The Limits of Limited Liability: Evidence from Industrial Pollution *

Pat Akey[†]
University of Toronto

Ian Appel[‡]
Boston College

March 21, 2018

Abstract

We study how parent liability for subsidiary environmental cleanup costs affects industrial pollution and production. Our empirical setting exploits a Supreme Court case 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 10% increase in toxic emissions by subsidiaries. This decision is also associated with abnormal returns of over 1% for parent firms with a relatively high exposure to the change in legal liability. We find evidence that the increase in pollution is driven by lower investment in abatement technologies rather than higher production. Cross-sectional tests suggest a risk-shifting motivation for these effects. Overall, our results highlight moral hazard problems associated with limited liability.

*We thank Thomas Bourveau, Mariana Khapko, Zygmunt Plater and seminar participants at Carnegie Mellon, University of Toronto, and 2016 Financial Research Association (early ideas session) for valuable comments and suggestions.

[†]University of Toronto. Phone: +1 (647) 545-7800, Email: pat.akey@rotman.utoronto.ca

[‡]Boston College. Phone: (617) 552-1459, Email: appeli@bc.edu

1 Introduction

For more than 150 years, limited liability for the owners of firms has been a defining characteristic of many business organizations. 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 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 allow creditors to "pierce the corporate veil" and impose liability on firm owners. Easterbrook and Fischel (1985) note that successful instances of veil piercing are almost entirely confined to closely-held corporations and parent-subsidiary relationships.

In this paper, we study the tradeoffs of limited liability in the parent-subsidiary 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 firm will not bear the costs of environmental remediation that exceed the value of the subsidiary's assets.

Our empirical setting uses a landmark 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* (hereafter *Bestfoods*) the Supreme Court implemented a strict legal standard for parent liability of subsidiary environmental cleanup costs under CERCLA. Prior to *Bestfoods*, some circuit courts held parent firms liable for cleanup costs under a relatively broad range of circumstances.[1] Specifically, these courts held parents liable if they had "actual control" of or the "ability to control" the subsidiary. In *Bestfoods*, the Supreme Court invalidated these tests and held that parent companies were liable only under narrow circumstances. We use this decision as a natural experiment in a difference-in-differences setting. The treatment group for the analysis consists of subsidiaries located in areas that had weaker liability protection prior to *Bestfoods*; the control group consists of those located in areas where strict standards were already in place.

We use plant-level data on toxic emissions from the Environmental Protection Agency (EPA) to examine the response of subsidiaries to the strengthening of parent liability protection resulting from *Bestfoods*. 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. We find that treated subsidiaries increase ground pollution by nearly 10% relative to the control group in the five years following *Bestfoods*. Our analysis suggests that this effect is driven by both intensive and extensive margins of pollution. Moreover, we document similar magnitudes for chemicals that are known to cause human harm (including cancer and other chronic diseases) and for other chemicals. Our results are robust to controlling for time-invariant heterogeneity at the plant level as well as time-varying heterogeneity at the parent-year, chemical-year, and industry-year levels. Moreover, we do not find evidence of an effect on stand-alone plants that do not have a parent, suggesting that our findings are not driven by local economic shocks.

We also find that the increase in parent liability protection has a significant impact on firm value. Specifically, we analyze cumulative abnormal returns around the oral arguments and decision dates for *Bestfoods*. We find that parent corporations with relatively high exposure to this change in legal liability (as measured by an above median number of subsidiaries in treated districts) have CARs of approximately 1.5% for the (-1, 10) window around oral arguments for the case.

We next analyze why firms increase pollution output. Stronger liability protections may decrease the incentives to invest in pollution abatement because parents do not fully inter-

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

nalize the risk of environmental disasters. However, such protections may also decrease the variable cost of using pollutive technologies and therefore lead to an increase in production. While these channels are not mutually exclusive, our evidence suggests the results are driven by reduced incentives to engage in pollution abatement. Specifically, using plant-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 12-25% relative to the sample mean. We do not, however, find evidence consistent with the increased production channel; 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 subsidiary employment, measured using the National Establishment Time-Series (NETS) database. The lack of a change in subsidiary size and output 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 examine the types of parents and subsidiaries that drive main findings. 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, measured using a plant's Paydex score. We also find the effects are concentrated among subsidiaries 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 risk-shifting motivation for the increase in pollution and decrease in abatement activities. Specifically, the effects are concentrated in firms that have higher leverage and are less solvent, measured using Altmans unlevered Z-score.

Our paper contributes to the broad literature on the economics of industrial pollution. One strand of this literature studies environmental monitoring and enforcement.[2] 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 regard-

[2]See Gray and Shimshack (2011) for a review of this literature.

less 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) argues 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)), and financial characteristics (e.g., Chang et al. (2016)). Our paper contributes to this literature by showing that limited liability for parent firms also plays 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 optimal 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. In addition, Koudijs and Salisbury (2016) finds that increased limited liability protection for household assets in the 1850s increased household risk-taking only if the increase in protection was modest.

Finally, our cross-sectional tests highlight the role of firms' leverage and 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 real harm, to other stakeholders.

2 Background

The United States Congress passed CERCLA in 1980 as a response to the high-profile Love Canal disaster (Greenstone and Gallagher, 2008).[3] 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 based on known or threatened hazardous emissions.[4] 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).

[3]The Love Canal in New York State was a canal site where Hooker Chemicals & Plastics Corporation (now Occidental Chemical Corporation) disposed of a large amount of toxic chemicals which caused environmental problems and increased rates of cancer in the community that lived nearby.

[4]See `https://www.epa.gov/superfund/superfund-national-priorities-list-npl` for further details on this process.

The expenses associated with environmental remediation can be substantial, and in many cases the process takes decades to complete. The Government Accountability Office estimates cleanup costs for the 142 largest NPL sites average \$140 million, or about \$20 billion in total (Government Accountability Office, 2005). Two of the earliest and highest profile CERCLA sites were Love Canal in New York and Berkeley Pit in Montana, which were designated as NPL sites in 1980 and 1983, respectively. Love Canal was removed from the NPL following a cleanup effort that lasted 21 years and cost \$400 million (DePalma, 2004). The cleanup at Berkeley Pit, however, remains a work in progress. In fact, in 2016, more than 30 years after the cleanup began, thousands of migrating geese landed in the Berkeley Pit and died from exposure to the toxic heavy metals (Guarino, 2016). The human costs associated with the emission of CERCLA-covered chemicals can also be substantial. For example, prior to the start of cleanup efforts, communities around these two sites had unusually high rates of miscarriage and birth defects, including double rows of teeth, enlarged hearts and visual/hearing impairment. Residents also suffered from high incidents of attempted suicide, nervous breakdowns, epilepsy, asthma, urinary tract infections as well as some of the highest cancer rates in the country (Tuholske, 1993).

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 imposes liability on the "owners or operators" of toxic sites that require cleanup. Such liability may arise if cleanup costs exceed the value of the subsidiary that produced the pollution. This seemingly simple idea has engendered significant confusion in the courts, especially regarding parent-subsidiary relationships. Specifically, under state corporate law, a parent is not responsible for the acts of its subsidiary except in narrow circumstances. However, the text of CERCLA does not specify a specific legal standard for parent liability (Cook, 1998).[5] Lacking such a directive, individual federal judges had discretion to impose legal standards for lawsuits under CERCLA. The nature of these standards varied across federal circuit courts.[6] Specifically, each of the circuit courts adopted one of the following tests for when a parent company can be held liable for the cleanup costs of its subsidiaries under CERCLA (Cook, 1998):

- **Authority-to-Control (ATC)** is the broadest standard that defines an "owner or 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 Circuit Courts.

- **Actual-Control (AC)** is a narrower standard that 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 strictest standard. Under this test, parents are liable for subsidiary cleanup costs only if the corporate veil can be pierced under state law. 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 Circuit Courts.

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.

In 1998, the Supreme Court resolved the ambiguity surrounding parent company liability under CERCLA in *Unites States v. Bestfoods.* The unanimous opinion expressly rejected the authority-to-control and actual control standards that had broadened parent liability relative

[5]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.*).

