the Ability-to-Control or Actual Control standards for parent company liability. Robust standard errors clustered by court circuit are reported in parentheses. The fixed effects used in each specification are noted in the table. The symbols \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Ln(1 + Lbs Water Pollution)				Ln(1 + Lbs Air Pollution)			
	All Subs		Subs w/ Public Parent		All Subs		Subs w/ Public Parent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Bestfoods</i>	0.0156 (0.0163)	0.0214 (0.0173)	0.0164 (0.0309)	0.0177 (0.0343)	0.0366 (0.0207)	0.0241 (0.0217)	0.0382 (0.0344)	0.0324 (0.0283)
Plant FE	x	x	x	x	x	x	x	x
Chem-Year FE	x	x	x	x	x	x	x	x
Parent-Year FE	x	x	x	x	x	x	x	x
Industry-Year FE		x		x		x		x
Observations	488,740	488,010	154,404	153,951	488,744	488,014	154,407	153,954
R-squared	0.602	0.607	0.606	0.612	0.699	0.703	0.717	0.724

Table 6: **Cumulative Abnormal Returns**

This table uses OLS regressions to test the effect of *Bestfoods* on cumulative abnormal returns (CARs). CARs are calculated using the Fama-French three factor model. *High Exposure* is a binary variable that takes the value of one if the plant has an above median proportion of plants in Ability-to-Control or Actual-Control (treatment) districts. Specifications (1) – (3) use CARs around the date of oral arguments for *Bestfoods*, and specifications (4) – (6) use the date of the unanimous decision. Robust standard errors are reported in parentheses. The symbols \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Oral Argument CARs			Decision (Unanimous) CARs		
	(-1,+1) (1)	(-1,+5) (2)	(-1,+10) (3)	(-1,+1) (4)	(-1,+5) (5)	(-1,+10) (6)
<b>Panel A: All Firms</b>						
<i>High Exposure</i>	0.00344 (0.00268)	0.00826* (0.00428)	0.0148** (0.00619)	-0.00274 (0.00274)	-0.00220 (0.00436)	-0.00368 (0.00580)
Observations	771	771	771	771	771	771
R-squared	0.002	0.005	0.007	0.001	0.000	0.001
<b>Panel B: Multi-Plant Firms</b>						
<i>High Exposure</i>	0.00586* (0.00304)	0.0109** (0.00488)	0.0160** (0.00660)	-0.000830 (0.00313)	-0.00347 (0.00511)	-0.00236 (0.00721)
Observations	501	501	501	500	500	500
R-squared	0.007	0.010	0.012	0.000	0.001	0.000

Table 7: **Effect of *Bestfoods* on Pollution Abatement Activities**

This table uses OLS regressions to test the effect of the *Bestfoods* court decision on abatement activities. The dependent variable is an indicator variable that takes the value of one if the plant invested in pollution abatement for operations or for process. *Bestfoods* is an indicator that takes the value of 1 after 1998, (the year of the *Bestfoods* decision) for plants that are located in the circuits that had previously adopted the Ability-to-Control or Actual Control standards for parent company liability. Robust standard errors clustered by court circuit are reported in parentheses. The fixed effects used in each specification are noted in the table. The symbols \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	1(Abatement - Operations)				1(Abatement - Process)			
	All Subs		Subs w/ Public Parent		All Subs		Subs w/ Public Parent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Bestfoods</i>	0.0000 (0.0058)	0.0006 (0.0077)	0.0000 (0.0098)	-0.0013 (0.0127)	-0.0083** (0.0033)	-0.0076** (0.0028)	-0.0163*** (0.0039)	-0.0176*** (0.0041)
Plant FE	x	x	x	x	x	x	x	x
Chem-Year FE	x	x	x	x	x	x	x	x
Parent-Year FE	x	x	x	x	x	x	x	x
Industry-Year FE		x		x		x		x
Observations	488,744	488,014	154,407	153,954	488,744	488,014	154,407	153,954
R-squared	0.615	0.626	0.600	0.622	0.470	0.482	0.418	0.446

