# Circuit Splits: Liability Reform and Likelihood of Environmental Risk in the Hazardous Waste Industry

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March 23, 2022

Do firms factor in expected liability costs when entering contracts? This paper evaluates how joint liability laws influence market structure through contracting decisions between upstream and downstream partners. Using data on contracts from 2001-2017 between hazardous waste generators and disposal firms, I investigate whether weak joint liability rules increase the market share of disposal firms with higher rates of spills and accidents. I leverage a natural experiment created by the resolution of circuit split on the extent of joint liability prescribed by the Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA) and compare market shares for accident prone disposal firms in circuits where joint liability was weakened to those in circuits where expected liability costs of contracting were not affected. I find that the difference in market share between dirty and clean firms grew 28.7% on average in treated markets after the resolution of the circuit split with the greatest gains going to the dirtiest firms. These results suggest that firms actively make contracting decisions based on expected future liability costs and that removing joint liability rules may have significant effects on the likelihood of environmental damages.

## 1 Introduction

All legal systems have provisions for apportioning liability in the case where a single harm may have been caused by multiple tortfeasors. Motivated by the principle that the injure should bear the cost of the harm, US courts have adopted a theory of "joint and several liability" whereby a victim may collect the entirety of compensation for a harm from any subset of the defendants responsible for injury (Scheske). Economic perspectives on joint liability beginning with Landes and Posner have largely focused on whether joint liability schemes give rise to an efficient ex-ante level of precaution by firms in models where firms independently choose activity levels that cause damages. However in cases where damages arise from contracted activity between firms, for example carbon emissions throughout a supply chain, a firm can also minimize liability exposure by choosing to contract with a partner who is likely to incur fewer damages. This paper asks how joint liability rules affect aggregate levels of care within an industry through the margin of partner choice.

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Joint liability is present in many settings where a firm's choice of partner affects the probability of damages. Examples include franchise and franchisee relationship where the franchiser can be held liable for labor violations at the franchisee, or contracts between manufacturers and distributors where distributors can be held liable for product defects. The high-stakes setting explored by this paper is the arrangement between producers of hazardous waste and the firms they contract for disposal. Under joint liability created by the Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA), also known as Superfund, producers of hazardous waste may pay for the cost of clean-up of contamination at the site of their contracted disposal firm. I will refer to this kind of liability as "CERCLA liability" throughout. The treatment, storage and disposal facilities (TSDFs) that manage hazardous waste comprise a highly regulated $9.6 billion industry that handles 267.8 million tons of waste annually (McGinley). Firms operating in this industry are subject to strict environmental regulation due to the high health risks associated with spills of toxic chemicals (Vrijheid).

Following other trends in tort reform, judicial interpretation of CERCLA liability has weakened over time (Brown). Using an extensive data set of hazardous waste contracts, I use a natural experiment created by the resolution of a circuit split on CERCLA liability to study the impact of joint liability on partner choices and find that relaxing joint liability lead to a 28.7% increase in the market share of violation-prone TSDFs. This evidence is consistent with the theory that generators of hazardous waste respond to joint liability schemes through the margin of partner choice; namely, after a negative shock to joint liability, generators shifted contracts from cleaner partners towards partners with higher expected liability costs but lower prices.

This project contributes to a number of economic literatures. First, it contributes to a long, largely theoretical literature on tort reform (Landes and Posner; Kornhauser and Revesz; Shavell; Tietenberg). Recent work has sought to empirically test predictions of the impact of various liability schemes on outcomes of interest, mostly in the medical or environmental context (Alberini and Austin; Chang and Sigman; Currie and MacLeod; Avraham; Boomhower). This paper is the first, to my knowledge, to empirically estimate the effects of tort reform on contracting decisions and to explicitly consider partner choice as the outcome of interest. Second, this paper contributes to a literature on reputation incentives and their effects on market composition (Mailath and Samuelson; Tadelis; Hörner; Crémer and Khalil; Kranton) which predicts that firms have an incentive to produce high quality to maintain their reputations with consumers. I extend the notion of reputation for quality to an environmental context and directly test whether joint liability affects the returns to a good reputation.

This paper will explore how liability for environmental damages from hazardous waste affect the firm's contracting decisions. The following section explains the primary regulations in the hazardous waste market and the history of joint liability within the industry. Section 3 sets up a formal model to capture the contracting decision by the firm and outlines conditions under which liability regimes affect partner choice. The model predicts that weak liability rules will increase the market share of dirty firms. Section 4 outlines the data and the construction of the joint liability measure. Section 5 explains the triple-differences econometric strategy and the natural experiment. The penultimate section details the results from this natural experiment and shows that the market concentration of dirty firms increases under weakened joint liability. Finally, Section 6 concludes.

# 2 Background on Hazardous Waste Policy

## 2.1 Resource Conservation and Recovery Act

The Resource Conservation and Recovery Act (RCRA) of 1976 is the primary federal legislation in the United States governing the management and disposal of hazardous waste. An all-encompassing piece of legislation, RCRA proposed a comprehensive set of goals for reducing the health and environmental impacts of waste disposal and established programs to oversee solid waste, hazardous waste and underground storage tanks. Subtitle C, the hazardous waste management program of RCRA, created a “cradle-to-grave” regulatory system that governs waste throughout its life cycle. Namely, Subtitle C (1) identifies and lists hazardous wastes, (2) sets standards for waste generators, transporters and treatment, storage and disposal facilities (TSDFs), and (3) establishes a permitting program that requires waste handlers to maintain records of all waste transfers.

Enforcement of RCRA is handled by state regulators and the EPA and largely takes place through facility evaluations. Firms with permits to handle hazardous waste are required to be inspected at least once every two years during which inspectors assess whether firms are in compliance with the terms of their permit. Permit violations can take place knowingly or unknowingly by the firm, i.e. RCRA is a strict liability statute. For example, generators may violate permit standards by shipping waste to an un-permitted treatment facility or a TSDF may be found in violation for improper storage. As a federal regulation, RCRA established the minimum level of standards hazardous waste management. States can choose to adopt stricter permit standards if they have been authorized by the EPA to manage their own waste program.

## 2.2 Comprehensive Environmental Response, Compensation and Liability Act

While RCRA establishes proactive regulations to avoid hazardous waste emissions, it is the Comprehensive Environmental Response, Compensation and Liability Act (CERCLA) which addresses the remediation of contaminated sites. More commonly known as “Superfund,” CERCLA was established in 1980 as a response to the discovery of a large number of abandoned, leaking hazardous waste sites, including the tragedies at Love Canal and Valley of the Drums (Florio). CERCLA provided a two-pronged approach to cleaning up hazardous waste spills. First, it created a $1.6 billion federal trust fund to finance and authorize government clean-up of the most serious toxic sites in case of emergency or lack of a viable responsible party. Second, CERCLA established a complex legal framework to assign liability for clean-up costs to potentially responsible parties (PRPs) after a spill. The cost of liability for a PRPs can be incredibly high; the average liability cost is $2,958,054, not including legal fees.

Because the liability structure of CERCLA is the primary focus of this paper, it is useful to understand how liability functions in the hazardous waste industry. CERCLA liability provisions hold PRPs retroactively, strictly, and jointly and severally liable for the clean-up costs of a hazardous waste site. Each feature of the liability structure has strong implications. Retroactive liability allows firms to be held accountable for past actions, and strict liability implies that firms can be liable for damage regardless of negligence. Most importantly for this paper, joint and several liability implies that any one responsible party can be held liable for the entire clean-up of the site if costs cannot be apportioned between the relevant parties. Specifically, it is the joint and several liability feature of CERCLA that creates disincentives for generators of hazardous waste to partner with "sloppy" disposers; if generator is found to be a responsible party, it may pay up to the full cost of the damages caused by the disposer.