[6]When there is a lack of Supreme Court jurisprudence, individual circuit courts can arrive at vastly different conclusions when presented with an ambiguous legal statute (i.e., a "circuit split").

to traditional corporate law standards. Specifically, the Court ruled that parents were liable for environmental remediation costs under two circumstances. First, parents can be held liable under the traditional veil piercing standard. Under state corporate law, satisfying this standard requires showing an abuse of the corporate form (e.g., using a subsidiary to deliberately defraud creditors). Second, parents are responsible if they, themselves, operated the facility (rather than the subsidiary) responsible for the pollution. Satisfying one of these conditions requires involvement in facility operations that is "eccentric under the accepted norms of parental oversight of a subsidiarys facility" (*U.S. v. Bestfoods*). Such actions may include the parent leasing the site from the subsidiary, a joint-venture with a subsidiary, or direct control of facility operations by an employee of the parent. 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, the *Bestfoods* case significantly increased the difficulty of holding parent corporations liable under CERCLA (Plater et al., 2016). In courts that had adopted the weaker standards, the government 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). This differential change in parent liability for facilities located in areas that used less strict standards is central to our identification strategy.

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, operates in one of roughly 400 industries defined at the six-digit NAICS level, and uses one of nearly 600 chemicals.[7] Appendix A.7 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%), merchant wholesalers, non-durable goods (4.4%) and utilities (4.3%). 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 monitors the data for potential errors and can initiate civil enforcement actions for non-compliance. For example, Lucas-Milhaupt Warwick LLC, a metal company located in Warwick, RI, paid a fine of $69,000 in 2015 due to improper TRI reporting.[8]

For each chemical subject to TRI reporting, plants are required to provide the number of pounds released into the ground, air, and water. 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 non-carcinogenic chemicals, which are chosen for inclusion in the database according to po-

[7] 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.

[8] See https://www.epa.gov/newsreleases/metal-products-company-settles-epa-chemical-reporting-lapses-warwick-ri-facility.

tential 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.[9] The second most common abatement activist 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 listed both types of abatement are provided in Table A.6. 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 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 $\frac{\#\, Refrigerators\, Produced_t}{\#\, Refrigerators\, Produced_{t-1}}$. If a chemical is used in a capacity not directly related to production (e.g., for 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

[9] See https://www.epa.gov/toxics-release-inventory-tri-program/pollution-prevention-p2-and-tri.

for year t is given by $\frac{\#\, Molds\, Cleaned_t}{\#\, Molds\, Cleaned_{t-1}}$. 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 and Bradstreet. We use plant Paydex score and number of employees from NETS to analyze subsets of the main sample. Paydex score, which ranges from 0 to 100, is a business credit score based on trade credit performance provided to Dun and 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 and Bradstreet determines plant employment by directly contacting entities and using statistical models to estimate missing values; excluding estimated employment data does not materially affect our findings. 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 also 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. Specifically, for each plant, the databse 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. Treatment status is based on the location of the plant and is *not* affected by the location of the parent or its state of incorporation. 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 24% of the subsidiaries are located in districts that adopted the “actual control” standard (the first of our treatment groups), 28% are in districts with the "ability to control" standard (the second of our treatment groups), and 48% 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 7,833 parent corporations which have an average 2.91 subsidiaries. Each of these subsidiaries report emissions for, on average, 3.98 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, subsidiaries average 36 thousand pounds of ground pollution for each chemical reported in TRI, though nearly 90% do not report ground emissions. Air and water emissions average about 25 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 subsidiary employs 315 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).[10]. For our initial analysis, the primary dependent variable is the natural logarithm of 1 plus the pounds of emissions (chemical-level) for each plant.[11] The granular nature of the data allows for the use of fixed effects that exploit variation from the same parent company operating

[10]The court decision was in June of 1998, so the classification of 1998 as either treatment or control is somewhat arbitrary. Results are qualitatively similar when excluding 1998.

[11]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.

subsidiaries in different districts. Specifically, our main specification takes the following form:

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

where p indexes a plant belonging to parent firm i, c indexes chemical, and t indexes time. We include plant fixed effects (α_p) to control for time-invariant heterogeneity at the subsidiary level. In addition, we include parent-year fixed effects ($\alpha_{i,t}$) to control for time-varying heterogeneity at the parent-level, and chemical-year fixed effects ($\alpha_{c,t}$) to control for time-varying heterogeneity at the chemical-year.[12] As Chatterji et al. (2009) and DiGiuli (2013) note, there is not a clear way of aggregating pollutants or easily comparing their environmental impact, however the chemical-year fixed effects allow us to exploit within-chemical-time variation. We also show that our main results are robust to the inclusion of industry-year fixed effects, defined using the primary 4-digit SIC code for each plant. Robust standard errors are clustered at the circuit level.

In later tests we use indicators for different types of abatement and the production ratio as outcomes using the above specification. We also 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., leverage). The specifications used for these tests is the same as above.

4 Results

4.1 Effect of Parent Liability on Subsidiary Pollution

In this section, we ask whether the relative increase in parent liability protection stemming from *Bestfoods* affects emissions by subsidiaries. The primary outcome of interest is ground pollution, which is the focus of CERCLA enforcement actions, although we analyze the effect on air and water pollution as well. We also study differential effects of the *Bestfoods* decision

[12]The inclusion of these fixed effects accounts for the indicators for pre-treatment time periods and treatment/control status since plants do not change location.

across different types of chemicals.

4.1.1 Subsidiary Ground Emissions

Table 2 examines the effect of the *Bestfoods* decision on ground pollution by subsidiaries. The dependent variable for this table is the natural logarithm of one plus pounds of ground pollution. Columns (1) – (4) indicate that subsidiaries located in areas that experienced a relative increase in parent liability protection also increased ground emissions following *Bestfoods*. The magnitude of the effect ranges from 0.0428 in the model with plant and year fixed-effects (Column (1)) to 0.0756 in the model with plant, parent firm-year, and chemical-year fixed effects (Column (3)). The increase in emissions is economically large: the average value of the dependent variable is 0.746, indicating an increase of between 5.7% and 10.1% relative to the sample average. Because the columns (3) and (4) contain parent-year fixed effects, the estimates for these specifications are relative to plants of the same parent located in areas where higher liability standards were already in place. This assuages concerns that the estimates reflect other types of changes (e.g., demand shocks) at the parent level.

The remainder of Table 2 analyzes the effect of *Bestfoods* on different subsets of plants. In columns (5) and (6), we estimate the treatment effect separately for subsidiaries in each of the jurisdictions with relatively weaker standards prior to *Bestfoods* (i.e., for plants located in the Ability-To-Control and Actual-Control areas). 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, columns (7) and (8) restrict the sample to subsidiaries with publicly traded parents. We document larger point estimates of about 0.18 for this sample of firms, or about 17% relative to the sub-sample mean. Finally, columns (9) and (10) restrict analysis to plants that do not have a parent listed in the TRI database. Because such firms do not have a parent, we omit parent-year fixed effects from the regression specifications. Consistent with the idea that a change in parent liability should only affect plants with a parent corporation, we find no effect for this subset of plants. The point estimates are both economically small (ranging from -0.001 to 0.02) and statistically indistinguishable from zero. This analysis serves as a useful falsification test as it suggests there was not a confounding shock that broadly affected emissions by all plants (both subsidiaries and stand-alone) in treated areas around the time of the *Bestfoods* decision.

Figure 4 plots the coefficient dynamics for ground pollution. We construct this figure by replacing the pooled treatment variable, $Bestfoods$ 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 standards changed for the treated group. While the "parallel trends" assumption necessary for empirical identification in our setting is ultimately untestable, this figure provides evidence that is consistent with the assumption.