Table 8: **Effect of *Bestfoods* on Subsidiary Production**

This table uses OLS regressions to test the effect of the *Bestfoods* court decision on plant production. The dependent variable is the Production Ratio reported in the TRI database in specifications (1) – (4) and the natural logarithm of plant-level employment from the NETS database in specifications (5) – (8). *Bestfoods* is an indicator that takes the value of 1 after 1998, (the year of the *Bestfoods* decision) for plants that are located in the circuits that had previously adopted the Ability-to-Control or Actual Control standards for parent company liability. Robust standard errors clustered by court circuit are reported in parentheses. The fixed effects used in each specification are noted in the table. The symbols \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Productivity Ratio				Employment (Plant Level)			
	All Subs		Subs w/ Public Parent		All Subs		Subs w/ Public Parent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Bestfoods</i>	0.0097 (0.0073)	0.0028 (0.0062)	0.0078 (0.0097)	0.0103 (0.0100)	-0.0146 (0.0178)	-0.0174 (0.0203)	-0.0535* (0.0267)	-0.0449 (0.0270)
Plant FE	x	x	x	x	x	x	x	x
Chem-Year FE	x	x	x	x	x	x	x	x
Parent-Year FE	x	x	x	x	x	x	x	x
Industry-Year FE		x		x		x		x
Observations	463,955	463,336	146,572	146,141	60,190	59,303	21,605	20,654
R-squared	0.482	0.502	0.450	0.491	0.922	0.930	0.909	0.923



Table 9: **Differential Effects by Subsidiary Solvency**

This table uses OLS regressions to test the effect of the *Bestfoods* court decision on the output of ground pollution or the likelihood of firms implementing pollution abatement investment. The dependent variable is either the log of one plus pounds of ground pollution or an indicator variable that takes the value of one if the plant invested in pollution abatement for operations. *Bestfoods* is an indicator that takes the value of 1 after 1998, (the year of the *Bestfoods* decision) for plants that are located in the circuits that had previously adopted the Ability-to-Control or Actual Control standards for parent company liability. The sample is split according to whether the plant had a Paydex score in 1997 that was above or below the sample median. Robust standard errors clustered by court circuit are reported in parentheses. The fixed effects used in each specification are noted in the table. The symbols \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Ground Pollution		$\mathbb{1}(\text{Abatement} - \text{Process})$	
	(1)	(2)	(3)	(4)
<b>Low Plant Paydex</b>				
<i>Bestfoods</i>	0.0859** (0.0365)	0.0893* (0.0491)	-0.0170** (0.0062)	-0.0168** (0.0069)
Observations	154,256	153,809	154,256	153,809
R-squared	0.666	0.677	0.524	0.547
<b>High Plant Paydex</b>				
<i>Bestfoods</i>	-0.0503* (0.0270)	-0.0563 (0.0325)	0.00829 (0.0143)	0.0194 (0.0132)
Observations	140,396	140,032	140,398	140,034
R-squared	0.708	0.714	0.519	0.544
Plant FE	x	x	x	x
Chem-Year FE	x	x	x	x
Parent-Year FE	x	x	x	x
Industry-Year FE		x		x