## 2.3 Arranger Liability Background

While the text of CERCLA outlines conditions under which firms qualify as a PRP and costs are divisible, in practice these guidelines have been notoriously difficult to interpret for courts (Rasmussen). Particularly contentious has been the "arranger liability" clause outlined in Section 107(a)(3) which states that generators can be liable as "arrangers" if they arranged for the disposal or treatment of waste at the contaminated site. If a generator is proven to be a PRP under arranger liability, then it will be subject to the joint and several liability that requires them to potentially pay the full cost of contamination incurred at the disposer.

This article will exploit spatial and temporal differences in the judicial interpretation of arranger liability to understand how joint liability incentivizes generators to partner with reputable firms. Here spatial variation refers to differences in judicial interpretation across the thirteen US Circuit Courts, each of which is assigned to hear appeals from the district courts within their geographical jurisdiction. Longstanding differences between Circuit Courts are referred to as "circuit splits." It is important to note that while very few cases reach a Circuit Court, the decisions made at the appellate level have out-sized influence on the decisions of lower courts. This paper will assume that Circuit Court rulings set standards for district courts in their jurisdiction. Over time, Circuit Courts may reverse previous decisions or be over-ruled by the Supreme Court (Songer, Segal, and Cameron). Because this paper relies on changes over time in Circuit Court interpretations of arranger liability for variation in treatment, it is helpful to understand what these differences refer to and how they were resolved in 2009 by the Supreme Court.

The broadest interpretation of arranger liability asserts that those who arrange for disposal are subject to strict liability, regardless of their control over the contamination (Brown; Rasmussen). For example, in *United States v. Aceto Agricultural Corp.*, the United States Court of Appeals for the Eight Circuit found companies that supplied chemicals to a pesticide manufacturer liable for contamination at the manufacturer's site, despite the fact that spills were entirely caused by the manufacturer and chemicals were sold as useful inputs in the pesticide production. Other courts came to a similar conclusion as *Aceto*, emphasizing that intent for disposal was not required for arranger liability (Brown; Foy). Some courts, however, have taken a narrower view of arranger liability that emphasizes whether generators intend to dispose of the hazardous material. These courts consider the "useful product doctrine" as a defense to arranger liability, where generators that sell a useful product containing hazardous materials are not considered to have an intent to dispose (Henson).

The Supreme Court's 2009 decision in *Burlington Northern & Santa Fe Railway Co. v. United States* effectively resolved a nearly three-decade long circuit split on the scope of arranger liability (Brown). Ruling in favor of the useful product doctrine, the *Burlington Northern* decision was considered to have such a strong impact on CERCLA jurisprudence that it was referred to as a "Super Quake"(Judy). The Court held Shell Oil Company not liable for clean-up costs as an arranger after Shell sold soil fumigant to an agricultural chemical distributor, Brown & Bryant. Despite the fact that Shell was aware of and sold the chemicals that contributed to the "sloppy practices" at Brown & Bryant, the Court argued that Shell was not liable as an arranger because it did not intend for the soil fumigant to be disposed of during the transaction with the chemical distributor. The Court's decision emphasized that mere knowledge of or participation in contamination was no longer sufficient for ascribing arranger liability, effectively overturning the broad interpretation adopted by some circuits. While arranger liability remains litigated after *Burlington Northern*, the decision was widely acknowledged to increase the difficulty in proving arranger liability (Brown).

# 3 Theory

This section introduces a model of the effect of joint liability reform on generator shipment decisions. This model extends the standard tort model by explicitly accounting for the fact that under joint liability, the level of care chosen by the firm is in part captured by their contracting decisions. In the hazardous waste context, generators invest in care both directly by making decisions regarding their own production and indirectly by choosing to ship their waste to a treatment, storage and disposal facility (TSDF) with some known standard of care. An existing literature on torts analyzes how ex-post liability can lead to inefficiencies where firms will exert too little care in their *own* production choices relative to the social optimum (Kolstad, Ulen, and Johnson; Shavell; Currie and MacLeod). However, the focus of this paper is to understand how liability, in creating an additional transaction cost between the generator and the TSDF, can also increase the level of care through the contracting decision. The addition of a new margin by which firms trade off costs and care can affect the optimality of a ex-post liability scheme.

## 3.1 Model with one good and two firms

I examine a partial-equilibrium model of an upstream firm's waste allocation in the context of heterogeneous downstream firms and joint liability. For simplicity, upstream firms can be though of as waste generators that produce a homogeneous good and face identical cost and production functions. The hazardous waste byproduct of activity in the generator market is a fixed quantity $q$, which is subject to environmental regulation. I normalize $q$ to one for ease of notation. In this model, the firm is assumed to have a capacity constraint regarding the amount of waste it can treat on-site, so it must ship waste off-site if the capacity constraint is breached.

Consider the case of two possible downstream TSDFs, one of which, firm $d$, has a higher incidence of spills than the other, firm $c$. The TSDF types, dirty and clean, respectively, are known to all generators. The generators minimizes transaction costs by choosing a fraction $\alpha$, of its waste to send to the dirty firm. Formally,

$$\min_{\alpha} TC = C_c(1-\alpha) + C_d(\alpha) + \lambda(L_c(1-\alpha) + L_d(\alpha)) \tag{1}$$

where $C_j(\cdot)$ and $L_j(\cdot)$ are continuous, convex cost and expected liability functions associated with shipping waste to firm $j \in \{c, d\}$. The clean firm has a lower expected probability of spills such that $L_c < L_d$, but also charges more for its services so $C_c > C_D$. I interpret liability as encompassing both the cost of damages from contamination and any litigation costs.

The impact of of expected liability on the cost function is mediated by the joint and several liability rule, $0 < \lambda < 1$. When a complete joint liability regime exists $\lambda$ equals one, and the full expected liabilities of the TSDF are passed onto the generator. In the absence of any joint liability $\lambda$ is equal to zero, and the firm's decision is identical to the simple ex-post liability outcome discussed above. It is impossible to fully identify all the components which encompass $\lambda$, but I will assume any changes that narrow or broaden the joint liability operate through this term. Specifically, $\lambda$ will be increasing in the stringency of judicial interpretation of arranger liability discussed in Section II. Increasing the difficulty of ascribing arranger liability, as in the case of *Burlington Northern*, will correspond to a decrease in $\lambda$ as it makes it less likely that a generator will be held liable for the clean-up costs of the TSDF.

### 3.2 Joint liability effect

The first order condition of this minimization problem shows that the generator will allocate waste between the clean and dirty firm to equalize marginal shipping and liability costs. Re-arranging the first order condition yields the following expression:

$$L'_d - L'_c = \frac{C'_c - C'_d}{\lambda} \tag{2}$$

This equation shows that the joint liability rule essentially mediates the extent to which shipping costs loom larger than liability costs in the generator's decision. In the case of perfect joint liability, a dollar of additional liability must be offset by a one dollar decrease in shipping costs. However, when $\lambda < 1$ in the case of incomplete joint liability, differences in dirtiness between the dirty and clean TSDF must be much larger to justify sending waste to the relatively higher shipping cost clean firm.

My empirical application examines the effect of a negative shock to the joint liability scheme on the market share of dirty firms. It is straightforward to show that the model predicts a weakening of the joint liability rule will lead to an increase in market share for the dirty firm, $\alpha$. Taking a total derivative of the first order condition and re-arranging terms, we find that

$$\frac{d\alpha}{d\lambda} = \frac{-(L'_d - L'_c)}{C''_c + C''_d + \lambda(L'_c + L'_d)} < 0 \tag{3}$$

where the inequality follows from the assumption of convex costs. While assessing the impact of joint liability directly on environmental outcomes is beyond the scope of this paper, another natural prediction from the model is that environmental outcomes will worsen in states that experienced shocks to joint liabiliy.