We report additional robustness tests in the supplementary appendix. First, we verify that our results are not driven by any individual court circuit by iteratively removing one circuit and rerunning our main analysis. This analysis 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. Next, in Table A.1 we remove industries added to the TRI database after the *Bestfoods* decision. The estimated coefficients in columns (1) – (4) are similar, both in terms of magnitude and statistical significance, to the main analysis. In Tables A.2 we find evidence that the main effect is driven both by the intensive and extensive margins. Specifically, in columns (1) – (4) we find an increase in the natural logarithm of ground pollution for plants with (strictly) positive ground pollution in 1997. Columns (5) – (8) indicate an increase in the likelihood of emitting a positive amount of ground pollution. As with the main analysis, the findings are stronger (both in terms of magnitude and statistical significance) when the sample is restricted to subsidiaries with publicly traded parents. Moreover, in Table A.3, we examine the effect of *Bestfoods* on (log) total pollution emissions in columns (1) – (4) as further verification that our main results are not the result of observations with zero ground pollution since there are few observations without total pollution emissions. We also examine whether the fraction of ground emissions reported for a given chemical as a proportion of total emissions (i.e., as a fraction of ground, water, and air pollution) increases. Columns (5) – (8) suggest that ground pollution accounts for a larger fraction of overall pollution output following *Bestfoods*. We verify that our main results are robust to collapsing data to contain only one pre-treatment and one post-treatment time period in Table A.4, as suggested by Bertrand et al. (2004). We further verify that our results are robust to our method of computing standard errors. Panel A of Table A.5 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 unobserved serial correlation for subsidiaries that share a parent.

4.1.2 Chemical Toxicity

The previous results suggest that increased liability protection is associated with an increase in ground pollution. We next analyze the types of chemicals emitted by subsidiaries by classifying them according to their potential harm to humans. 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 to be either classified as known to be harmful or non-classified based off of the IRIS definitions. Approximately 57% of the chemical observations in the full sample have known adverse effects on humans. Overall, the results of this analysis suggests the increase in ground emissions is not driven by inert substances. Rather, we find little evidence of differences in changes to ground pollution produced using harmful chemicals according to IRIS and chemicals not classified by this database.

The results of this analysis are reported in Table 3. Panel A reports the impact of the *Bestfoods* decision 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 publicly traded parents. Overall, estimates for both samples are similar to each other and comparable to the baseline evidence presented above. In particular, the full-sample baseline estimate is 6.8% for harmful chemicals (column (3)) and 7.6% for unclassified chemicals (column (5)). Panel B further categorizes harmful chemicals based on the biological system they harm. We find that there are increases in toxic pollution that harm a variety of biological systems, with particularly strong results for chemicals that effect the nervous, urinary, and developmental systems.

4.1.3 Other Types of Pollution

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 does cover disposals into waterways, the EPA has historically had lax enforcement of this type of pollution. The reason for this stems from the fact that it is often difficult to identify the polluters of waterways (e.g., if many firms use the same river to dispose of waste), and cleaning up such sites often comes at considerable expense and questionable efficacy. For these reasons, the focus of CERCLA cleanups is "on upland sites, with rivers all but forgotten." (DePalma, 2012). However, *Bestfoods* could 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 4 reports the effect of *Bestfoods* on water and air emissions. The dependent variable 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 changes in parent liability primarily pertaining to ground pollution affect other types of emissions. Specifically, while point estimates for water emissions are positive across different specifications, they are not significant at conventional levels. In addition, the point estimate for air pollution is positive and weakly significant for the sample of all subsidiaries (column (5)), but there is little evidence for the sample of subsidiaries with public parents. Overall, the lack of evidence for a change in other types of emissions is consistent with Greenstone (2003), who finds little evidence of a change in the output of non-regulated pollution output 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 corporation incurs costs associated with subsidiary environmental cleanups. This may, in turn, have a positive effect on firm value. However, the magnitude of such an effect is unclear as it is a function of both the magnitude and likelihood of environmental remediation.

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 questions to attorneys 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) located 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 5 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. This effect is 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 may have anticipated the unanimous decision.

4.3 The Channel

In this section we investigate the channel linking parent liability protections to increased subsidiary emissions. We specifically consider whether higher emissions result from an increase in economic activity or a decrease in firms efforts to reduce pollution output. The extent to which parent limited liability protections lead to a change in output depends on the nature of firms' costs impacted by the decision. If, for example, the *Bestfoods* lowered current fixed costs (e.g., those pertaining to pollution abatement) or expected future fixed cleanup costs, the changed in parent liability protection would not lead to a change in current production.[13] However, if the decision instead impacted variable costs borne by firms, this would lead to an increase in production. The evidence in this section is consistent with *Bestfoods* impacting fixed costs. Specifically, we document a drop in abatement efforts related to the manufacturing process but find no evidence of an increase in subsidiary output.

4.3.1 Pollution Abatement

A strengthening of parent liability protection may lead to a decrease in pollution abatement activities if such activities affect the likelihood of enforcement actions under CERCLA. We

[13] EPA (2011) notes that, in contrast to actions to address air or water pollution, cleanup costs for ground pollution are largely fixed because such programs "often require remediation of hazardous materials left over from earlier uses that are not related to the current use, except by geography."

test this hypothesis using data from the EPAs 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. We analyze whether firms are less likely to implement pollution abatement activity in these two categories of actions following the *Bestfoods* decision.

Table 6 presents the results of this 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, our results indicate subsidiaries decrease abatement activities for actions related to the production process but not for activities related to plant operations. Specifically, the magnitude of the estimated coefficients for operating practices are both economically small (ranging from 0.001 to 0.004) and statistically indistinguishable from zero. However, for abatement related to the manufacturing process, estimates are both larger (ranging from -0.006 to -0.014) and statistically significant at conventional levels. The effects for process-related abatement are sizable relative to the sample mean, implying a drop of 12–25%. As with the pollution estimates, the findings are particularly strong for subsidiaries with a publicly traded parent. This reduction in abatement activities is consistent with the idea that less investment in abatement activity leads to a larger increase in emissions. In unreported analysis we examine less common types of abatement actions taken by firms. We find evidence of a decrease in efforts to improve inventory management, but estimates for other types of abatement are statistically indistinguishable from zero, but these activities are uncommon to begin with.

4.3.2 Plant Production and Employment

We next examine whether strengthening parent liability protection affects subsidiary output. The expansion of legal protection for parent companies resulting from *Bestfoods* can be viewed as a decrease in the expected cost of using pollutive technology. A natural question to ask is, to what extent can the increase in pollution that we document be due increased production as a result of lower expected costs? 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 data and subsidiary employment data from NETS.

Table 7 reports the results of this analysis. The results in 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 not significant at conventional levels. Point estimates for subsidiaries with public parents (columns (3) and (4)), which have relatively large changes in ground pollution, are smaller in magnitude and statistically indistinguishable from zero. Due to reporting errors, we limit production ratios to the [0, 3] range for our analysis, but in unreported analysis we find qualitatively similar results using ranges of [0, 2] or [0, 5].

We next examine the effect of *Bestfoods* on subsidiary employment, which serves as a proxy for the size of the subsidiary. The results of this analysis are reported in columns (5) – (8), where the dependent variable is the natural logarithm of subsidiary employment. We omit chemical-year fixed effects from the regression specifications because employment is defined the plant, rather than chemical, level. Overall, we find little evidence of changes to employment. In particular, the point estimates for this analysis are *negative*, though statistically insignificant at conventional levels.

Taken together, these results suggest that economic activity did not increase in subsidiaries for which their parent companies received an increase in legal protection despite there being an increase in pollution emissions. These findings are 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, EPA (2011) notes that 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." 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 leverage/risk of distress.