Table 10: **Differential Effects by Parent Tangibility**

This table uses OLS regressions to test the effect of the *Bestfoods* court decision on the output of ground pollution or the likelihood of firms implementing pollution abatement investment. The dependent variable is either the log of one plus pounds of ground pollution or an indicator variable that takes the value of one if the plant invested in pollution abatement for operations. *Bestfoods* is an indicator that takes the value of 1 after 1998, (the year of the *Bestfoods* decision) for plants that are located in the circuits that had previously adopted the Ability-to-Control or Actual Control standards for parent company liability. The sample is split according to whether the plant belongs to a parent company that had above or below median asset tangibility in 1997. Robust standard errors clustered by court circuit are reported in parentheses. The fixed effects used in each specification are noted in the table. The symbols \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Ground Pollution		1(Abatement - Process)	
	(1)	(2)	(3)	(4)
<b>High Parent Tangibility</b>				
<i>Bestfoods</i>	0.270*** (0.0566)	0.291*** (0.0539)	-0.0179*** (0.0053)	-0.0220** (0.0070)
Observations	97,577	97,177	97,580	97,180
R-squared	0.750	0.756	0.410	0.442
<b>Low Parent Tangibility</b>				
<i>Bestfoods</i>	0.124* (0.0601)	0.152*** (0.0347)	-0.0144* (0.0067)	-0.0091 (0.0108)
Observations	56,018	55,655	56,018	55,655
R-squared	0.716	0.730	0.446	0.497
Plant FE	x	x	x	x
Chem-Year FE	x	x	x	x
Parent-Year FE	x	x	x	x
Industry-Year FE		x		x

Table 11: **Differential Effects by Parent Solvency**

This table uses OLS regressions to test the effect of the *Bestfoods* court decision on the output of ground pollution or the likelihood of firms implementing pollution abatement investment. The dependent variable is either the log of one plus pounds of ground pollution or an indicator variable that takes the value of one if the plant invested in pollution abatement for operations. *Bestfoods* is an indicator that takes the value of 1 after 1998, (the year of the *Bestfoods* decision) for plants that are located in the circuits that had previously adopted the Ability-to-Control or Actual Control standards for parent company liability. The sample is split according whether the plant belongs to a parent company that had above or below median Altman's unlevered Z-score in 1997. Robust standard errors clustered by court circuit are reported in parentheses. The fixed effects used in each specification are noted in the table. The symbols \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Ground Pollution		1(Abatement - Process)	
	(1)	(2)	(3)	(4)
<b>Low Parent Z-Score</b>				
<i>Bestfoods</i>	0.378*** (0.0756)	0.389*** (0.111)	-0.0300*** (0.0078)	-0.0300*** (0.0059)
Observations	69,690	69,225	69,690	69,225
R-squared	0.782	0.787	0.454	0.497
<b>High Parent Z-Score</b>				
<i>Bestfoods</i>	0.125** (0.0489)	0.111* (0.0554)	-0.0090 (0.0083)	-0.0116 (0.0143)
Observations	65,753	65,345	65,754	65,346
R-squared	0.584	0.605	0.413	0.454
Plant FE	x	x	x	x
Chem-Year FE	x	x	x	x
Parent-Year FE	x	x	x	x
Industry-Year FE		x		x

## Supplementary Appendix

Figure A.1: **Robustness to Removing Court Circuits**

The figure below plots point estimates and confidence intervals for the coefficient *Treated* in the regression described in Table 2 after iteratively removing one court circuit for each estimation of the regression. The dependent variable is the natural logarithm of one plus the amount of ground pollution. The model includes plant, parent company-year, and chemical-year fixed effects. Standard errors are clustered by court circuit.

