

Insolvency and Incentives for Efficient Care*

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Abstract

Limited liability has long been recognized to incentivize owners of firms near bankruptcy to take suboptimal care to prevent harm to third parties. I use violations of the Clean Water Act to study these incentives. I show that as firms approach bankruptcy (as measured by their credit ratings) they indeed become more likely to violate laws designed to protect third parties. A move from the best to worst credit rating is associated with a seven-fold increase in violation frequency. These results are robust to time and company fixed effects, an instrumental variables strategy, and controls for company liquidity, leverage and profitability. I also propose a policy solution that can improve incentives for firms near bankruptcy. This proposal calls for agencies such as the EPA to increase monitoring of firms closer to insolvency. This can be implemented without legislative changes, and without disrupting foundations of corporate law such as limited liability.

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1 Introduction

The priority system for claims in a corporate bankruptcy comes with a paradox. If a firm incurs tort or other civil liability the day before it enters bankruptcy, that liability will be afforded low priority in bankruptcy. Frequently it will be mostly or totally discharged. Yet, if the firm commits the same harmful action one day after entering bankruptcy, the opposite result holds. The claim will be a high priority administrative expense and will likely be paid in full. Prudent bystanders are thus put on notice: if they plan to be run over by the delivery truck of a financially precarious firm, they should do so after the firm's bankruptcy filing, not before. If they fail to do so, it is not the place of the bankruptcy court to make up for their poorly chosen timing. Chief Justice Warren remarked on the strangeness of this result in his dissent in *Reading Co. v. Brown* (391 U.S. 1968): “after today's decision, the status of a tort claimant depends entirely upon whether he is fortunate enough to have been injured after rather than before a [bankruptcy] receiver has been appointed.”¹

This paradox and similar issues facing companies near insolvency have attracted substantial attention in legal and economic literature. Posner (1976) discusses how limited liability can incentivize firms near insolvency to take inefficiently little care to protect third parties. The inefficiencies stem from two facts. First, if a firm becomes insolvent, its owners will not need to pay the full cost of harms they cause. The firm becomes “judgment proof.” Second, it is not feasible for a firm to contract in advance with, for instance, each bystander whom they may harm through tortious conduct. These parties thus represent “involuntary creditors,” since they end up with claims stemming from activities that they never bargained for. Schwartz (1981) discusses how the priority for secured credit in bankruptcy can exacerbate this issue. In the absence of this priority, secured creditors would have incentives to monitor firms they lend to and enforce at least somewhat more efficient precautions.

Over the past four decades, theorists have charted variations on these basic scenarios. They have explored the efficiency implications of different nuances to the relationships between the concerned parties and have considered changes to a host of legal rules with the hopes of improving efficiency.²

¹Warren's proposed solution to the paradox was to assign the same low priority to the tort claimant in either situation.

²Section 2 reviews this literature in greater detail.

Yet, there has been far less empirical evidence available to shed light on precisely if and how firms' activities are affected by the prospects of becoming judgment proof. A need for better empirical evidence regarding these effects has been noted in the literature (Hansmann and Kraakman, 1991).

This paper seeks to remedy this gap in the empirical literature. Theory predicts that as a firm approaches bankruptcy, its incentives to take sub-optimal care to prevent harm to others should increase. I present here the first investigation to document these effects in practice.³ Nothing in my tests suggests these results stem from firm owners maliciously scheming to take advantage of limited liability by harming others and getting away from it. Instead, it is more likely, and still congruent with theory, that this is simply a result of exigencies building up amongst firms in distress, and the relative priority for avoiding harm to third parties dropping lower than it would be if owners actively worried about losing their homes, savings accounts, etc. in the event they went out of business with unpaid civil liabilities.

To study these effects, I take as a case study civil violations by corporations under the National Pollutant Discharge Elimination System (NPDES) system, established pursuant to the Clean Water Act (CWA) (86 Stat. 816) and enforced by the U.S. Environmental Protection Agency (EPA) and its partner state agencies. From this data, I build a panel that observes 627 firms on a quarterly basis over twenty-two years, from 1995 to 2016. I show that when considering a given firm at multiple points in time, during periods in which the firm is more likely to become bankrupt (as measured by credit ratings on its bonds), it is also more likely to violate NPDES regulations designed to protect the health of other parties. These effects are substantial. For instance, a firm moving from the best to worst credit rating in my data is associated with a seven-fold increase in the risk that it will violate certain NPDES provisions.

These findings are exactly what theory on the incentive effects of limited liability would predict. At the same time, my empirical specifications do not amount to a direct "causal" test for the impact of limited liability. They do not, for example, identify an instance of firms somehow assigned at random or quasi-random to be governed by limited liability or not. As such, are these findings actually informative regarding the existence and magnitude of the effects of limited liability on companies near insolvency?

To build the case that the findings I present are strong, even if not definitive, evidence of the effects

³Past studies have examined whether other financial metrics, such as profitability, are predictive of harm firms cause to third parties. But, these metrics are at best roughly correlated with probability of bankruptcy. Section 2 discusses empirical work related to this paper.

of limited liability on firm behavior, I consider in turn a host of other mechanisms that might explain my findings. I show that none of these alternatives can account for my observation that firms consistently reduce the levels of care they take to prevent harm to third parties as they move closer to insolvency.

Do firms nearing bankruptcy reduce efforts to prevent harm to third parties simply because they cannot afford to prevent such harm? I show that controlling for the liquid funds firms have available does nothing to reduce the association between the risks of bankruptcy and harm to third parties. Does poor management cause firms to both approach bankruptcy and increase harm to third parties? I show that controlling for firm profitability and stock returns likewise brings no significant reduction on my key results. Do changes in leverage and the incentives for risk-taking this creates (Jensen and Meckling, 1976) explain my findings? Controlling for firm leverage also leaves the key results unchanged.

Are there more difficult to control for aspects of firms that could explain the association between the risk of bankruptcy and of harm to third parties? Perhaps changes in firm management and the risk preferences of managers could explain the association. This could occur, for instance, if risk-preferring managers are more likely to lead their companies near bankruptcy and to hazard harm to third parties.⁴

To address this possibility, I devise an instrumental variables (IV) strategy to predict firm credit ratings based on changes in macroeconomic conditions (such as interest rates and the price of oil) that differentially affect specific industries (such as manufacturing, transportation, or mining). This strategy thus isolates variation in firms' probabilities of bankruptcy based on factors that are outside of their control. I show that firms' risks of bankruptcy remain strongly predictive of their likelihoods of violating NPDES provisions even under this IV formulation. This further suggests that changes in risk-preferences, skill, or similar aspects of firm management cannot explain my results.