4.4.1 Subsidiary Solvency

The *Bestfoods* decision decreased the likelihood of parent liability for cleanup costs of pollution disasters that exceed the value of the subsidiary's assets. Because less-solvent subsidiaries are more likely to go into bankruptcy as a result of environmental liabilities (all else equal), the likelihood of parent liability is (partially) a function of subsidiary financial solvency. In this section, we test whether the effects of *Bestfoods* are more salient for less-solvent subsidiaries. We measure solvency at the plant-level using Dun and Bradstreets 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 8 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) also include subsidiary industry-year fixed effects. We find that our previous results for both pollution emission and for pollution prevention are concentrated in plants that were in poorer financial health (i.e., those with 1997 Paydex scores less than 69). For example, column (2) indicates that the point estimate for the less solvent subsidiaries is 0.083 (significant at the 5% level) whereas the point estimate for more solvent subsidiaries is -0.045 (insignificant at conventional levels). There are similar patterns in column (4), where the point estimate for less solvent subsidiaries is -0.017 (significant at the 5% level) and 0.0168 (insignificant at conventional levels) for the subsidiaries that were more solvent. The differences between the coefficients for the high and low subsidiary solvency samples are statistically significant at the 10% level or lower across the different specifications. In unreported analysis we run this test on the subset of subsidiaries that have public parent companies and find qualitatively similar results, but with a substantially reduced sample.

4.4.2 Parent Tangibility

We next examine how the main results vary across parents with different levels of tangible assets. In our previous analysis, we found that the *Bestfoods* decision led to a decrease in pollution abatement activities related to production. Such activities potentially entail significant fixed costs, especially for firms with a higher proportion of tangible assets. Thus, the disincentive to invest in abatement following the change in liability standards may be particularly strong for this set of firms. To test this idea, we use parent-level data from Compustat in 1997 (i.e., the year before *Bestfoods*) to classify parents as having above or below median proportion of tangible assets (net plant, property and equipment/total assets). We then repeat our main analysis for the two groups.

Table 9 presents the results of this analysis. Columns (1) and (2) report results for ground pollution, and columns (3) and (4) report results for investment in process pollution abatement. Columns (1) and (3) use the baseline specification, and columns (2) and (4) also include subsidiary industry-year fixed effects. Consistent with our conjecture, we find stronger results for subsidiaries of parent companies that have a higher fraction of tangible assets. For example, in Column (1) we find that in the subsample of parent companies with high tangible assets, the coefficient is 0.225 (significant at the 1% level) whereas the corresponding point estimate for the low-tangibility sample (.103) is less than half this magnitude and significant at the 5% level. We find a similar difference for investment in process abatement. The estimate in column (3) is -0.0166 (significant at the 1% level) for the sample of parent companies with high tangible assets, whereas the corresponding coefficient for the low-tangibility sample is -0.009 (insignificant at conventional levels). For the most part, these differences are suggestive in nature and not statistically significant at conventional levels.

4.4.3 Parent Leverage and Risk of Distress

We finally examine how the leverage and financial health of the parent-firm impacts the extent of the response to strengthening of 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 stronger 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 changes in liability for subsidiary pollution relative to more solvent firms because managers of distressed firms 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 ex-post cost liabilities incurred under CERCLA. If such economic harm shifting incentives are at play, firms with relatively high leverage and high risk of distress (i.e., a low Altman's unlevered Z-score) may disproportionately respond to changes in parent liability.

We first examine whether firms with higher solvency respond differently to the *Bestfoods* decision. We repeat the analysis from Table 9 but define firms as having above or below median parent unlevered Z-score in 1997. Panel A of Table 10 presents the results of this analysis. Columns (1) and (2) report results for ground pollution, and columns (3) and (4) report results for investment in process pollution abatement. The increase in pollution and decrease in pollution abatement investment is concentrated in those firms with low Z-scores (i.e., those firms that are the least financially solvent). For example, in column (2) we find that in the subsample of low Z-score parent companies the coefficient is 0.337 (significant at the 1% level) whereas the corresponding coefficient for the high Z-score sample is three times smaller, 0.088, (insignificant at conventional levels). We find a similar difference for investment in process abatement. The coefficient in specification (4) is -0.0302 (significant at the 1% level) for the low-Z-score sample, whereas the corresponding coefficient for the high Z-score sample is -0.006 (insignificant at conventional levels). The difference between the coefficients for the samples with high/low parent solvency is statistically noisy for column (4), but otherwise significant at conventional levels.

We repeat the same analysis for parent companies with above or below median leverage. Panel B of Table 10 reports the results. Our results on pollution and abatement are concentrated in subsidiaries of parent companies with higher leverage. For example, in column (2) we find that in the subsample of high leverage parent companies the coefficient is 0.234 (significant at the 1% level) whereas the corresponding coefficient for the low-leverage sample is 0.144 (significant at the 1% level). We find a similar difference for investment in process abatement; the coefficient in column (4) is -0.0158 (significant at the 1% level) for the high-leverage sample, whereas the corresponding coefficient for the low-leverage sample is -0.007 (insignificant at conventional levels). However, these results are suggestive as the differences between coefficients are not statistically significant.

Taken together, the above results indicate significant cross-sectional heterogeneity in the response to the *Bestfoods* decision. First, the main findings 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 subsidiaries 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 subsidiaries of parents that are closer to distress. Such firms are more likely to benefit from reducing short term investment in pollution abatement, potentially shifting economic harm to other stakeholders.

5 Conclusion

Limited liability is a ubiquitous feature of modern economic organization. However, despite being credited as one of the major reasons for capital market development, economists have long recognized the inherent moral hazard problem associated with limited liability. Specifically, because shareholders are not responsible for obligations that exceed the value of the firm, they do not bear all costs associated with risky activities. These 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 waste emissions as a setting to analyze the tradeoffs of limited liability in the parent-subsidiary context. Our identification strategy uses a landmark Supreme Court case (*United States v. Bestfoods*) that clarified parent company liability under CERCLA as a natural experiment to study how changing the limited liability protection of parent companies affects the pollution activity of their subsidiaries. We find this increase in parent liability protections is associated with an increase in ground pollution of 10% for treated firms. Chemicals with known adverse health effects on humans constitute part of the increase. While higher pollution is not necessarily indicative of a welfare loss for society, we find little evidence of increased production or employment by subsidiaries. Rather, evidence suggests the increase is driven by lower investment in abatement technologies.

Our results are driven by less solvent subsidiaries that are more likely to impose liability on parents and also by firms with relatively high tangible assets that would likely benefit most from reducing costly expenditures on pollution abatement. We find evidence of a risk-shifting motivation for increasing pollution emissions — our results are concentrated in highly levered parent companies and parent companies that are more likely to be financially insolvent. These parent firms are most likely to benefit from a reduction in short term costs at the potential expense of longer term harm.

Overall, our results highlight costs 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 shareholders with those of other constituencies.

References

Admati, Anat R (2017), "A skeptical view of financialized corporate governance." *The Journal of Economic Perspectives*, 31, 131–150.

Alberini, Anna and David Austin (2002), "Accidents waiting to happen: Liability policy and toxic pollution releases." *Review of Economics and Statistics*, 84, 729–741.

Andrade, Gregor and Steven N Kaplan (1998), "How costly is financial (not economic) distress? Evidence from highly leveraged transactions that became distressed." *The Journal of Finance*, 53, 1443–1493.

Bartley, Erin C (2005), "The government always wins: The government can now recover certain oversight costs under CERCLA sec. 107." *Missouri Environmental Law and Policy Review*, 13, 241.

Bertrand, Marianne, Esther Duflo, and Senhil Mullainathan (2004), "How Much Should We Trust Differences-in-Differences Estimates?" *Quarterly Journal of Economics*, 119, 245–275.

Biais, Bruno, Thomas Mariotti, Jean-Charles Rochet, and Stéphane Villeneuve (2010), "Large risks, limited liability, and dynamic moral hazard." *Econometrica*, 78, 73–118.

Chaigneau, Pierre, Alex Edmans, and Daniel Gottlieb (2014), "The value of performance signals under contracting constraints." Technical report, National Bureau of Economic Research.

Chang, Xin, Kangkang Fu, Tao Li, Lewis H.K. Tam, and George Wong (2016), "Corporate environmental liabilities and capital structure." Working paper.

Chatterji, Aaron K, David I Levine, and Michael W Toffel (2009), "How well do social ratings actually measure corporate social responsibility?" *Journal of Economics & Management Strategy*, 18, 125–169.