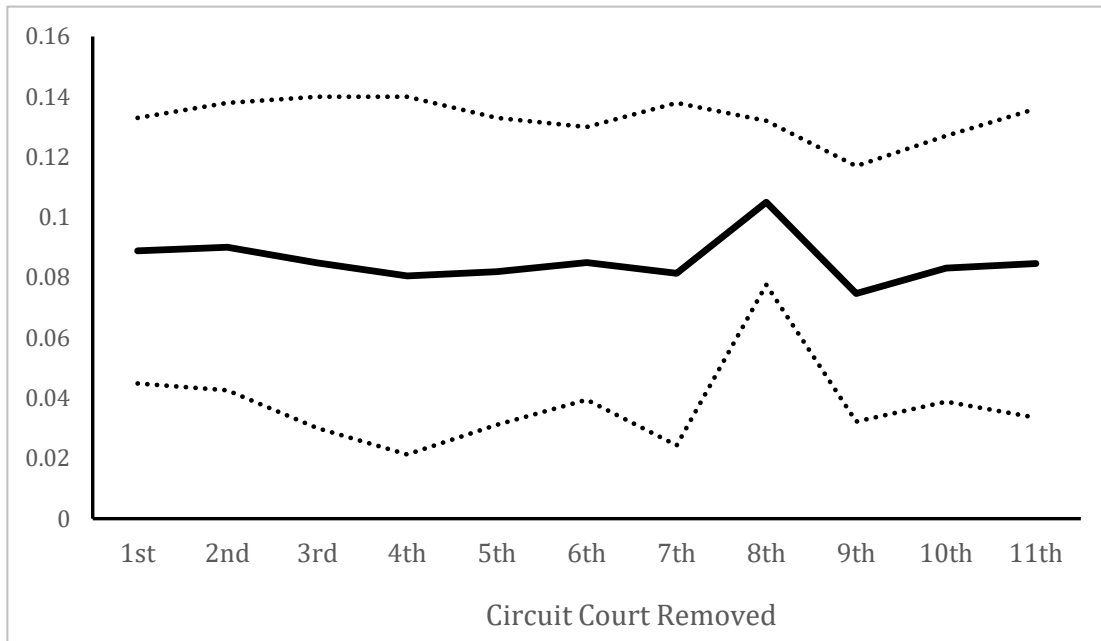


Table A.1: Effect of *Bestfoods* on Fraction of Subsidiary Ground Pollution

This table uses OLS regressions to test the effect of the *Bestfoods* court decision on ground pollution using an alternative dependent variable. The dependent variable is the ratio of ground pollution to total pollution for a given chemical. *Bestfoods* is an indicator that takes the value of 1 after 1998, (the year of the *Bestfoods* decision) for plants that are located in the circuits that had previously adopted the Ability-to-Control or Actual Control standards for parent company liability. *AC* and *ATC* are indicators defined similarly to *Bestfoods*, but take the value of one after 1998 for plants located in Actual Control or Ability-to-Control circuits, respectively. Robust standard errors clustered by court circuit are reported in parentheses. The fixed effects used in each specification are noted in the table. The symbols \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	<i>LBS Ground Pollution</i> <i>LBS Total Pollution</i>									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
<i>Bestfoods</i>	0.00453** (0.00172)	0.00400 (0.00232)	0.00582*** (0.00163)	0.00571*** (0.00161)			0.0146*** (0.00226)	0.0146*** (0.00293)	-0.000644 (0.00190)	-0.00289 (0.00371)
<i>ATC</i>					0.00496** (0.00190)	0.00559** (0.00191)				
<i>AC</i>					0.00699*** (0.00172)	0.00587*** (0.00167)				
Plant FE	x	x	x	x	x	x	x	x	x	x
Year FE	x									
Chem-Year FE		x	x	x	x	x	x	x	x	x
Parent-Year FE			x	x	x	x	x	x	x	x
Industry-Year FE				x		x		x		x
Observations	501,259	500,553	488,739	488,009	488,739	488,009	154,404	153,951	107,695	106,839
R-squared	0.552	0.646	0.673	0.679	0.673	0.679	0.723	0.731	0.657	0.685