As a final check, I compare my results with those from the one other published study that has investigated bankruptcy risk as a predictor of harm to third parties. Feinstein (1989) considers the likelihood of nuclear power plants to violate safety regulations as a function of their bankruptcy risk. Unlike the firms in my sample, all of those studied by Feinstein are required to carry third-party liability insurance to cover damages that would otherwise be discharged in bankruptcy. And, critically, under

⁴Existing evidence documents that CEOs carry pre-existing risk preferences that influence the strategies they adopt (Bernile et al., 2017).

these conditions Feinstein finds no association between bankruptcy risk and harm to third parties.

In other words, in a situation in which a party (the insurer) will bear liability in the event of a firm's insolvency,⁵ the association between the risk of bankruptcy and harm to third parties disappears. This further suggests that the results that I find are not being driven by some more general association between financial distress and harm to third parties.

Having established the robustness of this core finding, I also consider whether different types of firms respond differently to the incentive effects of limited liability and proximity to insolvency. Interestingly, I find no significant differences between public vs. private firms. By construction of my study, however, all firms I examine issue public debt. Thus, even those firms without public equity are generally not representative of small, closely held companies, and may well be quite similar in management to firms with public equity. I also do not find significant differences for firms with different amounts of unsecured debt, which likely reflects the limited ability of unsecured creditors to exercise oversight over borrowers.

Beyond these empirical findings, this paper makes several theoretical contributions. While my results are in line with past predictions regarding the incentives of firm owners and creditors, much less attention has been paid to the incentives of firm managers. Managers, particularly of public firms, may have significant autonomy from owners. Are my findings surprising given manager incentives? I show that they are not. In particular, I extend the theoretical literature by showing that manager incentives, particularly given the operation of bankruptcy law, are likely to align with firm owners to favor strategies that increase risk to third parties as firms near insolvency.

Past theoretical work on limited liability has suggested dramatic interventions to promote more socially efficient levels of care.⁶ Though each proposal has certain advantages, they may also be difficult, costly, and disruptive to implement (Grundfest, 1992). In place of more drastic proposals, and in response to the evidence that I document that proximity to bankruptcy weakens incentives for firm owners to take efficient levels of care, I offer a relatively simple and easy to implement policy response. My proposal is based on the fact that a positive probability of insolvency lowers the expected cost of any

⁵And all but certainly these insurers have some ability to impact the behavior of the firms they insure.

⁶These proposals have included imposing liability on shareholders of insolvent firms (Hansmann and Kraakman, 1991), reducing the priority of secured debt in bankruptcy (Segerson, 1993), and other legal changes. I discuss these in greater detail in Section 2.

liability to owners of a firm. Provided that penalties are set efficiently for firms remote from bankruptcy,⁷ then if expected penalties are lowered by the prospect of insolvency, an incentive for inefficient levels of care is all but guaranteed.

Efficient incentives can be restored, however, if monitoring agencies such as the EPA increase the probability of detecting violations by firms near bankruptcy. Heightened detection probabilities offset the decreased likelihood, stemming from limited liability, that firm owners will be liable to pay penalties.⁸ Where enforcement levels are already at or near optimum for firms far from bankruptcy, this solution can directly improve social welfare. Where enforcement levels are significantly below optimal, focusing enforcement on firms near bankruptcy will still frequently result in the greatest marginal return on enforcement expenditures, although that outcome is no longer guaranteed in every situation.

The remainder of this paper proceeds as follows. Section 2 surveys prior literature. Section 3 discusses the theory of manager incentives. Section 4 discusses the data I use. Section 5 presents empirical results. Section 6 discusses policy recommendations and Section 7 offers concluding remarks.

2 Prior Literature

The analyses in this paper relate to a robust, though mostly theoretical debate within the academic literature that has spanned the past four decades. The debate has focused on several questions. First, do firm owners and creditors seek to use limited liability and priority for secured creditors to avoid paying for harms to third parties? Or are there other forces that would constrain their incentive or ability to do so? Second, if owners and creditors do have the ability and incentive to avoid liability in this way, does this cause them to take inefficient levels of care? Finally, if yes to these questions, what legal changes could create more efficient incentives for owners of firms near insolvency?

Key theoretical works arguing for the existence of incentives to take inefficient care because of the operation of limited liability and the low priority for claims of involuntary creditors in bankruptcy include Posner (1976), LoPucki (1996), Bebchuk and Fried (1995), and Hansmann and Kraakman

⁷I also consider variations in which penalties are inefficiently low or high for firms remote from bankruptcy.

⁸This proposal bears similarities the CAMELS system of bank inspections used by federal regulators. It also bears similarities to proposals by Filer and Golbe (2003) and Earnhart and Segerson (2012) that suggest monitoring firms based on their profitability or liquidity. In Section 6 I discuss ways in which my proposals are similar to these existing policies and proposals as well as unique contributions my proposals make.

(1991). Prominent works asserting that such incentive effects are over-stated include White (1998), Hill (2001), and Schwarcz (1997). The major solutions suggested (and in turn questioned) in the theoretical literature have included requiring firms to post bonds to cover harms to third parties (Posner, 1976), imposing liability for shareholders of firms (Hansmann and Kraakman, 1991), mandating liability insurance (Shavell, 1984b,a), increasing the bankruptcy priority of involuntary claims (Segerson, 1993; Che and Spier, 2008), regulatory supervision to directly enforce efficient levels of care (Shavell, 1984b), minimum capital requirements to reduce the likelihood of insolvency (Shavell, 2005; Beard, 1990), and adjustments to standards of care (e.g. strict liability, negligence, gross-negligence), (Summers, 1983; Pitchford, 1995; Lewis and Sappington, 2001; Ganuza and Gomez, 2008).

The empirical work on this topic has been more limited. To date, no study has shown a direct relationship between a firm's risk of bankruptcy and its likelihood to harm third parties. Much of the existing research has focused on investigating whether firms take steps to increase the extent to which limited liability enables them to avoid paying damages to third parties. Ringleb and Wiggins (1990) provide evidence that industries more likely to generate liability to their employees for carcinogenic exposure saw an increase in the number of small (and thus more likely to be judgment-proof) firms.

White (1998) and Lawton and Oswald (2008) offer counterpoints of sorts to Ringleb and Wiggins (1990), though with very small samples and very informal statistical tools. Listokin (2008) shows that firms in industries that are more susceptible to tort liabilities do not have more secured debt than firms in other industries. This suggests they may not be using secured debt to avoid liability to third parties.

Another strain of literature examines whether financial characteristics of firms predict risks that can externalize harms to third parties.⁹ Much of this has focused on whether more highly leveraged firms risk harm to third parties more, based on the theoretical predictions in Jensen and Meckling (1976). Dionne et al. (1997) investigate whether airlines with higher debt to equity ratios are more likely to be involved in accidents, as well as whether those with negative equity, from an accounting standpoint, are more likely to have accidents.¹⁰ Ohlogge (2017) uses time and company fixed effects along with an instrumental variables strategy to demonstrate that banks with higher levels of leverage systematically

⁹Other studies, such as Morantz (2013), look at whether non-financial factors like union membership impact risk of harms by corporations.