## 4 Data

I construct a novel dataset on bi-annual hazardous material sales and regulatory enforcement outcomes from 2003-2017 using publicly available data published by the EPA. The data collection is inspired by the natural experiment created by the May 4th 2009 *Burlington Northern* ruling which weakened joint liability in a subset of states across the United States by overruling the arranger liability interpretations of several circuits courts. To fully analyze the impact of the Supreme Court decision on the market share of dirty hazardous waste treatment facilities, I collect information on all contracts entered before and after the ruling, industry characteristics and a measure of "dirtiness" for each TSDF.

## 4.1 Universe of firms

Data on the universe of firms potentially subject to CERCLA liability come from the 2003-2017 Biennial Report of the Resource Conservation and Recovery Act Information (RCRAInfo) compiled by the EPA. Following the passage of RCRA in 1976, firms dealing with hazardous materials are required to register a unique identifier with the EPA for each site and report their activities on a biennial basis, including the quantity of waste generated, transported or treated. The full data provides a complete description of nearly all operating sites and all trades of hazardous waste carried out between generators and receivers. This is the first study, to my knowledge, to use the extensive contracting data contained in the RCRA Biennial Report.

There are 536,904 hazardous waste generators, 13,965 sites listed as received hazardous waste and 9,254,609 recorded trades between 2003-2017. Each site is considered a unique firm for the purposes of this analysis. Counts of waste traded are annually reviewed by state environmental agencies before compilation by the EPA and audited under threat of fine during quasi-random compliance visits by regulators. As a quality check, I measure the degree of under-reporting by comparing the quantity sold listed by the generator to the quantity bought listed by the TSDF. I find little evidence that generators under report quantities sold. In instances where discrepancies arise, I keep the record of the transaction with the higher listed quantity.

## 4.2 Market shares

The transaction data is used to construct the relevant outcome variable: hazardous waste market share of the TSDF. This outcome variable requires me to first define a market, and second calculate the share of hazardous waste produced by this market that is handled by the treatment facility. I define a market at the narrow 4-digit NAICS by state level, and each generator is matched to a market. For example, generators that are sited in Massachusetts and are in NAICS code 3254 are coded as being in a single market, the Massachusetts medical manufacturing market. Panel B of Table 1 summarizes the features of each market and how they differ across circuits with weak and joint liability.

A TSDF's share of a given market is defined as the fraction of total trades handled by the facility, where a trade corresponds to a shipment by the generator to the TSDF for a specific waste type and an intended disposal method. For example, if the Massachusetts medical manufacturing market had 10,000 shipments of hazardous waste in 2009, and 5,000 shipments were received by a landfill in NJ, the 2009 market share of the NJ landfill in the Massachusetts medical manufacturing market is 0.5. In the absence of data on the value of trades between generators and TSDFs, the number of trades is a stronger proxy for market activity than the total quantity which is recorded in tons. Wastes are treated in various forms and limited data on waste management prices suggest a highly irregular relationship between total weight and cost of management (Agency).

NAICS codes for each firm in the Biennial Report are constructed using a range of sources. Firms are required to self-report their NAICS code when submitting the Biennial Report, Notification, Part A disclosure, or other related EPA forms. I use the modal value of the first 4 digits of the reported code to construct the firm-level NAICS code used in the market definition. I similarly use the modal value of the first 3 digits to construct markets in a robustness check.

### 4.3 Regulatory enforcement

Data on site compliance with environmental statutes is obtained from the RCRA violations module. Sites are listed in the module by their RCRA identifier with data on every inspection conducted between 1981-2017 and its outcome. 276,864 sites have listed inspections, and the average firm in our sample is evaluated 1.67 times a year and receives on average of 4.278 evaluations across the time they appear in the sample. Each inspection lists the number and type of violations found at the site, if any, and the subsequent actions taken by the firm and EPA to address the violation. I use the annual number of violations to determine whether TSDFs are coded as "clean" or "dirty" and defer discussion of the full modeling process to Section 5.1. Panel C of Table 1 describes how TSDF characteristics differ between clean and dirty firms.

### 4.4 Legal decisions

Court decisions regarding the "useful product defense" in establishing arranger liability as outlined in Section 107(a)(3) of CERCLA are manually collected from a review of 349 cases. Cases were eligible for review through the following process. First, three landmark cases on the "useful product defense" were selected: *Burlington Northern & Santa Fe Ry. v. United States*, *United States v. Aceto Agricultural Chemicals Corp* and *Cadillac Fairview/California Inc. v. United States.* Second, any cases cited by the three major rulings in passages on arranger liability were reviewed. Finally, any cases cited in relevant passages by the second round of cases were reviewed. Only cases which were decided between the passage of CERCLA in 1980 to the end of our sample in 2017 were considered.

Cases which presented a decision that hinged on the relevancy of the "useful product defense" for de-

Table 1: Summary statistics of circuit, market, and TSDF characteristics, by circuit type

| *Panel A: Circuit characteristics* | Control | Treatment |
|---|---|---|
| Number of TSDFs | 574 | 528 |
| Number of markets | 1,712 | 1,292 |
| Number of states | 18 | 17 |
| Number of trades | 2,159,771 | 1,948,057 |

| *Panel B: Market characteristics* | Control | Treatment |
|---|---|---|
| Number of TSDFs | 27.702 | 27.921 |
| | (15.743) | (17.898) |
| Number of generators | 48.162 | 84.415 |
| | (100.737) | (391.123) |
| Number of periods active | 8 | 8 |
| | (0) | (0) |
| Annual number of trades | 11.04 | 11.363 |
| | (8.026) | (9.23) |
| Fraction of trades contain priority chemicals | 0.165 | 0.204 |
| | (0.114) | (0.129) |

| *Panel C: TSDF characteristics* | Control | | Treatment | |
|---|---|---|---|---|
| | Dirty | Clean | Dirty | Clean |
| Pre-2009 market share | 0.096 | 0.069 | 0.094 | 0.071 |
| | (0.132) | (0.108) | (0.134) | (0.114) |
| Annual number of trades | 86.164 | 32.788 | 59.461 | 25.988 |
| | (167.528) | (68.558) | (94.114) | (42.857) |
| Biennial violations | 4.842 | 2.148 | 5.03 | 2.039 |
| | (9.013) | (4.78) | (9.05) | (4.539) |
| Fraction of trades in manufacturing | 0.499 | 0.387 | 0.472 | 0.374 |
| | (0.314) | (0.386) | (0.296) | (0.348) |
| Fraction of trades with government | 0.055 | 0.029 | 0.062 | 0.060 |
| | (0.171) | (0.122) | (0.162) | (0.181) |
| Number of periods active | 5.824 | 6.359 | 5.798 | 6.028 |
| | (2.417) | (2.011) | (2.368) | (2.004) |

*Notes*: This table summarizes the merged Biennial Report, judicial review and violations data used for analysis in Section IV. The following observations are excluded: markets in non-contiguous US, trades with non-NAICS matched generators, markets with only one generator and markets that are not persistent across all 14 years. Data is summarized by circuit type, where narrow refers to a weak joint liability regime and broad refers to a strong joint liability rule. Panels B and C display means with standard deviations below in parentheses. Panel C list characteristics for TSDFs, by type, that handle waste in one of the two circuit types. For example, the mean pre-2009 market share for dirty TSDFs that received trades for markets in a narrow circuit is 0.102.

termining liability were included in the final sample. These decisions analyzed the importance of intent, knowledge and control of the generator in their arrangement to dispose of hazardous material, the relevance of the original use of the material, and whether the material was a secondary or virgin product. Rulings on other facets of arranger liability, for example, whether parent corporations can be held liable as arrangers, were not included as they do not provide direct signals to the generators of interest on the probability of settlement. The final sample includes 79 federal cases: 52 cases from district courts, 27 cases tried in US Court of Appeals, and 1 case heard by the US Supreme Court. Cases from the two federal circuit courts were not included. All states are affected by at least one of the lower court decisions, except Colorado, Kansas, New Mexico, Wyoming and Louisiana. California, for example, has 19 relevant rulings.