Table A.2: **Robustness to Industries Continuously Required to Report**

This table uses OLS regressions to test the effect of the *Bestfoods* court decision on the output of ground pollution or the likelihood of firms implementing pollution abatement investment. The dependent variable is either the log of one plus pounds of ground pollution or an indicator variable that takes the value of one if the plant invested in pollution abatement for operations. *Bestfoods* is an indicator that takes the value of 1 after 1998, (the year of the *Bestfoods* decision) for plants that are located in the circuits that had previously adopted the Ability-to-Control or Actual Control standards for parent company liability. The sample contains only industries required to report emissions data continuously throughout the sample. Robust standard errors clustered by court circuit are reported in parentheses. The fixed effects used in each specification are noted in the table. The symbols \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Ln(1 + Lbs Ground Pollution)				1(Abatement - Process)			
	All Subs		Subs w/ Public Parent		All Subs		Subs w/ Public Parent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Bestfoods</i>	0.0812*** (0.0226)	0.0750*** (0.0220)	0.218*** (0.0395)	0.223*** (0.0430)	-0.00853** (0.00383)	-0.00764** (0.00309)	-0.0175*** (0.00401)	-0.0176*** (0.00374)
Plant FE	x	x	x	x	x	x	x	x
Chem-Year FE	x	x	x	x	x	x	x	x
Parent-Year FE	x	x	x	x	x	x	x	x
Industry-Year FE		x		x		x		x
Observations	418,960	418,270	125,220	124,775	418,963	418,273	125,221	124,776
R-squared	0.551	0.558	0.527	0.544	0.467	0.479	0.411	0.440

Table A.3: Robustness to Collapsing Observations

This table uses OLS regressions to test the effect of the *Bestfoods* court decision on the output of ground pollution or the likelihood of firms implementing pollution abatement investment. The sample has been averaged at the plant-chemical level to contain one observation before the *Bestfoods* decision and one observation after the decision. The dependent variable is either the log of one plus pounds of ground pollution or an indicator variable that takes the value of one if the plant invested in pollution abatement for operations. *Bestfoods* is an indicator that takes the value of 1 after 1998, (the year of the *Bestfoods* decision) for plants that are located in the circuits that had previously adopted the Ability-to-Control or Actual Control standards for parent company liability. Robust standard errors clustered by court circuit are reported in parentheses. The fixed effects used in each specification are noted in the table. The symbols \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Ln(1 + Lbs Ground Pollution)				1(Abatement - Process)			
	All Subs		Subs w/ Public Parent		All Subs		Subs w/ Public Parent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Bestfoods</i>	0.0775** (0.0285)	0.0692** (0.0254)	0.235*** (0.0399)	0.209*** (0.0378)	-0.00816** (0.00301)	-0.00645* (0.00353)	-0.0176*** (0.00403)	-0.0154* (0.00719)
Plant FE	x	x	x	x	x	x	x	x
Chem-Year FE	x	x	x	x	x	x	x	x
Parent-Year FE	x	x	x	x	x	x	x	x
Industry-Year FE		x		x		x		x
Observations	124,665	124,481	39,370	39,257	124,665	124,481	39,370	39,257
R-squared	0.675	0.676	0.735	0.738	0.540	0.548	0.506	0.520



Table A.4: **Robustness to Alternative Clustering**

This table uses OLS regressions to test the effect of the *Bestfoods* court decision on the output of ground pollution or the likelihood of firms implementing pollution abatement investment. The dependent variable is either the log of one plus pounds of ground pollution or an indicator variable that takes the value of one if the plant invested in pollution abatement for operations. *Bestfoods* is an indicator that takes the value of 1 after 1998, (the year of the *Bestfoods* decision) for plants that are located in the circuits that had previously adopted the Ability-to-Control or Actual Control standards for parent company liability. Panel A presents regression estimates with robust standard errors clustered by state, while Panel B presents regression estimates with robust standard errors clustered by state and parent company. The fixed effects used in each specification are noted in the table. The symbols \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively.

<b>Panel A — Clustering by State</b>								
	Ln(1 + Lbs Ground Pollution)				I(Abatement - Process)			
	All Subs		Subs w/ Public Parent		All Subs		Subs w/ Public Parent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Bestfoods</i>	0.0861*** (0.0231)	0.0812*** (0.0220)	0.220*** (0.0371)	0.224*** (0.0395)	-0.00829** (0.00346)	-0.00759** (0.00351)	-0.0163** (0.00623)	-0.0176** (0.00685)
Plant FE	x	x	x	x	x	x	x	x
Chem-Year FE	x	x	x	x	x	x	x	x
Parent-Year FE	x	x	x	x	x	x	x	x
Industry-Year FE		x		x		x		x
Observations	488,739	488,009	154,404	153,951	488,744	488,014	154,407	153,954
R-squared	0.683	0.688	0.741	0.748	0.470	0.482	0.418	0.446