¹⁰The study is cross-sectional, thus employing no company fixed effects or other techniques to bolster causal inference from its associations.

make riskier investments which then can externalize harm to third parties when they perform poorly.

Rose (1990) considers a panel of thirty five airlines and shows using company fixed effects that less profitable airlines are more likely to violate safety rules. Rose (1990) discusses the notion that profitability may be a proxy for risk of bankruptcy, though it would seem a relatively rough one at that.¹¹ Earnhart and Segerson (2012) look at companies' ratios of current assets to current liabilities (the "current ratio"),¹² and find that this ratio has no power to predict the likelihood firms will violate EPA regulations or the effectiveness of EPA enforcement actions in deterring violations.¹³

The study that is methodologically closest to this one is Feinstein (1989), which models the probability of safety violations by nuclear power plants as a function of their credit ratings. A critical and fortunate difference compared to this current study is that the nuclear plants are all required to be heavily insured. Therefore losses they suffer from liability will not fall on involuntary creditors but instead on the insurers.¹⁴ Since all of the parties who will bear losses also have some ability to influence the power plants' operations, it is perhaps not surprising that Feinstein (1989) finds no connection between likelihood of bankruptcy and of safety violations. This result is informative when contrasted with the results in this study, since the firms I study do not carry third-party liability insurance. In sum, while past empirical studies have generated interesting findings that relate to the topics addressed in this study, none so far has shown rigorous statistical evidence for a systematic relationship between risk of bankruptcy and likelihood of externalizing harms to third parties.

3 Theoretical Background

Prior theory has focused on incentives that firm owners and creditors face to take inefficiently low levels of care as firms approach bankruptcy. If managers have significantly different incentives, and

¹¹Many firms remain unprofitable for significant periods of time without entering bankruptcy. Firms pursuing high risk strategies can have high profits yet still be at substantial risk of bankruptcy. In my data, there is almost no correlation between bankruptcy risk and profitability. This result is not overly surprising. It is easy to think of firms that are very profitable but at high risk of bankruptcy (e.g. investment banks), as well as firms with low profits and low risks of bankruptcy (e.g. Amazon, for most of its history, Uber, many public utilities, and so on).

¹²Earnhart and Segerson (2012) suggest that this ratio may be correlated with risk of bankruptcy. This is an unconventional assertion as typically the current ratio is considered a metric of liquidity. In my data, I find no correlation between current ratios and risks of bankruptcy.

¹³Many other studies conduct analyses similar to those in Rose (1990) and Earnhart and Segerson (2012), investigating the relationship between financial measures, such as profitability or liquidity, and the likelihood of violating safety or other regulatory provisions. The empirical methods in these other studies tend to be considerably less robust than those in Rose (1990) and Earnhart and Segerson (2012). As such, it is unclear what conclusions can be drawn from their findings, and discussion of them is omitted for brevity.

¹⁴Losses may potentially also fall on debt and equity holders, in the event of higher premia from the insurers.

if they can act on those incentives, then theoretical predictions about incentives of owners may be of limited relevance. And, if this is true, the empirical findings in this paper may seem less plausible.

Managers may be more risk averse than owners or creditors since they cannot easily diversify away the risk of losing their corporate offices.¹⁵ Precautions to avoid liability to third parties are essentially an insurance measure and thus may be favored by managers more than by firm owners. Nevertheless, there are solid theoretical reasons for managers to still largely share the incentives of firm owners and creditors to reduce efforts to prevent harm to third parties as firms near bankruptcy.

Suppose first that a firm has the option to spend \$1 on precautionary measures that will prevent \$2 in expected harms to third parties. Thus, this is a socially efficient precaution to take. Suppose that it is also legally mandated, with a fine of F imposed on firms caught not taking the precaution. One year from now, any failure to take the precaution will be detected with probability P_D .

The firm is in a precarious financial condition. If the firm spends the \$1 on the precautionary measure, the managers believe the probability of solvency in one year is P_S . If the firm does not spend \$1 on prevention, it can direct this money towards increasing profitability, e.g. by purchasing new equipment. This will increase the probability of remaining solvent by δ . If the firm is caught not taking the precaution and is assessed the fine F , it will be forced into insolvency for certain. Finally, for simplicity, assume the probabilities of bankruptcy and of the fine being assessed are independent.

If the firm takes the precaution, its probability of solvency is P_S . If the firm does not take the precaution, its probability of solvency is $(P_S + \delta) * (1 - P_D)$. In other words, the firm has an added δ probability of remaining solvent from the cost savings of not taking the precaution, but this will only help the firm in the event that the violation is not detected, which has probability of $1 - P_D$. Thus, for firm managers who wish only to maximize the likelihood of the firm remaining solvent, it will be efficient *not* to take the precautionary measure whenever:

$$(P_S + \delta) * (1 - P_D) > P_S \Leftrightarrow \delta > \frac{P_S P_D}{1 - P_D} \quad (1)$$

To give a specific example, suppose the probability of solvency is 80%, and the probability of detection is 10%.¹⁶ As long as cost savings from not taking the precaution will increase the probability of

¹⁵Managers will also generally enjoy less upside benefit from an outcome with high firm profits.

¹⁶Perhaps the fine in this scenario would be set to \$20 to generate efficient incentives for firms not close to bankruptcy.

solvency by at least 8.9%, it will be optimal for managers to not take the precaution.

This scenario is obviously very simple, and it could be made more realistic in countless ways.¹⁷ None of these would alter the fundamental premise of the analysis here which is that, under a set of relatively reasonable assumptions, it may be optimal for firm managers to take socially inefficient care, even if the only incentive of those managers is to minimize the likelihood of bankruptcy.

Of course, in Equation 1, if $\delta < \frac{P_S P_D}{1 - P_D}$ a manager whose only interest is to minimize bankruptcy risk will prefer to take the precaution. Yet, in many scenarios, the preference may be small, and thus relatively easy for firm owners to overcome. Similarly, to the extent that managers own stocks or are compensated with options - their incentives will align more closely with the firm's owners. Serious conflicts would arise only in situations where managers have a very strong preference for taking the precaution. Even here, owners may still at times prevail in imposing their will on managers.

Suppose next that managers have more nuanced interests. Their first preference is to avoid bankruptcy. But, in the event of bankruptcy, they would like to maximize the chances of reorganization, rather than liquidation. In this case, their incentive to avoid efficient care is likely to be stronger.

Any penalties assessed for not taking the precaution pre-bankruptcy will have low priority in bankruptcy and thus will be significantly discharged.¹⁸ Even to the extent that they are not, they would be converted into an equity or other low-priority claim on the reorganized entity. As such they would not significantly impair the firm's profitability and thus the viability of a reorganization.¹⁹ Thus, pre-bankruptcy penalties do little to deter managers who hope, as a second choice, to see the firm reorganized.