After constructing the final sample of cases, I read through each case and coded whether the Circuit Court's decision supported the broad or narrow interpretation of arranger liability described in Section II. Any potential ambiguities in the intentions of a Circuit Court's ruling were resolved by reviewing the cases of lower district courts within the circuit and through secondary legal literature (Brown; Foy; Henson; Judy; Gray and Shimshack). Five circuits were coded as narrow and three as broad. Data from the three circuits without an any Circuit Court decisions were excluded from analysis. Panel A of Table 1 shows that the number of states and active firms are roughly balanced between the narrow and broad circuits.

# 5 Model

This paper uses a triple differences-in-differences design to capture the impact of the 2009 *Burlington Northern* ruling on the market shares of dirty firms in circuits where the joint liability was weakened. A simple double difference would compare outcomes pre- and post-2009 and between circuits with narrow and broad rulings. This specification would test a concentration hypothesis, namely whether market shares increased on average in treated circuits after the ruling. However, the goal of this analysis is not to understand whether the hazardous waste industry became more concentrated, but to determine if the share of waste allocated to dirty firms increased. Testing this hypothesis requires the addition of a third difference, whether the market share is held by a dirty or clean TSDF, to the specification.

## 5.1 TSDF reputation for environmental quality

In order to construct the third difference, I need to determine whether a TSDF is perceived as being a clean or dirty type from the perspective of the upstream generator. The generator's belief about the TSDF's type can be thought of as the reputation of the TSDF. I propose a measure of environmental quality that constitutes the TSDF's reputation and a model by which reputations are formed over time.

Recall from Section 3.1 that dirty firms have a higher expected probability of accidents and that this feature gives rise to the rank ordering of liability costs between the two types of firms, ie $L_d > L_c$. A natural object of interest for the generator then is the probability of accident from contracting with a TSDF. Formally, let there exist some threshold value $\bar{v} \geq 0$ such that the risk of accident for TSDF $i$ is defined as $Pr(v_i > \bar{v})$, where $v_i$ is the number of accidents. When $\bar{v} = 0$, the risk of accident is simply the probability that an accident occurs. In settings where accidents are common, it may be appropriate to set $\bar{v} > 0$ to ensure that the probability measure has full support. Intuitively, $\bar{v} > 0$ implies a model where the generator is only concerned about liability costs after some number of accidents.

I model the generator's beliefs regarding the risk of accident from contracting with a TSDF using a Bayesian learning processes. In this model, the generator does not know the TSDF'S true accident probability, $\pi_i$. Instead, at the end of each period $t$ the generator observes whether the TSDF's number of accidents $v_{i,t}$ exceeds the benchmark $\bar{v}$ and updates their belief regarding the TSDF's reputation. Each draw of accident outcomes is assumed to be independent and comes from a stationary Bernoulli distribution with parameter $\pi_i$. Following DeGroot, the generator's beliefs on the true distribution of accident risk is then distributed $Beta(\alpha,\beta)$ such that the conditional expected probability $p_i$ of risk from TSDF $i$ in period $t$ is

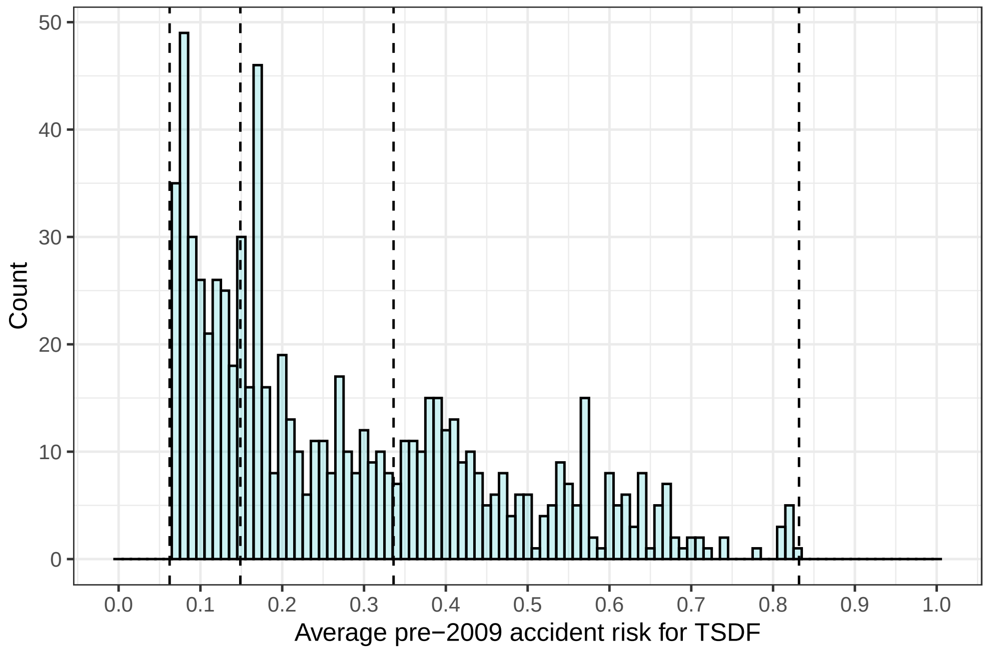
$$E[p_i|S_{it}, t] = \frac{S_{it} + \alpha}{t + \alpha + \beta}, \tag{4}$$

where $S_{it} = \sum_{\tau=1}^{t} \mathbb{1}(v_{i\tau} > \bar{v})$, and $\alpha$ and $\beta$ are parameters which determine the distribution of initial beliefs.

I set the initial distribution parameters by matching the first two moments of the empirical accident risk distribution to the first two moments of the Beta distribution (Davis; Gallagher). The empirical risk distribution is constructed from the regulatory enforcement data from the EPA which records the number of violations found during an inspection of the TSDF. Each violation is considered an "accident" and each period corresponds to the two years prior to the report cycle; for example, generators in 2003 update their belief for TSDF $i$ after observing the TSDF's number of violations from 2000-2001. The moment matching approach assumes that generators set their initial expectation of accident risk using the mean risk of accident for a TSDF. Conditional on being inspected, the probability that a TSDF has at least one violation is high. As a result, I choose $\bar{v}$ using the information set at 2001, the report cycle immediately before the beginning of our sample, and let it equal the mean number of violations between 1999-2000. I show in Figure 4 in the Appendix that the mean number of violations is near constant across report cycles over the sample period, suggesting that it is an appropriate threshold for mapping accident counts into risk.

The result of Equation (4) is a biennial panel of accident risk. In econometric specifications where "dirty"

Figure 1: Distribution of baseline TSDF accident risk




*Notes*: Each observation in this histogram corresponds to the mean, pre-*Burlington Northern*, biennial, accident risk for a TSDF. Only TSDFs used in analysis are included. Biennial accident risk for each TSDF is constructed using Bayesian learning model in Section 4. Dashed lines delineate the risk terciles.

is defined as a continuous variable, $\text{dirty}_{it}$ is simply equal to the accident risk for TSDF $i$ in report cycle $t$. In order to translate the panel of accident risk into TSDF types, I estimate the mean, pre-2009 risk for each TSDF and construct terciles from the mean baseline risk estimates; TSDFs in the first and third tercile are coded as having clean and dirty reputations, respectively. Figure 1 shows the distribution of the mean baseline risk and the cutoff points used to form each tercile. The results show significant variation in the mean probability of risk among TSDFs, and the baseline risk of accident is at least twice as large for firms with dirty rather than clean reputations.