Chay, Kenneth Y and Michael Greenstone (2003), "The impact of air pollution on infant mortality: Evidence from geographic variation in pollution shocks induced by a recession." *The Quarterly Journal of Economics*, 118, 1121–1167.

Clark Jr., William H and D Alicia Hickok (2016), "Repricing limited liability and separate entity status." *Seattle University Law Review*, 40, 497.

Coase, Ronald Harry (1960), "The problem of social cost." *The Journal of Law and Economics*, 3, 1–44.

Cohn, Jonathan and Malcom Wardlaw (2016), "Financing constraints and workplace safety." *Journal of Finance*, 71, 2017–2058.

Cook, Layna (1998), "The impact of Unitd States v. Bestfoods on owner or operator liability under CERCLA." *Louisiana Law Review*, 59, 1003.

Denes, Matthew (2016), "When do firm risk shift? Evidence from venture capital." Carnegie Mellon working paper.

DePalma, Anthony (2004), "Love canal declared clean, ending toxic horror." *The Washington Post*.

DePalma, Anthony (2012), "Superfund cleanup stirs troubled waters." *New York Times*.

DiGiuli, Alberta (2013), "Pollution and firm value." Unpublished working paper.

Dionne, Georges, Robert Gagné, François Gagnon, and Charles Vanasse (1997), "Debt, moral hazard and airline safety: An empirical evidence." *Journal of Econometrics*, 79, 379–402.

Duflo, Esther, Michael Greenstone, Rohini Pande, and Nicholas Ryan (2013), "Truth-telling by third-party auditors and the response of polluting firms: Experimental evidence from India." *The Quarterly Journal of Economics*, 128, 1499–1545.

Easterbrook, Frank H and Daniel R Fischel (1985), "Limited liability and the corporation." *The University of Chicago Law Review*, 52, 89–117.

Eisdorfer, Assaf (2008), "Empirical evidence of risk shifting in financially distressed firms." *The Journal of Finance*, 63, 609–637.

EPA (2011), "Handbook on the benefits, costs, and impacts of land cleanup and reuse." URL `https://yosemite.epa.gov/ee/epa/eerm.nsf/vwAN/EE-0569-02.pdf/$file/EE-0569-02.pdf`.

Esty, Benjamin C (1997), "A case study of organizational form and risk shifting in the savings and loan industry." *Journal of Financial Economics*, 44, 57–76.

Esty, Daniel C (2008), "Rethinking global environmental governance to deal with climate change: The multiple logics of global collective action." *The American Economic Review*, 98, 116–121.

Gaba, Jeffrey M (2015), "The private causes of action under CERCLA: Navigating the intersection of sections 107 (a) and 113 (f)." *Michigan Journal of Environmental & Administrative Law*, 5, 177–168.

Gilje, Erik P (2016), "Do firms engage in risk-shifting? Empirical evidence." *The Review of Financial Studies*, 29, 2925–2954.

Gormley, Todd A and David A Matsa (2011), "Growing out of trouble? Corporate responses to liability risk." *The Review of Financial Studies*, 24, 2781–2821.

Government Accountability Office (2005), "EPA should do more to ensure that liable parties meet their cleanup obligations." Technical report, Government Accountability Office.

Graff Zivin, Joshua and Matthew Neidell (2012), "The impact of pollution on worker productivity." *American Economic Review*, 102.

Gray, Wayne B and Jay P Shimshack (2011), "The effectiveness of environmental monitoring and enforcement: A review of the emprical evidence." *Review of Environmental Economics and Policy*, 5, 3–24.

Greenstone, Michael (2003), "Estimating regulation-induced substitution: The effect of the Clean Air Act on water and ground pollution." *The American Economic Review*, 93, 442–448.

Greenstone, Michael and Justin Gallagher (2008), "Does hazardous waste matter? Evidence from the housing market and the Superfund program." *The Quarterly Journal of Economics*, 123, 951–1003.

Grossman, Richard S (2001), "Double liability and bank risk taking." *Journal of Money, Credit and Banking*, 143–159.

Guarino, Ben (2016), "Thousands of Montana snow geese die after landing in toxic, acidic mine pit." *The Washington Post*.

Jensen, Michael C and William H Meckling (1976), "Theory of the firm: Managerial behavior, agency costs and ownership structure." *Journal of Financial Economics*, 3, 305–360.

Karpoff, Jonathan M, John R Lott, Jr, and Eric W Wehrly (2005), "The reputational penalties for environmental violations: Empirical evidence." *Journal of Law and Economics*, 68, 653–675.

Koudijs, Peter and Laura Salisbury (2016), "Bankruptcy and investment: Evidence from changes in marital property laws in the US south, 1840-1850." Carnegie Mellon working paper.

Laffont, Jean-Jacques (1995), "Regulation, moral hazard and insurance of environmental risks." *Journal of Public Economics*, 58, 319–336.

Landier, Augustin, David Alexandre Sraer, and David Thesmar (2015), "The risk-shifting hypothesis: Evidence from subprime originations." Berkeley working paper.

Manne, Henry G (1967), "Our two corporation systems: Law and economics." *Virginia Law Review*, 53, 259–284.

Phillips, Gordon and Giorgo Sertsios (2013), "How do firm financial conditions affect product quality and pricing?" *Management Science*, 59, 1764–1782.

Plater, Zygmunt JB, Robert H Abrams, Robert L Graham, Lisa Heinzerling, David A Wirth, Noah D Hall, Robert H Abrams, and Robert L Graham (2016), *Environmental law and policy: Nature, law, and society*. Wolters Kluwer Law & Business.

Shapira, Roy and Luigi Zingales (2017), "Is pollution value-maximizing? The DuPont case." NBER working paper.

Shapiro, Joseph S and Reed Walker (2015), "Why is pollution from US manufacturing declining? The roles of trade, regulation, productivity, and preferences." NBER working paper.

Shavell, Steven (1984), "A model of the optimal use of liability and safety regulation." *The RAND Journal of Economics*, 15, 271–280.

Stafford, Sarah L. (2002), "The effect of punishment on firm compliance with hazardous waste regulations." *Journal of Environmental Economics and Management*, 44, 290–308.

Tuholske, Lilly (1993), "Ignoring the obvious: The Agency of Toxic Substances and Disease Registry's failure to monitor public health on the Clark Fork River Superfund sites." University of Montana working paper.