By contrast, there are many plausible scenarios in which managers will see an increased likelihood of reorganization by diverting funds away from precautions and towards other purposes. Consider an investment in capital equipment. This will presumably increase firm profitability. Perhaps more importantly, the equipment would likely sell at a steep discount in a liquidation. The new equipment thus increases the difference between the firm's value in reorganization and in liquidation. In so doing, it increases the probability of reorganization. Similar reasoning applies to many other expenditures.²⁰

¹⁷For instance, the timing of the detection could be random, the amount of harm caused and/or the amount of the fine could vary along a probability distribution, or many other features.

¹⁸I assume that in the event that the firm enters bankruptcy, the trustee will begin taking the precaution to prevent harm to third parties, as penalties will now be administrative expenses. This assumption, however, has little impact on the results of this modeling exercise.

¹⁹Indeed, this is much the purpose of reorganization - to write down obligations to levels needed to enable the firm to operate profitably.

²⁰For instance, managers could retain key personnel by paying them more, or maintain better relations with suppliers or creditors by

Thus, by considering managers' incentives, particularly as shaped by the bankruptcy code, it is evident that under a wide range of scenarios, managers of firms near insolvency will share with owners a preference for socially inefficient levels of care. In many other cases, managers will be close to indifferent, and thus will not be a significant constraint on the incentives of firm owners to take socially inefficient care. As such, empirical findings linking risk of bankruptcy to risk of harm to third parties are congruent with theoretical incentives for firm owners, creditors, and managers alike.

4 Data

4.1 Illegal Toxic Chemical Discharge Data

The data at the core of this study is available as a result of provisions in the 1972 Clean Water Act (86 Stat. 816). The Act requires companies that discharge wastewater into lakes, rivers, and oceans in the United States to apply for a National Pollutant Discharge Elimination System (NPDES) permit. These permits specify the maximum acceptable levels of pollutants that may be discharged into public waters. Firms are required to monitor their pollution levels and submit regular reports to the EPA. The EPA also conducts its own spot investigations of water discharges by companies in order to promote accurate self-reporting. In the event that a firm violates the conditions of its permit by releasing un-approved chemicals, or releasing amounts of chemicals that exceed permitted levels, the EPA may impose sanctions. The EPA may issue monetary penalties, it may revoke or deny permits, or it may require the firm to create a plan to correct and prevent future violations. Failure to comply with such a plan in a timely manner may result in additional fines or penalties.²¹

The EPA releases information it collects pursuant to these NPDES permits, including information on firms' permit violations.²² I consider the following four categories of violations:²³

- Upgrade Compliance: The EPA requires a company to upgrade its pollution control capacities by

directing more funds to settle their claims pre-bankruptcy. This is subject of course to qualifications that doing so avoids being classified as preferential transfers or the like, and subject also to the qualification that such pre-bankruptcy payments may not actually be decisive in whether such constituencies maintain their relationships with the firm post-reorganization. See generally *In re Kmart Corp.*, 359 F.3d 866.

²¹For a useful overview of the NPDES program, see Gaba (2007).

²²See <https://echo.epa.gov/tools/data-downloads>

²³See <https://echo.epa.gov/help/water-dashboard-help> for additional details on each of these violation types.

a certain date and the facility fails to do so.²⁴

- Self-Reported: A company identifies that it has released harmful chemicals in ways it was not permitted to, and reports these voluntarily to the EPA as part of its regular compliance reporting.²⁵
- Reporting Failure: A company fails to submit a mandated report on its compliance record and systems.²⁶
- EPA-Detected: The EPA or an authorized state environmental agency working with the EPA directly detects a violation via ongoing monitoring efforts (e.g. of waterways) or periodic on-site inspections. The violation can involve release of chemicals that are not authorized by a facility's permit, attempts by the firm to bypass mandated monitoring equipment, or similar infractions.²⁷

4.2 Corporate Insolvency Risk Data

A corporate credit rating reflects a firm's "capacity and willingness to meet its financial commitments as they come due."²⁸ This language, not coincidentally, closely mirrors the conditions for an involuntary bankruptcy petition, which may occur if "the debtor is generally not paying such debtor's debts as such debts become due" (11 U.S.C.A. §303(h)(1)). The three major corporate credit rating agencies: S&P, Moody's, and Fitch, whose business is to forecast the probability a corporation will fail to pay its bond obligations, are thus forecasting a condition that aligns very closely with a firm either being in bankruptcy or kept out of bankruptcy only by the agreement of its creditors. As such, corporate credit ratings, which are available on thousands of private firms, are an ideal metric to use when investigating whether firms that are more likely to become bankrupt are also more likely to violate pollution laws.

I access an extensive set of credit ratings from the Mergent Fixed Income Security Database (FISD). Table 1 lists, for S&P, each of the ratings and the number of company-quarter observations for which the given rating applies. To convey the riskiness of each rating, the table also lists the percent of companies that have had each rating and defaulted on their obligations within 1-year and 5-year time horizons.

²⁴I include in this category what the EPA terms "Compliance Schedule" and "Permit Schedule" violations. These violations can also include a company's failure to conduct an adequate assessment of its capacities.

²⁵The EPA refers to these as "numeric effluent violations," since they occur when amounts of chemicals released exceed permitted limits.

²⁶The EPA refers to these as DMR, or Discharge Monitoring Report violations.

²⁷The EPA refers to these as "Single Event" violations.

²⁸"S&P Global Ratings Definitions," August 18, 2016, www.standardandpoors.com/ratingsdirect.

In the event that a rating for a corporation is unavailable from S&P, I find the most closely comparable rating from Moody's or Fitch, based on rating descriptions and historical default frequencies.

For the purpose of some of my statistical models, I assign each rating a numeric equivalent, which is also listed in Table 1. To make these intuitive, I assign the lowest credit rating a value of one, and the highest a value of eighteen. Thus, higher numbers correspond with higher (better) credit ratings.²⁹

4.3 Data Merging and Construction

The EPA's NPDES database tracks violations by the facility in which they occur, rather than at a company level. There are approximately 330,000 facilities within the database. Each facility comes with a name and a unique numeric ID to track its compliance history. Often, the facility name will simply be the name of the company, for instance "AEP Industries Inc." Other times, particularly where a company has multiple facilities in the database, the name will reflect both the company and information on the facility, for instance "3M Company - Arch Street Plant."

The FISC credit database has information on approximately 9,000 firms. To match between the NPDES and FISC databases, I start with an algorithm for "fuzzy string matching."³⁰ This process finds names in the two databases that are very similar and yields roughly 2,000 name matches. I then manually review these matches for accuracy, yielding roughly 1,500 verified matches. When a given corporation has multiple facilities in the database, I consolidate them into a single record for all pollution violations by any of the company's facilities. After this consolidation, I identify a total of 627 distinct firms for which I have both bond ratings and pollution violation records.