## 5.2 Econometric specification

To estimate the impact of relaxing joint liability on the market share of the dirty firm, I estimate a triple differences-in-differences design of the following form:

$$s_{imcjt} = \beta Treat_{jct} + \gamma_t + \gamma_j + \gamma_c + \phi_{tj} + \phi_{tc} + \phi_{cj} + \epsilon_{imcjt}. \tag{5}$$

Here $s_{imcjt}$ refers to the log market share of firm $i$ in market $m$ in year $t$. The TSDF has a type $j$ which is either dirty or clean and receives waste from a market which lies in circuit $c$. $Treat_{jct}$ is an indicator for treatment that equals one if a market share-firm observation takes places after 2009, the market is in a broad circuit $c$ that had joint liability restricted by *Burlington Northern* and the firm is the dirty type $j$.

The coefficient of interest is $\beta$, which captures the treatment effect of relaxing joint liability for dirty firms in markets affected by the 2009 *Burlington Northern* ruling. I include a rich set of fixed-effects, including yearly fixed effect $\gamma_t$, a dirty firm indicator $j$ and circuit dummy $c$ which captures whether the market operates in a circuit affected by *Burlington*. In preferred specification, I include market fixed effects instead of circuit dummies. The difference in means between dirty and clean firms each year is captured by the $Year \times Dirty$, $\phi_{tj}$. This fixed effect controls for the difference in incentives faced by dirty and clean firms over time, for example changes in overall regulatory scrutiny or other EPA rulings on waste. The $Year \times Broad$ fixed effect $\phi_{tm}$, allows for firm-level market shares to vary each year between circuits with narrow and broad interpretations of arranger liability, accounting for potential circuit-level shocks. Finally the $Broad \times Dirty$ fixed effect $\phi_{cj}$ controls for the difference in mean market share for dirty firms between and circuits with narrow and broad interpretations. If circuits with broad interpretations of joint liability have other features which affect incentives for dirty firms, they will be captured by this fixed effect. All standard errors are clustered at the market level.

I also estimate a dynamic-treatment effect to construct an event study for the effect of *Burlington* over-time. The reduced form equation for the event study is estimated using

$$s_{imcjt} = \sum_{\tau=-3}^{4} \delta_\tau \mathbb{1}(t = 2009 + 2\tau) Treat_{jc} + \gamma_t + \gamma_j + \gamma_c + \phi_{tj} + \phi_{tc} + \phi_{cj} + \epsilon_{imcjt}. \tag{6}$$

where $s_{imcjt}$ is the log hazardous waste share of market $m$ by firm $i$ in year $t$. $Treat_{jc}$ is a dummy variable for whether the market is in a circuit $c$ that was affected by *Burlington Northern* and the firm's type $j$ is dirty. $\mathbb{1}(t = 2009 + 2\tau)$ indicates the market share is recorded $\tau$ cycles after the Supreme Court ruling in 2009. I omit the year 2009, so all coefficients $\delta_\tau$ measure differences in the treatment and control markets relative to the year the ruling was made. All fixed effects are defined identically to those used in Equation (4) and standard errors are clustered at the market level.

A recent literature discusses issues with identification and interpretation that may arise when the timing is used to identify treatment effects. This study uses a control group that is never treated; narrow circuits never experience further contraction (or expansion) of arranger liability and only broad circuits experience a weakening of th joint liability regime. As a result, the specifications above do not suffer from the identification issues that arise in conventional event-study designs with never-treated units (Borusyak and Jaravel) or difference-in-differences designs with staggered timing (Goodman-Bacon). Variation in outcomes is identified by firms that are either always or never treated, and not from firms that come in and out of treatment.

### 5.3 Identifying assumptions

The key assumption for this analysis is that the market shares of dirty firms in treated markets would follow a similar trajectory to those in untreated markets absent the Supreme Court ruling. Formally Equation (4) is identified if the triple interaction term $Treat_{jct}$ is independent of the error conditional on the fixed effects:

$$E[Treat_{jct}\epsilon_{imcjt}|\gamma_t + \gamma_j + \gamma_c + \phi_{tj} + \phi_{tc} + \phi_{cj}] = 0. \tag{7}$$

This assumption would be violated if, for example, there is an unobserved shock to municipal level R&D which causes a large number of firms to enter a market. Mergers, bankruptcy or other supply shocks that affect hazardous waste management prices and, in turn, contracting decisions may also lead to violations.

I take two steps to alleviate concerns surrounding the identifying assumption. First, I report an event study graph of outcomes relative to the year *Burlington Northern* decision was announced. This graph corresponds directly to estimates of $\delta_\tau$ from Equation (5) and would identify pre-trends in treatment effects prior to 2011. Because contracting decisions during 2009 are unaffected by the ruling, I take 2011 to be the reference year. Public data on hazardous waste contracts indicate that the average contract length lasts 18-24 months, suggesting that firms would not be able to shift contracting decisions until 2011 at least (Agency).

Second, we may be concerned that shocks to prices or overall market concentration will have an effect on the trajectory of the dirty firm market share. One potential solution to this concern to restrict analysis to larger markets that are less likely to see first order effects of such shocks. As a result, I report effects of the treatment using a sample that includes all markets, as well as results from a restricted sample which only includes a markets with a large number of TSDFs and generators.

## 6 Results

### 6.1 Effect of weak joint liability on waste share

Table 2 shows that weakened joint liability rules lead to a significant increase in the market share of dirty firms in treated states. Column (1) uses data from all markets in the cleaned sample described in the notes of Table 1 and estimates Equation (5). It shows that the difference in log market share between dirty and clean firms grew 0.354 (SE 0.042) points on average in treated markets after *Burlington Northern.* This effect translates to a 42.4% increase in the relative market share of dirty firms. Standard errors for all columns are clustered at the market level. The remaining columns assess the impact of the liability regime

Table 2: Impact of weakened joint liability on market shares of dirty firms

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treat | 0.354*** | 0.252*** | 0.199*** | 0.111*** |
| | (0.042) | (0.032) | (0.045) | (0.029) |
| FE | Circuit | Market | Market | Market, TSDF |
| Weighted | No | No | Yes | No |
| Markets | 3002 | 3002 | 3002 | 3002 |
| Observations | 197,957 | 197,957 | 197,957 | 197,957 |
| $R^2$ | 0.040 | 0.408 | 0.343 | 0.511 |

*Note*: This table shows the results of four separate regressions of log market share on a treatment indicator and a complete set of two and one-way fixed effects. The specification corresponds to the triple-difference outlined in Equation (4) with market fixed effects and standard errors clustered at the market level. A market is defined at the 4-digit NAICS code and state level, and an observation is a share the share of shipped hazardous waste received by a TSDF (treatment, storage, or disposal facility). All Columns are estimated from the sample described in the notes of Table 1.

change using finer fixed effects specifications. Column (2), the preferred specification, re-estimates Equation (5) with market level fixed effects and finds a 28.7% increase the relative market share of dirty firms. This estimate falls when observations are re-weighted by the number of market participants in Column (3) or when TSDF fixed effects are included in Column (4). The TSDF fixed effects are not included in the preferred specification as TSFS's may have dramatically different market shares in different markets, due to distance from the generator or industry needs. Taken together these results suggest that the market share of dirty firms increased significantly relative to clean firms after joint liability regimes were weakened, although the magnitude of this increase is sensitive to the exact specification of fixed effects.