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

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

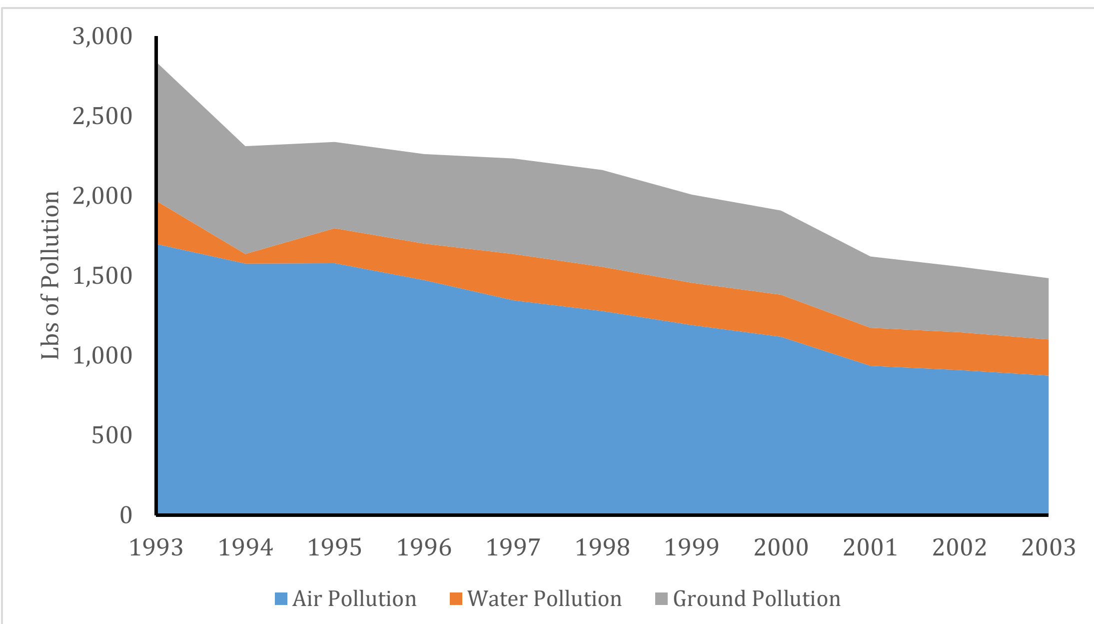

Figure 2: **Treatment and Control States**

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

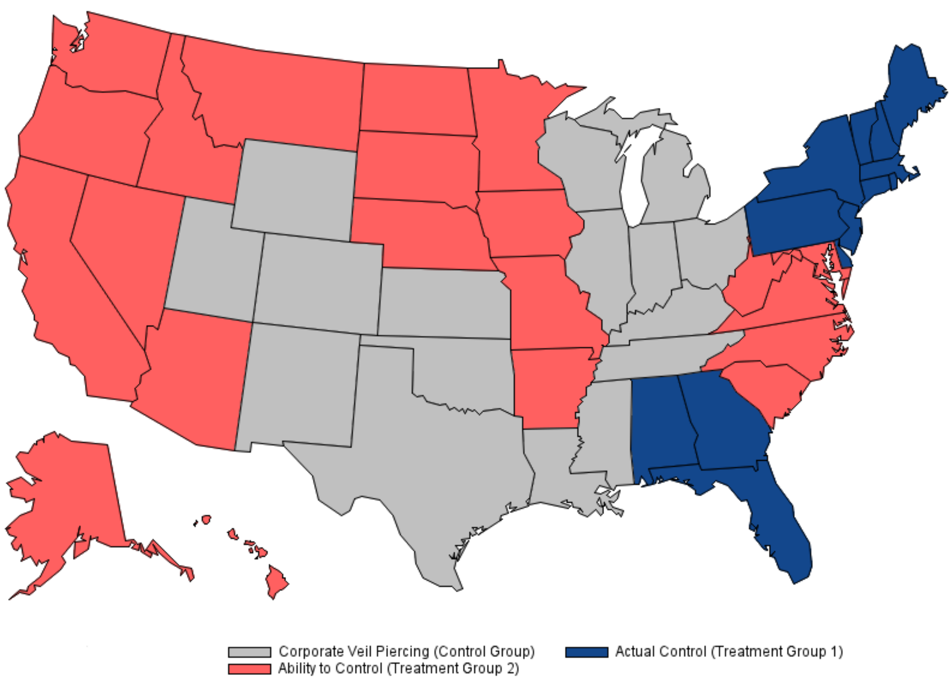

Figure 3: **Distribution of Plants to Court Circuits and Treatment Groups**

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

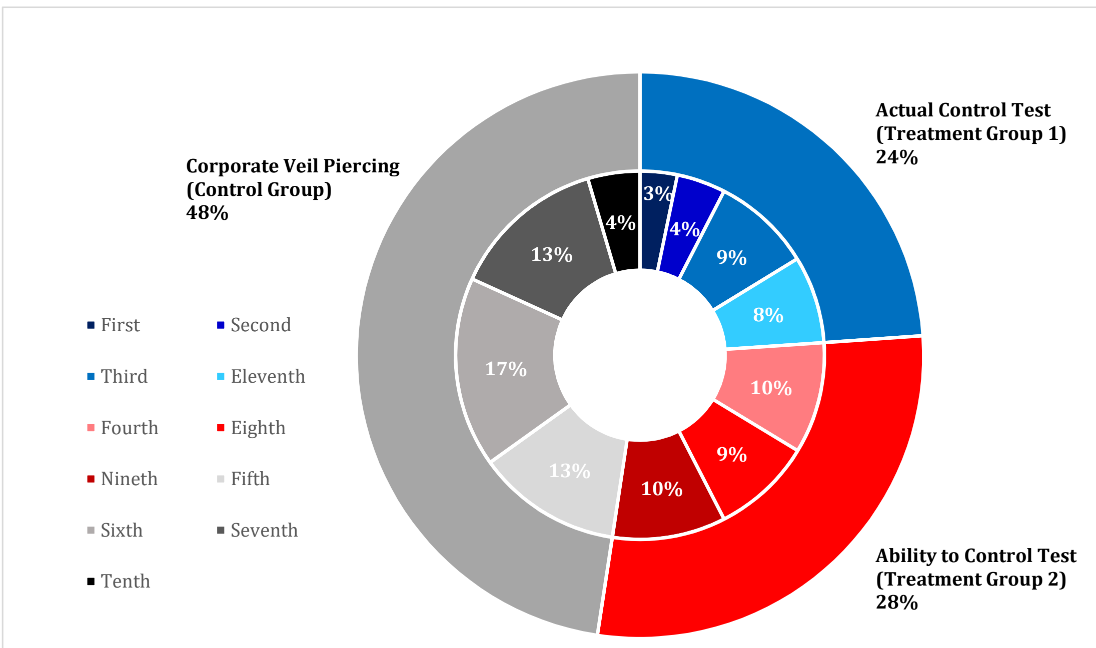

Figure 4: **Treatment Effect Dynamics – Ground Pollution**

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.

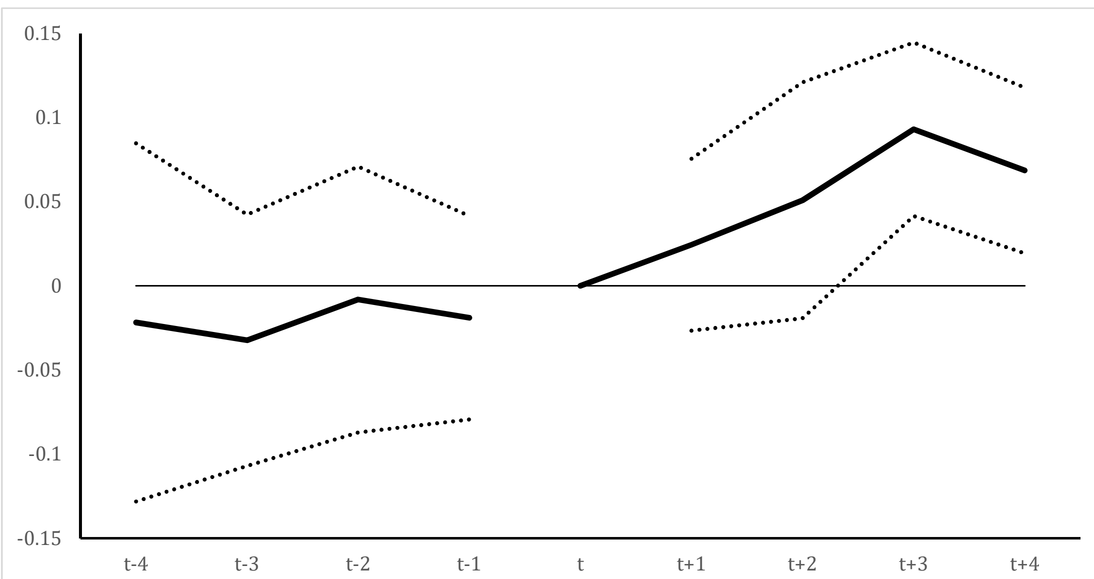

Table 1: **Summary Statistics**

The table reports summary statistics for the full sample and for firms that are subsidiaries of public parent companies. Pollution emission data, abatement data, and productivity ratio data are from the EPA Toxic Release Inventory, and employment data are from the National Establishment Time-Series database.