<b>Panel B — Clustering by State and Parent Company</b>								
	Ln(1 + Lbs Ground Pollution)				I(Abatement - Process)			
	All Subs		Subs w/ Public Parent		All Subs		Subs w/ Public Parent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Bestfoods</i>	0.0861** (0.0335)	0.0812** (0.0315)	0.220*** (0.0562)	0.224*** (0.0580)	-0.00829* (0.00445)	-0.00759* (0.00410)	-0.0163** (0.00789)	-0.0176** (0.00805)
Plant FE	x	x	x	x	x	x	x	x
Chem-Year FE	x	x	x	x	x	x	x	x
Parent-Year FE	x	x	x	x	x	x	x	x
Industry-Year FE		x		x		x		x
Observations	488,739	488,009	154,404	153,951	488,744	488,014	154,407	153,954
R-squared	0.683	0.688	0.741	0.748	0.470	0.482	0.418	0.446

Table A.5: **Process and Operating Abatement Activities**

This table lists abatement activities classified as process modifications or good operating practices under TRI reporting guidelines.

	<b>Process Modifications</b>	<b>Good Operating Practices</b>
1	Optimized reaction conditions or otherwise increased efficiency of synthesis	Improved maintenance scheduling, record keeping, or procedures
2	Instituted recirculation within a process	Changed production schedule to minimize equipment and feedstock changeovers
3	Modified equipment, layout, or piping	Introduced in-line product quality monitoring or other process analysis system
4	Use of a different process catalyst	Other changes in operating practices
5	Instituted better controls on operating bulk containers to minimize discarding of empty containers	
6	Changed from small volume containers to bulk containers to minimize discarding of empty containers	
7	Reduced or eliminated use of an organic solvent	
8	Used biotechnology in manufacturing process	
9	Other process modifications	

Table A.6: **Industries that Report Toxic Release Inventory**

Facilities in the following industries must report chemical emissions data (in 2015).

<b>NAICS Code</b>	<b>Description</b>	<b>Proportion of Sample</b>
325	Chemical Manufacturing	0.2506
332	Fabricated Metal Product Manufacturing	0.1096
331	Primary Metal Manufacturing	0.0912
336	Transportation Equipment Manufacturing	0.0693
324	Petroleum and Coal Products Manufacturing	0.0525
424	Merchant Wholesalers, Nondurable Goods	0.0438
326	Plastics and Rubber Products Manufacturing	0.0431
221	Utilities	0.0430
322	Paper Manufacturing	0.0394
333	Machinery Manufacturing	0.0386
311	Food Manufacturing	0.0336
334	Computer and Electronic Product Manufacturing	0.0317
327	Nonmetallic Mineral Product Manufacturing	0.0277
335	Electrical Equipment, Appliance, and Component Manufacturing	0.0226
562	Waste Management and Remediation Services	0.0201
321	Wood Product Manufacturing	0.0182
337	Furniture and Related Product Manufacturing	0.0174
339	Miscellaneous Manufacturing	0.0145
212	Mining (except Oil and Gas)	0.0081
313	Textile Mills	0.0074
323	Printing and Related Support Activities	0.0069
312	Beverage and Tobacco Product Manufacturing	0.0036
316	Leather and Allied Product Manufacturing	0.0027
314	Textile Product Mills	0.0019
541	Professional, Scientific, and Technical Services	0.0007
315	Apparel Manufacturing	0.0005
425	Wholesale Electronic Markets and Agents and Brokers	0.0005
811	Repair and Maintenance	0.0003
211	Oil and Gas Extraction	0.0002
488	Support Activities for Transportation	0.0002
111	Crop Production	0.0001
511	Publishing Industries (except Internet)	0.0001
113	Forestry and Logging	0.0001
512	Motion Picture and Sound Recording Industries	0.0000
519	Other Information Services	0.0000