Table 4 in the Appendix finds the weakened liability effect remains both statistically significant and large after a number of alterations. Notably, I find the results found by the preferred specification are robust to a number of alternate definitions of market share. Broadening the definition of a market to the 3-digit NAICS code by state level, which mechanically increases the number of participants in each market, only slightly decreases the magnitude of the result. I also find highly similar results when constructing market share as the share of quantities traded instead of the fraction of trades, suggesting that the market definition is effective in isolating similar types of transactions over time.

The results are also robust to different parameter specifications in the Bayesian learning model that are used to identify whether is a firm has a dirty or clean type. I relax the assumption in Equation (4) that firms operate with full information and allow them to discount past observations following the discounted learning model in Gallagher. I find discounting has very little effect on the results. The similarity of the result is unsurprising given that firms have easy access to TSDF's violation history through the EPA's ECHO database.

I also test whether the findings are sensitive to an alternate threshold value by setting $\bar{v} = 0$, which alters the construction of the risk probability; when the threshold risk is zero, generators sort TSDFs into dirty and clean categories based on the probability that they have any accidents in a given year (extensive accident margin) as opposed to an above average number of accidents (intensive margin). Lowering the threshold changes roughly a quarter of the TSDF types used in analysis and drops the point estimate to 0.095 (SE 0.029), suggesting that generators are re-allocating more waste to TSDFs that are likely to have many accidents. This difference in effect sizes is consistent with a theory model where liability costs are increasing in the number of accidents, but disposal costs are decreasing and generators trade off between these two types of costs when selecting a partner. The smaller point estimate also indicates that the preferred model of risk probability is picking up differences in TSDF types that are highly salient to firms.

## 6.2 Continuous treatment and heterogeneity

The triple-difference estimator identifies how the relative market shares shift between two different types of firms–dirty and clean. While this econometric model is helpful in understanding how weakened joint liability has affected market structure in the aggregate, it is not able to finely measure how generators trade off between expected liability and disposal costs. To better understand whether market shares grew for TSDFs with higher expected liability costs, I estimate a differences-in-differences model where the treatment varies in intensity of the TSDF's expected liability.

Specifically, I run a regression of the form

$$s_{imct} = \beta(Treat_{ct} \times Dirty_i) + \gamma_t + \gamma_m + \phi_{tc} + \epsilon_{imct}. \tag{8}$$

where $s_{imct}$ is TSDF $i$'s share of the market $m$ in year $t$. The market lies in circuit $c$ which either had joint liability weakened or maintained by *Burlington Northern*. $Treat_{ct}$ is a dummy variable that is one if the share is for a market in a circuit where joint liability regime weakened and the share is observed after the 2009 ruling. Each TSDF has a dirty score $Dirty_i$ equal to their mean pre-2009 perceived probability of accident risk such that $Dirty_i$ is continuous and varies across TSDF. I include year $\gamma_t$, circuit $\gamma_c$ and year-by-circuit $\phi_{tc}$ fixed effects. Again, preferred specifications use market instead of circuit fixed effects.

The coefficient $\beta$ captures whether TSDFs with higher perceived accident risk saw a greater change in market share after the weakening of the liability regime. The results of Equation (8) are listed in Column (2) of Table 3. Recall that the $Dirty_i$ is the mean baseline probability that the TSDF has an above average number of violations which ranges from 0-1. The coefficient in Column (2) indicates a 10 percentage point

Table 3: Heterogeneous treatment effect of weakened joint liability on market share of dirty firms

| | (1) | (2) | (3) |
|---|---|---|---|
| Treat × $\text{Dirty}_i$ | 0.738*** | 0.496*** | 1.278*** |
| | (0.050) | (0.038) | (0.151) |
| Treat × $\text{Dirty}_i^2$ | | | −0.870*** |
| | | | (0.163) |
| FE | Circuit | Market | Market |
| Markets | 3004 | 3004 | 3004 |
| Observations | 267,753 | 267,753 | 267,753 |
| $R^2$ | 0.026 | 0.398 | 0.398 |

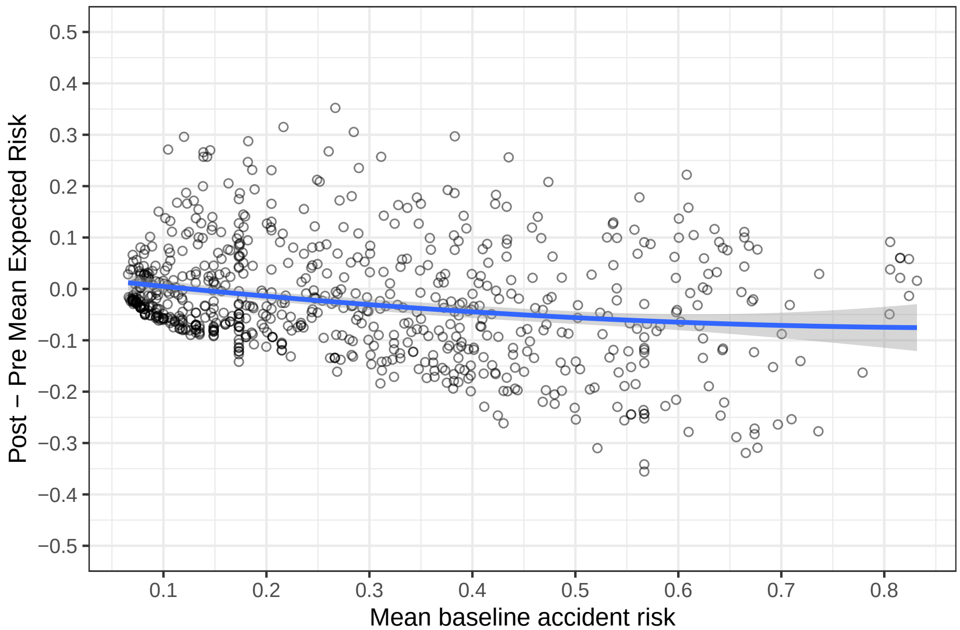
*Note*: This table shows the results of three separate regressions of log market share on a treatment indicator and a complete set of two and one-way fixed effects. All specifications have clustered standard errors at the market level. The specification corresponds to the triple-difference outlined in Equation (8). Columns (1)-(3) define Dirty as the mean pre-2009 probability of having an above average number of violations, where probability of above average violations is generated for each TSDF every year according to the Bayesian learning model in Equation (4).

increase in the perceived probability of risk led to a .0496 point rise in log market share. Put differently, a 10 percentage point increase in expected probability of risk led market shares to increase by 5.1% after the regime change, suggesting that gains from the weak joint liability rule are concentrated in the dirtiest TSDFs. I also estimate a regression in Column (3) which includes a treatment dummy interacted with a squared dirty score to estimate the curvature of the relationship between baseline risk probability and market share. The coefficient on the squared interaction term is negative which indicates additional market share gains from risk are limited.

The continuous measure of dirtiness used in Columns (1)-(3) of Table 3 and the binary types are all fixed across time, which may be a problematic assumption if TSDFs change their level of risky behavior in response to the Supreme Court ruling. In the scenario where firms change their behavior, the time invariant Dirty score will misclassify the risk from transacting with a TSDF and both estimators may be biased if firms selectively update their behavior. I can directly test if firms' expected risk probabilities change over time by comparing the average pre-2009 probability to the post-2009 probability for each firm. Figure 2 plots the difference in post and pre-expected accident probability for all TSDFs used in analysis against their mean baseline accident probability. If firms strategically update their behavior after the ruling, we would expect the change in risk to be correlated with their baseline mean probability.