	All Subs				**Subs w/ Public Parent**			
	Obs	Mean	Median	SD	Obs	Mean	Median	SD
Lbs Ground Pollution (1000s)	608,729	36.04	0	1,679.31	188,982	39.68	0	1,516.24
Lbs Air Pollution (1000s)	608,733	24.79	255	289.74	188,984	31.54	255	293.67
Lbs Water Pollution (1000s)	608,730	3.60	0	145.56	188,982	4.44	0	186.84
$\mathbb{1}$(Ground Polluter)	608,733	0.10	0	0.30	188,984	0.13	0	0.34
$\mathbb{1}$(Abatement - Operating)	608,733	0.08	0	0.27	188,984	0.08	0	0.28
$\mathbb{1}$(Abatement - Process)	608,733	0.05	0	0.22	188,984	0.05	0	0.22
Productivity Ratio	574,724	0.96	1	0.39	178,627	0.95	1	0.39
Employment (Plant)	111,103	315.19	135	671.17	31,791	418.72	180	880.14

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)
Bestfoods	0.0428***	0.0537**	0.0756***	0.0666***			0.184***	0.186***	0.0200	-0.000711
	(0.0125)	(0.0180)	(0.0219)	(0.0203)			(0.0306)	(0.0324)	(0.0259)	(0.0331)
ATC					0.0681**	0.0590**				
					(0.0304)	(0.0236)				
AC					0.0858***	0.0772***				
					(0.0160)	(0.0192)				
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		
Industry-Year FE				x		x		x		x
Observations	606,529	605,886	593,528	592,587	593,528	592,587	186,212	185,776	142,235	141,293
R-squared	0.539	0.627	0.651	0.655	0.651	0.655	0.717	0.724	0.578	0.603

Table 3: **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.

Panel A — Ground Pollution by Human Harm

	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)
Bestfoods	0.0678***	0.0565**	0.167***	0.151***	0.0761**	0.0675**	0.196***	0.231***
	(0.0213)	(0.0199)	(0.0393)	(0.0432)	(0.0305)	(0.0278)	(0.0342)	(0.0394)
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	330,087	329,317	100,210	99,674	247,730	247,110	84,050	83,577
R-squared	0.674	0.681	0.742	0.750	0.684	0.689	0.736	0.743

Panel B — Biological Impact of Chemicals

	Ln(1 + Lbs Ground Pollution), All Subs					
System Affected =	Nervous	Respiratory	Urinary	Developmental	Hematologic	Heptatic
	(1)	(2)	(3)	(4)	(5)	(6)
Bestfoods	0.0673***	0.0681	0.121***	0.0508***	0.0925*	0.00428
	(0.0112)	(0.0396)	(0.0216)	(0.0127)	(0.0453)	(0.0284)
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	130,224	90,888	66,374	62,010	53,051	41,171
R-squared	0.672	0.666	0.808	0.686	0.813	0.716

Table 4: **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 ground 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)
Bestfoods	0.0165	0.0183	0.0131	0.0136	0.0423*	0.0215	0.0206	-0.00500
	(0.0145)	(0.0159)	(0.0327)	(0.0328)	(0.0211)	(0.0251)	(0.0361)	(0.0273)
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	593,529	592,588	186,212	185,776	593,533	592,592	186,215	185,779
R-squared	0.531	0.536	0.541	0.547	0.710	0.714	0.726	0.732

Table 5: **Cumulative Abnormal Returns**

This table uses OLS regressions to test the effect of *Bestfoods* on cumulative abnormal returns (CARs). CARs are 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,+5)	(-1,+10)	(-1,+1)	(-1,+5)	(-1,+10)
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: All Firms					
High Exposure	0.00344	0.00826*	0.0148**	-0.00274	-0.00220	-0.00368
	(0.00268)	(0.00428)	(0.00619)	(0.00274)	(0.00436)	(0.00580)
Observations	771	771	771	771	771	771
R-squared	0.002	0.005	0.007	0.001	0.000	0.001
	Panel B: Multi-Plant Firms					
High Exposure	0.00586*	0.0109**	0.0160**	-0.000830	-0.00347	-0.00236
	(0.00304)	(0.00488)	(0.00660)	(0.00313)	(0.00511)	(0.00721)
Observations	501	501	501	500	500	500
R-squared	0.007	0.010	0.012	0.000	0.001	0.000

Table 6: **Effect of *Bestfoods* on Pollution Abatement Activities**

This table uses OLS regressions to test the effect of the *Bestfoods* court decision on the likelihood of firms implementing pollution abatement investment. The dependent variable is an indicator variable that takes the value of one if the plant has invests 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.

	$\mathbb{1}$(Abatement - Operations)				$\mathbb{1}$(Abatement - Process)			
	All Subs		Subs w/ Public Parent		All Subs		Subs w/ Public Parent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bestfoods	0.000998	0.00194	0.00462	0.00382	-0.00647*	-0.00614**	-0.0130***	-0.0144***
	(0.00533)	(0.00713)	(0.00749)	(0.0104)	(0.00302)	(0.00259)	(0.00287)	(0.00314)
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	593,533	592,592	186,215	185,779	593,533	592,592	186,215	185,779
R-squared	0.601	0.611	0.578	0.601	0.452	0.462	0.397	0.425

Table 7: **Effect of *Bestfoods* on Subsidiary Production and Employment**

This table uses OLS regressions to test the effect of the *Bestfoods* court decision on plant production and employment. The dependent variable is the Production Ratio reported in the TRI database in specifications (1) – (4) and the (plant level) log of employment 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)
Bestfoods	0.00706	0.00224	-0.000535	0.00333	-0.0140	-0.0213	-0.0279	-0.0289
	(0.00605)	(0.00520)	(0.00877)	(0.00843)	(0.0161)	(0.0177)	(0.0277)	(0.0238)
Plant FE	x	x	x	x	x	x	x	x
Chem-Year FE	x	x	x	x				
Parent-Year FE	x	x	x	x	x	x	x	x
Industry-Year FE		x		x		x		x
Observations	560,222	559,457	175,918	175,519	72,808	71,926	25,934	25,010
R-squared	0.476	0.495	0.437	0.477	0.921	0.928	0.901	0.917

Table 8: **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 has invests 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.

	Ground Pollution		$\mathbb{1}$(Abatement - Process)	
	(1)	(2)	(3)	(4)
	Low Plant Paydex			
Bestfoods	0.0771**	0.0835**	-0.0148**	-0.0172**
	(0.0265)	(0.0375)	(0.00491)	(0.00569)
Observations	188,375	187,883	188,375	187,883
R-squared	0.635	0.647	0.497	0.518
	High Plant Paydex			
Bestfoods	-0.0248	-0.0497	0.00855	0.0168
	(0.0334)	(0.0296)	(0.0127)	(0.0112)
Observations	171,922	171,517	171,924	171,519
R-squared	0.676	0.682	0.503	0.527
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 9: **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 has invests 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.

	Ground Pollution		𝟙(Abatement - Process)	
	(1)	(2)	(3)	(4)
	High Parent Tangibility			
Bestfoods	0.225***	0.262***	-0.0166***	-0.0191***
	(0.0533)	(0.0458)	(0.00360)	(0.00479)
Observations	113,218	112,830	113,221	112,833
R-squared	0.730	0.737	0.394	0.428
	Low Parent Tangibility			
Bestfoods	0.103**	0.115***	-0.00902	-0.00430
	(0.0438)	(0.0261)	(0.00529)	(0.00760)
Observations	72,063	71,744	72,063	71,744
R-squared	0.682	0.695	0.417	0.464
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 Solvency and Leverage**

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. *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.