In most cases, the companies I track are at the highest level in their corporate families. In some instances, the companies are part of larger organizations which may contain multiple issuers of public debt. For instance, one company in my data is Georgia Pacific, a subsidiary of Koch Industries. In these situations, I use the credit rating for the subsidiary, rather than for the parent company (if one exists). It is the subsidiary that is registered with the EPA and that is liable for breaches of regulations. Similarly,

²⁹The highest rating is AAA. I observe only very few firm with this rating. I omit such observations because the small sample size would make it difficult to obtain reliable estimates for it. I also omit a small number of observations where firms are already in default or receivership.

³⁰The algorithm I employ is based in part on calculating the Levenshtein distance between strings.

the bankruptcy of the subsidiary would determine whether any civil liabilities might be discharged.³¹

4.4 Data Descriptions and Summary Statistics

4.4.1 Pollution Violation Descriptive Statistics

My sample period covers 22 years, from the start of 1995 until the end of 2016. There are a small number of records in the NPDES and credit rating databases that go back before this, in some cases as early as 1970. But, coverage in both databases is very low for these earlier periods.³² Such a small number of companies provides little variation, and is particularly problematic for some of my supplemental analyses, described below, that break companies down by the industries that they are in. Although my core results are robust to significant extensions of my sample period, in order to maintain conformity across my analyses, I use the period starting in 1995 for analyses throughout this paper.

My observation frequency is quarterly. Thus, I aggregate all NPDES records for a company within each quarter. My primary outcome variable is a binary indicator for whether any pollution violations occur in a given quarter. I calculate these for each violation type described in Section 4.1.

In a few cases, companies have multiple violation records (of a given type) in a single quarter, though this is rare. In these cases, I record only the binary indicator marking a violation in the given quarter. There is no clear reason to believe that a single event that violates two separate requirements, is necessarily worse than an event that violates a single pollution requirement.

More generally, to the extent that I explicitly consider violation severity, it is via the four types of violations discussed in Section 4.1. Beyond this, violation severity becomes ambiguous. In many cases, records do not specify precisely what was emitted, just that it was an unpermitted toxic discharge, or one that exceeded the company's permitted limits. Even where specific chemicals are given, determining which amounts of which chemicals are more harmful than others is extremely difficult.

In some cases, monetary damages are listed for a violation, providing a possible metric of severity. Yet, these assessments frequently occur a substantial amount of time after the violation. As such, they

³¹I proceed similarly in situations where a corporation is acquired during my sample period but still continues to have outstanding debt in its own name and still continues to be registered with the EPA in its own name.

³²For instance, as of 1985, there are fewer than forty companies identified in both databases.

will be heavily influenced by the financial developments of the company post-violation.³³ Furthermore, where the penalty is a revocation of a pollution permit, a mandated upgrade to equipment, or a requirement to clean up a polluted area, it is almost impossible to determine the economic cost to the company. Thus, while it would no doubt be insightful to directly measure violation severity, such an investigation, if conceptually possible, would be best reserved for future research.

Table 2 gives summary statistics on the number of companies in the matched data that commit each of the four types of violations as well as the frequency of those violations. Some violations are relatively common. Missing compliance reports occur at a median rate of once every other year. Other more serious violations, such as the EPA-detected ones, are less common, occurring at a median rate of once every fourteen years per company. There is also significant dispersion in the violation rates amongst companies. Companies in the 75th percentile of each distribution frequently violate pollution laws at a rate of three to four times those for companies in the 25th percentile.

4.4.2 Credit Rating Descriptive Statistics

After constructing a company-by-quarter grid tracking firms' pollution violations, I add in information about the credit ratings on bonds issued by each company. In some instances, companies issue multiple series of bonds with differing seniority and differing ratings. Since failure to make good on any bond commitment is grounds for involuntary bankruptcy proceedings, I use the lowest (worst) available rating for companies with multiple bond issues. Figure 1 plots the distribution of ratings over all company-quarter observations in the data and shows significant diversity of scores.

Changes in a company's credit rating are crucial to the variation I exploit in my analyses. There is significant intra-company variation within my data. For each company, I compute the number of quarters that the company is observed in my sample and the number of times its credit rating changes. I then divide the number of rating changes by the number of quarters each company is observed.

The median company according to this metric changes its credit rating roughly once every 2.5 years. The company at the 25th percentile changes its score every 5 years, and the company at the 75th percentile changes its rating every 1.5 years. For each company, I also compute the range between the

³³For instance, a company that commits a violation and then ceases to operate due to a liquidation will have no penalty assessed.

highest and lowest observed credit ratings. For the median company, the difference between its highest and lowest observed credit rating is 5 (i.e. the difference between AA and BBB+, a substantial amount). For the 25th and 75th percentiles of this metric, respectively, the differences are 3 and 7.

4.4.3 Other Company-Level Data and Descriptive Statistics

The final type of data I use is a set of firm financial metrics gathered from Compustat and ultimately derived from SEC filings by the companies. I retrieve measures of company size (based on total assets), financial leverage ratio, defined as $\frac{\text{Assets}}{\text{Assets}-\text{Liabilities}}$, and the percentage of company debt that is secured. I also calculate the “current ratio,” which represents the ratio of short term assets to short term liabilities and is a commonly used metric of firm liquidity. Finally, I also calculate the annualized logarithmic return on each company’s stock price and the gross profits of the firm. Roughly half the companies in my data do not issue public equity and for these, this added financial data is unavailable.

In addition to using these attributes of companies directly in some of my analyses, they also serve to give a picture of the types of companies within my sample. Figures 2 to 4 give information on the size, financial leverage ratio, and amount of secured debt for the firms in my sample.

4.5 Challenges of Data and Measurement

Before proceeding further, I note two phenomena that could in theory lead to a spurious correlation between bankruptcy risk and pollution violations. In the introduction, I discuss a proposal that agencies such as the EPA increase monitoring of firms near insolvency. I have found no evidence that the EPA currently uses this strategy. The EPA has a detailed manual describing its NPDES inspection policies.³⁴ This manual makes no reference to considering the financial condition of firms.³⁵ I have also spoken with several knowledgeable experts in EPA enforcement policy, including former EPA general counsel Jon Cannon, and none of them have been aware of any such practice. If the EPA were already pursuing the strategy I advocate, that practice in and of itself would lead to a correlation between bankruptcy risk and pollution violations. But, all evidence weighs strongly against this being the case.

³⁴See: <https://www.epa.gov/compliance/clean-water-act-national-pollutant-discharge-elimination-system-compliance-monitoring>

³⁵Instead, the manual focuses on factors such as whether a facility has received public complaints about it, whether a facility is particularly at risk of endangering water used for human consumption, and so forth

Another concern is that the credit agencies, in determining ratings, may take into account precautions a firm takes to prevent violations of EPA regulations. Agencies such as S&P publish detailed guides on their rating procedures. For instance, S&P's rating criteria,³⁶ are focused on a firm's cash flow and leverage, diversification of its revenue, liquidity, risks facing a firm's country or industry in general, and its competitive position with respect to other firms. None of these factors that influence a firm's "anchor" credit rating would likely reflect compliance levels of firms with regards to EPA regulations.