The blue line, a second order quadratic polynomial fitted to the data, suggests there is very limited evidence for a relationship between baseline dirtiness and the change in accident probability. The fitted line is nearly flat at zero, where there is a large mass of points Furthermore we can directly count the number

Figure 2: Change in TSDF accident risk, pre- and post-*Burlington Northern*




*Notes*: This figure plots the difference in mean, biennial, accident risk pre- and post-*Burlington Northern* for each TSDF used in the double and triple-difference estimators. The x-axis lists the mean baseline accident probability. Biennial accident risk for each TSDF is constructed using Bayesian learning model in Section 4.

of firms whose mean expected accident probability changed so significantly as to change their type, ie those firms that would be misclassified in the triple-difference estimator. I find that only 0.7% of TSDFs switch from clean to dirty in the post period, and zero firms switch from being dirty to being clean. Taken together, these results imply that firms are not strategically updating their accident behavior and that our results are unlikely to ignore variation in generator beliefs from including time invariant dirty scores.

## 6.3 Lagged treatment effects

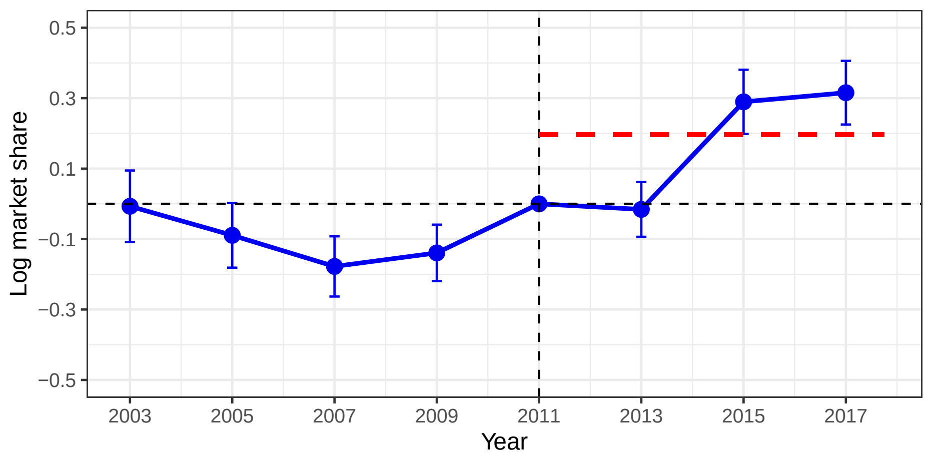
I plot event study graphs following Equation (6) for the triple-difference and double-difference estimators to estimate how the treatment effect evolves over the sample period. Both the triple-difference in Panel A of Figure 3 and the double-difference in Panel B show a similar trend over time: largely flat negative pre-trends that become positive after 2013.

Prior to the passage of *Burlington Northern* in 2009, coefficients mostly negative and are not trending, particularly in the double-difference estimator. The negative coefficient implies that the market share of dirty firms relative to clean firms is smaller in markets with strong joint liability rules.The sign on these coefficients is consistent with the theory that TSDFs are penalized for being dirty when joint liability passes liability costs from the TSDF to the generator; coefficients that are statistically indistinguishable from zero or positive could suggest that generators are not attentive to joint liability rules. Fairly stable pre-trends are suggestive that circuits with broad and narrow interpretations on joint liability are otherwise similar.

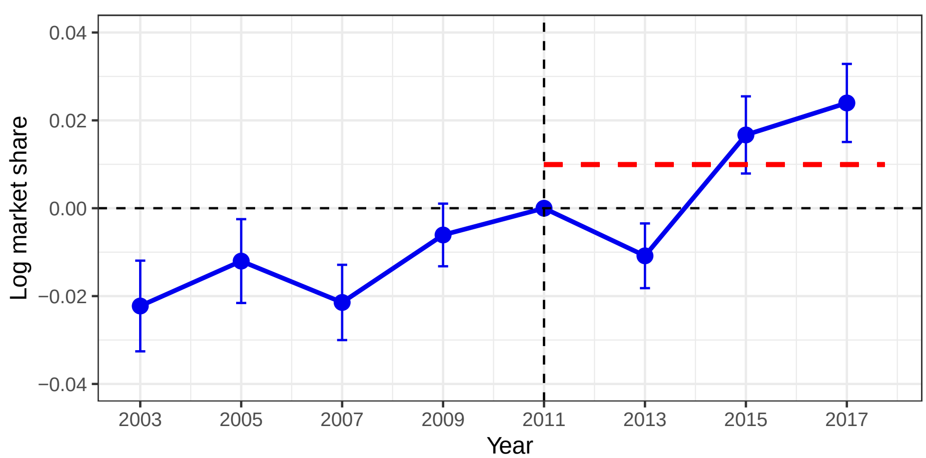
Interestingly, the relative market share of dirty TSDFs in treated circuits only begins to rise in 2015 when it jumps to 35% in the triple-difference. This is a significant and large shift in overall market composition that persists in 2015, and in the double-difference the effect even seems to slightly increase. The immediate interpretation of this figure is that strong joint liability rules were preventing over a third of the trades from going to dirty TSDFs, an estimate that is larger than the average treatment effects found in Tables **??** and 3 that also average across the zero treatment effects in 2011 and 2013.

Figure 3: Estimates of the effect of joint liability on market share

(a) Triple difference




(b) Double difference




*Notes*: This figure plots the effect of the relaxed joint liability ruling on market share for dirty firms over time, relative to the reference year. Panel A and Panel B show different results for the triple and double-difference estimators, respectively. Each point on the graph plots a coefficient $\delta_\tau$ from Equation (6) and dashed lines correspond to 95% confidence intervals clustered at the market (state and 4-digit NAICS code) level. The dashed, red horizontal line indicates the average treatment effect.

The event study suggests that generators do not immediately respond to the weak joint liability regime. The lag in treatment effects can be explained if we consider that generators and TSDFs enter long contracts, although I cannot directly confirm this hypothesis because we do not observe when contracts started or their official length in the data. If I use the average length of US government contracts with hazardous waste firms (18-24 months) (Agency), I can interpret Figure 3 as suggesting that *Burlington Northern* decreased market shares in the second round of available contracting decisions. In addition to long contracts, there are a number of reasons why generators may not have changed their behavior immediately. Generators may have waited to see how *Burlington* was interpreted by lower courts, or the immediate economic relevance of the decision may not have been salient.

# 7 Conclusion

While policy interventions have often focused on how firms can uphold a standard of care through investments in their own production technologies, this paper argues that contracting decisions throughout a firm's supply chain also represent meaningful investments in environmental quality. A simple model shows that joint liability is one reform that incentivizes investments along this margin; by shifting some fraction of the expected liability of a firm's partner into the firm's own profit function, joint liability can force the firm to trade-off greater cost savings with environmental quality and drive changes in the composition of the partner's industry. Using a natural experiment created by the resolution of a thirty year circuit split, I show that weakened joint liability rules increase the market concentration of dirty relative to clean hazardous waste facilities by 28.7%. These empirical results suggest that joint liability reforms can increase the overall level of care taken by a supply chain.

This paper leaves open a number of avenues for further research. First, the triple-difference estimator explores how the gap between mean market share increases between dirty and clean firms within treated markets, however it does not explore the possibility for substitution in production across markets. If firms operate multiple sites, they may shift production from areas of strict joint liability to those with weak liability rules. Data on multi-site property ownership is available and could be incorporated in future work to identify cross-site substitution patterns. Second, this paper takes the dirty firm's market share as a measure of negative environmental quality. A further step would be to estimate the impact of a change in joint liability regime directly to observed environmental harms (e.g. waste spills) and whether changes in market share explain variation in environmental outcomes. Public data on hazardous waste contamination could be incorporated into the current analysis to estimate an instrumental variables model of joint liability on damages. Finally, joint and several liability encourages firms to contract with partners with deep pockets.