Panel A — Altman's Unlevered Z-Score				
	Ground Pollution		$\mathbb{1}$(Abatement - Process)	
	(1)	(2)	(3)	(4)
	Low Parent Z-Score			
Bestfoods	0.296***	0.337***	-0.0281***	-0.0302***
	(0.0682)	(0.0980)	(0.00713)	(0.00520)
Observations	81,260	80,858	81,260	80,858
R-squared	0.764	0.769	0.439	0.480
	High Parent Z-Score			
Bestfoods	0.0988*	0.0879	-0.00453	-0.00585
	(0.0500)	(0.0504)	(0.00662)	(0.0118)
Observations	81,378	81,014	81,379	81,015
R-squared	0.548	0.570	0.388	0.429
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 Solvency and Leverage (continued)**

Panel B — Leverage

	Ground Pollution		$\mathbb{1}$(Abatement - Process)	
	(1)	(2)	(3)	(4)
	High Parent Leverage			
Bestfoods	0.229***	0.234***	-0.0147***	-0.0158***
	(0.0685)	(0.0636)	(0.00411)	(0.00335)
Observations	95,595	95,140	95,597	95,142
R-squared	0.754	0.760	0.407	0.452
	Low Parent Leverage			
Bestfoods	0.128**	0.144***	-0.0114*	-0.00668
	(0.0469)	(0.0440)	(0.00624)	(0.0102)
Observations	89,845	89,497	89,846	89,498
R-squared	0.623	0.639	0.400	0.439
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.

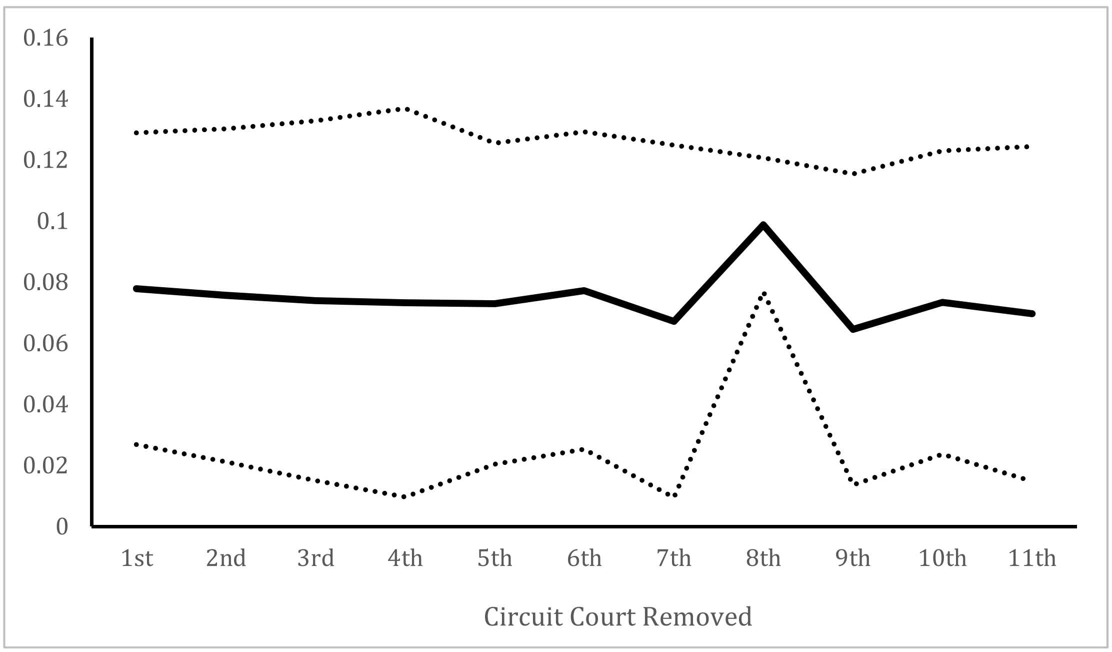

Table A.1: **Robustness to Industries Continuously Required to Report**

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 has invests 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. 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)				$\mathbb{1}$(Abatement - Process)			
	All Subs		Subs w/ Public Parent		All Subs		Subs w/ Public Parent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bestfoods	0.0679**	0.0591**	0.170***	0.178***	-0.00646*	-0.00584*	-0.0136***	-0.0136***
	(0.0244)	(0.0237)	(0.0378)	(0.0365)	(0.00343)	(0.00277)	(0.00292)	(0.00272)
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	516,335	515,449	154,100	153,674	516,338	515,452	154,101	153,675
R-squared	0.507	0.514	0.487	0.503	0.449	0.460	0.392	0.420

Table A.2: **Robustness to Ground Pollution Measurement**

This table uses OLS regressions to test the effect of the *Bestfoods* court decision on the output of ground pollution. The dependent variable is either the log of one plus pounds of ground pollution or an indicator for whether the plant released 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. 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 + Ground Pollution), 1997 Pollution > 0				$\mathbb{1}$(Ground Pollution)			
	All Subs		Subs w/ Public Parent		All Subs		Subs w/ Public Parent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bestfoods	0.254**	0.190	0.635***	0.908***	0.00716*	0.00586	0.0237***	0.0253***
	(0.1000)	(0.116)	(0.166)	(0.212)	(0.00382)	(0.00408)	(0.00333)	(0.00470)
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	92,404	92,168	26,451	26,283	593,533	592,592	186,215	185,779
R-squared	0.532	0.544	0.505	0.525	0.607	0.614	0.664	0.675

Table A.3: **Total Pollution and the Proportion of Ground Pollution**

This table uses OLS regressions to test the effect of the *Bestfoods* court decision on the output of total pollution and the fraction of pollution that is emitted in ground form. The dependent variable is either the log of one plus pounds of ground pollution, water, and air pollution or the proportion of pollution for a given chemical that is emitted as 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. 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 + Total Pollution)				$\frac{Ground\ Pollution}{Total\ Pollution}$			
	All Subs		Subs w/ Public Parent		All Subs		Subs w/ Public Parent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bestfoods	0.0586**	0.0379	0.0849*	0.0645**	0.00582***	0.00571***	0.0146***	0.0146***
	(0.0244)	(0.0293)	(0.0381)	(0.0276)	(0.00163)	(0.00161)	(0.00226)	(0.00293)
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	593,528	592,587	186,212	185,776	488,739	488,009	154,404	153,951
R-squared	0.684	0.688	0.704	0.711	0.673	0.679	0.723	0.731

Table A.4: **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 has invests 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.

	Ln(1 + Lbs Ground Pollution)				$\mathbb{1}$(Abatement - Process)			
	All Subs		Subs w/ Public Parent		All Subs		Subs w/ Public Parent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bestfoods	0.0633**	0.0571*	0.191***	0.179***	-0.00680**	-0.00561*	-0.0141***	-0.0127**
	(0.0269)	(0.0265)	(0.0325)	(0.0333)	(0.00271)	(0.00295)	(0.00362)	(0.00479)
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	150,660	150,430	47,273	47,146	150,660	150,430	47,273	47,146
R-squared	0.644	0.645	0.712	0.715	0.517	0.523	0.483	0.496

Table A.5: **Robustness to 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 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 has invests 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.

Panel A — Clustering by State

	Ln(1 + Lbs Ground Pollution)				$\mathbb{1}$(Abatement - Process)			
	All Subs		Subs w/ Public Parent		All Subs		Subs w/ Public Parent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bestfoods	0.0756***	0.0666***	0.184***	0.186***	-0.00647*	-0.00614*	-0.0130**	-0.0144**
	(0.0210)	(0.0197)	(0.0340)	(0.0339)	(0.00329)	(0.00323)	(0.00529)	(0.00584)
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	593,528	592,587	186,212	185,776	593,533	592,592	186,215	185,779
R-squared	0.651	0.655	0.717	0.724	0.452	0.462	0.397	0.425

Panel B — Clustering by State and Parent Company

	Ln(1 + Lbs Ground Pollution)				$\mathbb{1}$(Abatement - Process)			
	All Subs		Subs w/ Public Parent		All Subs		Subs w/ Public Parent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bestfoods	0.0756**	0.0666**	0.184***	0.186***	-0.00647	-0.00614	-0.0130*	-0.0144**
	(0.0286)	(0.0263)	(0.0477)	(0.0465)	(0.00429)	(0.00396)	(0.00693)	(0.00689)
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	593,528	592,587	186,212	185,776	593,533	592,592	186,215	185,779
R-squared	0.651	0.655	0.717	0.724	0.452	0.462	0.397	0.425

Table A.6: **Process and Operating Abatement Activities**

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

	Process Modifications	**Good Operating Practices**
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.7: **Industries that Report Toxic Release Inventory**

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

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