A firm's S&P "anchor" rating can be modified on account of six supplemental criteria. Only one of these six supplemental factors, "management and governance" could reflect compliance.³⁷ Even here, however, S&P makes no efforts to directly inspect firms to assess their regulatory compliance measures prospectively. Instead, it will only adjust ratings downward for firms that have histories of past regulatory violations that significantly deviate from industry norms and pose a direct risk to the financial health of the company. Furthermore, even if this were to have an impact on a firm's credit rating, given that it is one sub-criteria amongst sixty-four criteria within the "Management and Governance" category, and that itself is one category amongst six supplemental considerations that only in certain instances will modify a firm's "anchor" rating, it is difficult to imagine this in and of itself shifting a firm's credit rating more than a single point. An effect of this size then could not come close to explaining the magnitude of results that I observe in the empirical specifications here.

There are good reasons therefore to believe that there is little to no danger of the credit ratings already being significantly influenced by firms' likelihood of violating NPDES regulations. Nevertheless, I perform two specific tests to alleviate any remaining concerns. Section 5.5, which covers robustness checks, describes these in more detail. One test involves explicitly including the number of prior violations a company has committed as a predictor in the model. Another test excludes two, four, and six years of data from firms following observed regulatory violations in order to allow for any lingering residual impact of those violations to disperse. In each case, these procedures do not meaningfully change the size and significance of the key credit rating variable. These tests likewise address concerns that the EPA may more actively monitor facilities with a past history of compliance violations.

³⁶See: https://www.standardandpoors.com/es_LA/delegate/getPDF?articleId=1493895&type=COMMENTS&subType=CRITERIA

³⁷For S&P's full description of the management and governance considerations, see: https://erm.ncsu.edu/az/erm/i/chan/library/SP_MandG_Methodology.pdf

Secondly, I note that the IV specification I employ, described in Section 5.3, even more directly addresses concerns that a credit ratings may already reflect firms' risks of pollution violations. That procedure is explicitly designed to isolate variation in a firm's credit rating attributable only to factors outside of its control. As such, any fluctuations in a firm's rating that were attributable to its regulatory compliance measures would be removed from the predicted ratings generated by the IV procedure.

5 Analysis

I first investigate the threshold question of whether firms that approach bankruptcy systematically become more likely to violate EPA regulations. Section 5.1 presents baseline panel analyses to investigate this. Section 5.2 considers whether other firm factors, such as liquidity, profitability, or leverage might be driving this association, rather than bankruptcy risk itself. Section 5.3 presents my instrumental variables analysis, which isolates variation in firms' risks of bankruptcy due to factors beyond their control. Section 5.4 investigates whether the link between bankruptcy risk and likelihood of pollution violations manifests differently for different types of firms. Section 5.5 presents robustness checks.

5.1 Risks of Bankruptcy and Harm to Third Parties

As discussed in Section 4.4.1, the primary outcome I study is a binary indicator of whether a given company committed any of four types of pollution violations within a given calendar quarter. The main predictor that I use for the likelihood of these violations is the credit rating assigned to firms' public debt. I include company fixed effects in all of my models. In essence, this means I am comparing, for the same company, whether it is more likely to commit pollution violations during periods when its credit rating is lower than in periods when its rating is higher. I likewise include time fixed effects in my models, which mean in essence that I am also comparing, for a given point in time, whether firms with lower credit ratings are more likely to violate pollution laws than those with higher ratings.

Specifically, I use conditional logistic models of the following form:

$$\mathbf{P}[\text{Violation}_{it}] = \Lambda(\beta \text{Credit Rating}_{it} + \Gamma X_{it} + \gamma_i + \eta_t + \varepsilon_{it}) \quad (2)$$

Λ represents the conditional logit likelihood function,³⁸ i indexes companies, and t indexes quarters. γ_i is a company fixed effect and η_t is a quarterly time fixed effect. Violation_{it} indicates a violation by company i in quarter t . $\text{Credit Rating}_{it}$ reflects a firm's numeric credit score, as described in Table 1.

X_{it} is a vector of additional company-level predictors that I use in certain supplemental analyses. These predictors include firm-level liquidity, leverage, stock returns, size, and amount of secured debt. Since these are only available for publicly traded companies, I first consider baseline analyses that omit them. I then show in Section 5.2 that those baselines in fact yield the same results when run on the subset of observations from publicly traded companies.

There is no reason to assume a given functional form to the relationship between credit ratings and pollution risks. Even if companies with lower (worse) ratings are more likely to commit pollution violations, there are myriad ways that could manifest. There might, for instance, be a threshold effect, in which pollution risk is dramatically higher when a company is very near bankruptcy but relatively constant otherwise. At first, therefore, I treat the credit rating non-parametrically, as a factor variable with a unique coefficient for each rating. Based on results of these models, however, I determine that treating credit rating as a continuous linear predictor fits the data well. Later analyses make use of this.

My preferred measure of goodness of model fit is the area under the curve (AUC) of the receiver operator characteristic. AUC is a standard metric for classifiers such as logistic regression. It measures the accuracy of the classifier in terms of false positive and false negative classifications. The AUC ranges from 0.5, indicating a classifier no better than random, to 1, indicating perfect accuracy. Values above 0.7 are commonly considered good and those above 0.8 are considered excellent in terms of predictive ability (Hosmer and Lemeshow, 2004). The AUCs of all of my models are well above 0.8.

The first set of results that I consider is for a version of Equation 2 that predicts the likelihood of a firm being sanctioned for EPA-detected violations. This model treats credit rating as a factor variable, uses time and company fixed effects, but not other predictors. Figure 5 presents the fitted coefficients for each credit rating value from this model. Each coefficient in the plot is accompanied by a vertical line representing its 95% confidence interval with errors clustered at the company level.

I set the base level for these factors to be the highest credit rating, AA, or 18 in the numeric equiv-

³⁸Because my models involve company fixed effects, estimating each of these as a separate parameter, as in a regular logistic regression, would lead to the problem of incidental parameter bias, which the conditional logit avoids.

alents of Table 1. Thus, coefficient values for the other ratings represent pollution risk compared to this base level. Logit specifications model the impact of predictors on the “odds ratio,” or the relative probability of a violation compared to the probability of no violation. In other words:

$$\text{Odds Ratio (OR)} := \frac{\text{P}[\text{Violation} \mid \mathbf{X}]}{\text{P}[\text{No Violation} \mid \mathbf{X}]}$$

Coefficients in the logit model are interpreted by exponentiating them, after which they represent the proportional change in the odds ratio. In Figure 5 for instance, the coefficient on the lowest credit rating is 2.35. This means that if a firm moved from the highest to the lowest credit rating, its odds ratio, which reflects the likelihood of an EPA-detected pollution violation, would increase by a factor of $\exp(2.35) = 10.49$.³⁹ To put this in terms of absolute probabilities of a violation occurring, consider the mean probability of an EPA-detected violation occurring in a given company-quarter observation, which is 3.6%. A firm moving from the highest to the lowest rating would be associated with increasing the probability of an EPA-detected violation from 3.6% to 28.1%, a 6.8 fold increase in absolute pollution risk!⁴⁰ The other coefficients in Figure 5 likewise document a consistent effect in which firms become increasingly more likely to commit pollution violations as their probabilities of bankruptcy increase.