A generator level analysis of partner decisions that incorporates the relative size of the two partners would be able to disentangle differing effects of joint and several liability for small and large firms.

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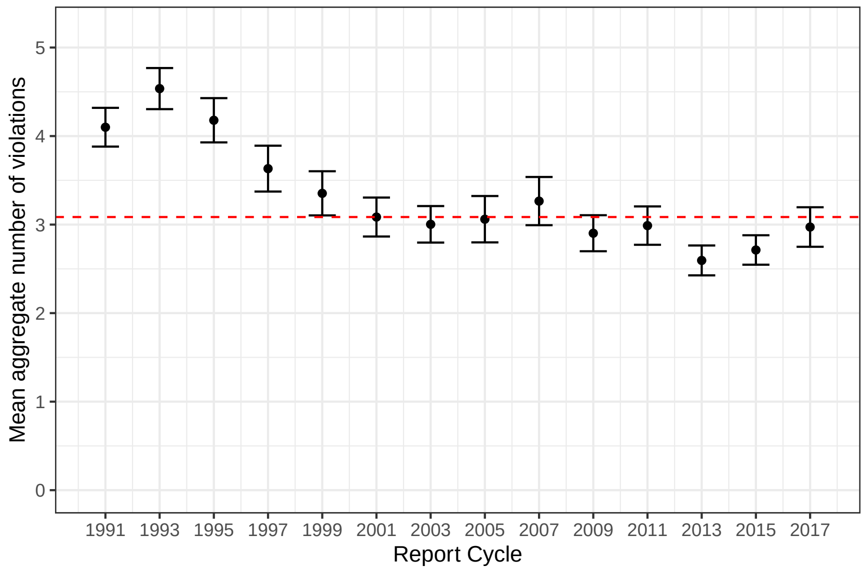
# Appendix

## A1 Bayesian learning model

Figure 4: Mean aggregate violations, 1991-2017




*Notes*: This figure plots the average number of violations found in the two years prior to the listed report cycle. The dashed horizontal line indicates the threshold value for accident risk $\bar{v}$, which is set to the mean number of violations found in 1999-2000. Bars around the mean refer to standard errors.

## A2 Robustness checks

The significance and general magnitude of effect found by the triple-difference estimator is consistent across a number of robustness checks.

### A2.1 Market selection

Panel A of Table 4 reports results from the preferred specification after certain markets are excluded from analysis. Column (1) restricts the sample to include markets with at least the median number of generators and TSDFs. This condition effectively trims the sample to only include the largest markets by number of participants and yields similar results to the base specification. This result suggests that the significance of the results are unlikely to be driven by thinner markets where market share is more likely to be affected by idiosyncratic features.

Column (2) examines whether treatment effects are concentrated within certain industries, specifically the hazardous waste industry itself. While TSDFs receive and treat waste from nearly all other markets, waste remediation, disposal and treatment firms also generate hazardous materials in the process of waste management. Often, these firms ship wastes off-site to other TSDFs. Since generators hazardous waste markets are most likely to be subject to potentially confounding changes in hazardous waste policy, Column (2) excludes hazardous waste markets from the sample and finds highly similar coefficient on the triple-difference term to the base specification.

Column (3) tests whether results are sensitive to the inclusion of markets in California, the state with the largest number of markets by far.

### A2.2 TSDF selection

Column (4) restricts analysis to the market shares of TSDFs that are active in all eight report cycles. These TSDFs are more likely to be downstream waste disposers as we classically think of them (eg landfills) than other kinds of firms such as recyclers or hazardous material re-sellers that contract with hazardous waste generators. The coefficient is half the size of the coefficient in our base specification, which is consistent with the theory that *Burlington Northern* relaxed joint liability most explicitly for TSDFs that do not "intend" to dispose of waste.

Table 4: Robustness checks for triple difference

*Panel A: Market and TSDF selection*

| | Thick markets (1) | No waste markets (2) | No CA markets (3) | TSDF in all cycles (4) |
|---|---|---|---|---|
| Treat | 0.230*** | 0.261*** | 0.252*** | 0.123*** |
| | (0.050) | (0.033) | (0.037) | (0.035) |
| Markets | 591 | 2900 | 2770 | 3002 |
| Observations | 83,236 | 186,920 | 169,894 | 172,467 |
| $R^2$ | 0.214 | 0.395 | 0.400 | 0.411 |

*Panel B: Outcome, market and dirty definition*

| | Level trade share (5) | Quantity share (6) | 3-digit NAICS (7) | $\bar{v} = 0$ (8) | Discounting (9) |
|---|---|---|---|---|---|
| Treat | 0.020*** | 0.237*** | 0.207*** | 0.095*** | 0.211*** |
| | (0.003) | (0.067) | (0.040) | (0.029) | (0.028) |
| Markets | 3002 | 3002 | 1619 | 3003 | 3004 |
| Observations | 197,957 | 197,943 | 142,302 | 201,452 | 184,450 |
| $R^2$ | 0.244 | 0.247 | 0.383 | 0.395 | 0.401 |

*Note*: This table shows the results of robustness checks for the results in Table 2. All regressions follow the preferred econometric specification in Column (2) of Table 2 with slight differences. Columns (1-3) restrict the kinds of markets used in analysis, where (1) only includes markets with above median number of generators and TSDFs, (2) drops any market with NAICS codes beginning in 56 to remove markets where generators are also in the hazardous waste industry, and (3) drops all markets in CA. Column (4) only keeps market shares for TSDFs that have listed contracts in all eight report cycles. Columns (5-6) re-run the preferred specification but use different definitions of market share: the level trade share instead of log and the share of quantity shipped, instead of share of trades. Column (7) defines markets using three-digit NAICS code as a proxy for industry instead of the four-digit code used in the main results. Columns (8-9) change the construction of the dirty dummy variable described in Section 5.1. Column (8) uses terciles constructed from mean baseline risk probabilities where $\bar{v} = 0$, and Column (9) allow generators to discount past beliefs by setting $\delta = 0.5$.

### A2.3 Market share definition

Panel B shows that the findings are robust to alternative constructions of the key variables. Column (6) constructs the market share to be the fraction of tons shipped in a market that is received by the TSDF, instead of the fraction of trades listed within a market. The coefficient on Treat is strikingly similar to preferred specification, suggesting that materials traded within a market are relatively homogeneous. Column (7) defines a market at the 3-digit NAICS code by state level instead of using the 4-digit code to identify the relevant industry and finds fairly similar results.

### A2.4 TSDF type determination

Columns (8) and (9) alter how the TSDF type is constructed. In the former, the threshold for accident risk is set to 0 such that TSDF type is determined by the probability that a firm has *an* accident, as opposed to a relatively high number of accidents. In general, setting $\bar{v} = 0$ forces the firm to update their beliefs regarding the intensive margin (the TSDF's decision to violate) rather than the extensive margin (the number of violations). Consider the case of a TSDF that routinely commits one violation per inspection; the probability that this firm has at least one violation is near unity, but the probability that this firm has an above average number of violations (roughly 3) is zero. Column (8) finds that market share of dirty TSDFs increases by 9.97% relative to clean TSDFS in markets where joint liability was weakened by *Burlington Northern*, a marked decreased from the 24% found in the preferred specification.

The model in Column (9) relaxes the assumption in Equation (4) that agents weight observations from each period equally. Following Gallagher, I allow generators to discount observations from older periods in constructing their beliefs by setting $\delta = 0.5$. The results are very close to those found in the basic model in Column (2) of Table 2.