I now turn to another type of pollution violation - failure to submit mandated reports. Figure 6 plots the coefficients and confidence intervals for this type of pollution risk - directly analogous to the model considered in Figure 5. The results are quite similar. In particular, the lowest credit ratings are associated with statistically significant elevations of violation risk as compared to the highest rating. In this case, the lowest credit rating has a coefficient estimate of 0.82. When exponentiated and evaluated at the mean probability of this type of pollution violation (17.6%), moving from the highest to the lowest credit rating is associated with a move from a quarterly violation probability of 17.6% to 32.7%.

Figures 5 and 6 both show a roughly linear relationship amongst the coefficients estimated for the various credit ratings. Is this a sensible result? For instance, the relation between credit ratings and probabilities of bankruptcy in Table 1 is anything but linear.⁴¹ The result is in fact reasonable. The

³⁹Of course, a change in credit score this large would be quite extraordinary, particularly within any relatively small period of time.

⁴⁰To follow this calculation specifically, note that a mean probability of 3.6% gives an odds ratio ($\frac{p}{1-p}$) of 0.037. Increasing this by a factor of 10.49 gives a new odds ratio of 0.392. Solving for $\frac{p'}{1-p'} = 0.392$, where p' is the new probability, gives $p' = 28.1\%$.

⁴¹Moving one rating, from B- to CCC+, is associated with an increase in the one-year default rate of 18.5 percentage points (from 8.74 to 27.22). Yet a one rating move from AA- to AA- is associated with a comparable change of only 0.01 percentage points (from 0.02 to 0.03).

reason is that the figures plot coefficients from the logistic model, and it is the exponent of those coefficients that represents the proportional change in the odds ratio. Thus, the roughly linear pattern in the coefficients represents an exponential relationship between credit ratings and pollution risks, which mirrors the exponential relationship between credit ratings and bankruptcy risks.

Given then that the results so far evidence a linear relation between credit ratings and pollution risk, and that this is reasonable from an interpretative perspective, I next consider a set of models that use credit rating as a continuous, linear predictor, rather than as a factor variable. This has the advantage of allowing me to consider and present results of multiple models more concisely, without need for separate coefficient plots and without loss of fidelity to the underlying relationships.⁴² Additionally, the linear predictor is more suited to formulations such as my IV analysis, described in Section 5.3.

Table 3 presents the results of analyses treating credit rating as a continuous predictor, considering each of the four types of EPA violations I study. For the EPA-detected and reporting failure violations, the results show the same strong, negative association between credit rating and pollution risk as was evident when considering credit rating as a factor variable.

Interestingly, for the two other types of violations, upgrade compliance and self-reported violations, Table 3 shows no statistically significant relationship between credit rating and violation risk. What can be made of these divergent results for different types of pollution violations? The coefficients for the upgrade compliance and self-reported violations are at least of the same sign as for the reporting failure and EPA-detected violations, and they are of roughly the same magnitude as for the reporting failure violations. So, one possibility is that there is still the same general relation between credit rating and violation risk for these types, but that it is a noisier one that does not rise to the level of statistical significance. Another possibility I discuss in Section 5.3 is that there may be a significant relation which is partially obscured by confounding factors which an IV analyses can control for.

In fact, however, the results in Table 3 may be more consistent than they at first seem. There is good reason to consider EPA-detected violations as the single best metric of risk of illegal pollution, since they are less subject to manipulation by companies reluctant to avoid self-reporting violations of

⁴²In particular, for all models I present using credit rating as a continuous predictor, I also, in unreported results, fit equivalent models treating credit rating as a factor. In each case the results are congruent.

pollution laws. The statistically significant result for reporting-failure violations also suggests that firms at heightened risk of bankruptcy cut back on their overall compliance expenditures. It should perhaps not be too surprising that these firms don't show such heightened levels of self-reported violations. Not only are they cutting back on their self-reporting compliance expenditures, they may even be doing so selectively to avoid reporting violations that cause consequences they would prefer to avoid or forestall.

This still leaves the question of what explains the lack of statistical significance for the "upgrade compliance" violations - that is, failures to implement mandatory pollution controls by a given date. One explanation could be that if the EPA mandates that a firm implement a new control by a given date, it is very easy for the agency to check on that date for compliance and issue sanctions in the event of non-performance. As such, if the probability of detection for such violations is at or near 100%, then provided sanctions are set relatively efficiently, there may be little incentive for firms to shirk them, even if they are near bankruptcy.⁴³ For the EPA-detected violations, however, a firm near bankruptcy may find it an acceptable bet to under-invest in pollution controls and hope they go undetected.⁴⁴

5.2 Potential Alternative Drivers of Risks

The results so far show a strong relation between the risk of bankruptcy and of pollution violations. If indeed it is bankruptcy risk that drives this association, then the results would give strong support to the theoretical predictions on the incentive effects of limited liability. Yet, it is also conceivable that these results are driven not by bankruptcy risk itself, but by other aspects of firms that may correlate with that risk. In particular, I consider three alternative hypothesis that could be driving these results.

The first hypothesis is that owners and managers of firms near bankruptcy have just as strong incentives to comply with EPA regulations as those of other firms, but simply lack the available funds to pay for necessary compliance measures.⁴⁵ The second possibility is that unskilled owners and managers are both more likely to lead their companies towards bankruptcy and to fail to adequately oversee their

⁴³Section 6 discusses the implications of certain detection in slightly more detail.

⁴⁴Indeed, this is exactly the prediction of the existing theory on the incentive effects of limited liability.

⁴⁵If owners and managers were truly incentivized to prevent harm to third parties, and were unable to pay for necessary precautions, they would seek reorganization or liquidation in bankruptcy. Thus, the decision to operate a business when cash-flow prevents efficient precautions is itself a decision to de-prioritize third parties, and almost certainly a decision that would be made differently in the absence of limited liability. Thus, even if cash flow could explain compliance, this paper's results would still be informative on the incentive effects of limited liability.

production processes, thus resulting in increased pollution violations. A final possibility is that high leverage could cause firms to be both more likely to become bankrupt and more likely to take risks by reducing compliance expenditures (Jensen and Meckling, 1976).

One way to test for the likelihood of these alternative explanations is to add controls to my main specifications that account for each of the mechanisms they suppose. To test whether lack of funds accounts for my initial results, I add a measure of firm liquidity in the form of the “current ratio.” This is a common metric of liquidity, measuring the ratio of short term assets to liabilities. Higher values indicate a firm is less liquidity constrained.⁴⁶ To test the hypothesis relating to manager skill, I include measures of firms gross profits (divided by total assets) and yearly stock returns. Finally, to test the leverage hypothesis, I include a measure of firm’s financial leverage ratios, defined in Section 4.4.3.

Table 4 presents results of these analyses. The four panels correspond to the four types of pollution violations I consider. The first column is a version of my analyses that includes only these additional predictors and not the credit rating variable. The second column contains just the credit rating variable, but restricted to the set of observations for public companies that also have these other variables available. The third column then combines the credit rating and the additional predictors.

The most important observation from Table 4 is that adding these additional predictors does essentially nothing to change the size or statistical significance of the credit rating variable. Furthermore, the results are consistent with those in Table 3. Namely, there is a strong, statistically significant, and negative relationship between credit rating and likelihood of EPA detected violations. There is likewise a pretty strong and statistically significant relationship between credit ratings and reporting failure violations. As in Table 3, upgrade compliance and self-reported violations do not show significant results.⁴⁷

The next observation from Table 4 is that in general, the additional predictors associated with the alternative hypotheses have little association with the incidence of pollution violations. There are in fact intuitive theoretical reasons for this. For instance, while Jensen and Meckling (1976) show that leverage may incentivize inefficient risk-taking, they also note that in most situations creditors will

⁴⁶In unreported tests, I also use other liquidity measures, such as cash on hand. The results are much the same.

⁴⁷The similarity between the results in Table 3 (which includes public and private companies) and Table 4 is also important for establishing the subset of public companies for which I have these additional predictors as a valid sample to test these alternative hypotheses with.

structure relations with borrowers to constrain these incentives.⁴⁸ Similarly, basic finance theory would suggest that if a firm finds it optimal to under-invest in precautionary measures, then the firm will do so regardless of how much or little profit it is making from its other operations. Finally, if a firm is truly still solvent, then in general it should be able to secure cash to fund its operations, for instance through mortgaging its assets. This suggests that it is only firms that are already essentially insolvent that should have significant shortfalls in liquidity that prevent compliance.

5.3 Exogenous Variation in Financial Condition

The company fixed effects in my models can control for time invariant firm characteristics that correlate with risks of both bankruptcy and pollution violations. For instance, mining firms have relatively low credit ratings and are also cited for pollution violations more frequently than many other firms. Almost certainly this reflects the nature of the mining industry, rather than any kind of evidence pertinent to the incentive effects of limited liability. Company fixed effects control for this fact, enabling me to look, for instance, at particular mining firms at different points in time and to ask whether those firms are even more likely to violate pollution laws when their likelihoods of bankruptcy are even greater than normal. As such, these fixed effects allow for more robust inference as to whether there may be a causal relationship between bankruptcy risk and pollution risk.

Nevertheless, firms may have time varying characteristics that influence both bankruptcy and pollution risks and that cannot be controlled for explicitly as I do for the characteristics discussed in Section 5.2. For instance, it is well established that prior life experiences of CEOs shape their risk preferences in ways that manifest in the corporate strategies they pursue (Bernile et al., 2017). A risk-preferring CEO may choose to invest less in precautionary measures and be more likely to lead their company into bankruptcy. Because a firm's CEO may change during my sample, company fixed effects are unable to fully control for this phenomenon.

Conversely, it is also possible that a significant degree of risk-taking is an optimal business strategy. In this case, such risk-taking could lead to better returns and higher credit ratings, which then become

⁴⁸The obvious exception are instances in which creditors are less worried about losing their investments even in the event of default by borrowers. Ohlrogge (2017), for instance, documents this effect for banks.

associated with higher likelihoods of pollution violations. A related possibility could lie in the potential that EPA penalties and detection rates are set at inefficiently low levels. In this case skilled managers, who may reduce the likelihood of their firms' bankruptcies, may optimally choose to under-invest (from a social perspective) in pollution prevention measures. Thus, there are ways that unobservable factors relating to changing company management could lead my baseline analyses to either over- or underestimate the association between high risks of bankruptcy and high risks of pollution violations.

In order to address possibilities such as these, I develop an instrumental variables (IV) strategy to identify variation in firms' likelihood of bankruptcy that stems from factors outside of their control. In particular, I take advantage of the fact that changes in macroeconomic conditions, such as interest rates, will affect firms in different industries differently based on their different business models. For instance, a high interest rate environment may be detrimental to a mining firm that relies heavily on borrowed funds to finance new operations, whereas a firm such as General Electric, which makes a large portion of its revenue through financing activities, may benefit from a high interest rate environment. I show that these macroeconomic fluctuations are significantly predictive of firms' credit ratings.

In particular, I construct my instrument as follows. I start by calculating the quarterly change in credit rating for each firm: $\Delta\text{Credit Rating}_{it}$. I then seek to predict these quarterly changes as a function of the quarterly changes in the macroeconomic factors.⁴⁹ In this prediction, I allow each industry, as defined at the NAICS2 level, to have a unique coefficient. Formally then, I represent this as:

$$\Delta\text{Credit Rating}_{it} = \alpha + \sum_{j=1}^n 1_{ij}\Delta X_t\beta_j + u_{it} \quad (3)$$

Here, as above, i indexes firms and t indexes time at a quarterly frequency. j indexes NAICS2 industries. X_t is the vector of macroeconomic factors, and β_j is the unique set of coefficient estimates for each industry. 1_{ij} equals one in the event that company i is in industry j and zero otherwise.

From these fitted models, I obtain predicted values for the changes in credit rating of each firm: $\widehat{\Delta\text{Credit Rating}_{it}}$. I sum these predicted changes to get predicted levels of the ratings for each firm:

$$\widehat{\text{Credit Rating}_{it}} = \sum_{s=1}^t \widehat{\Delta\text{Credit Rating}_{is}}$$

⁴⁹As a technical statistical matter, considering quarterly changes in these factors is necessary to achieve stationary series for analysis.

I then use these predicted ratings as an instrument for the actual ratings in a standard 2SLS procedure:

$$\text{Credit Rating}_{it} = \beta^{(1)} \widehat{\text{Credit Rating}}_{it} + \gamma_i^{(1)} + \eta_t^{(1)} + v_{it} \quad (4)$$

$$\text{Violation}_{it} = \beta^{(2)} \widehat{\text{Credit Rating}}_{it} + \gamma_i^{(2)} + \eta_t^{(2)} + \varepsilon_{it} \quad (5)$$

$\widehat{\text{Credit Rating}}_{it}$ is the predicted value for $\text{Credit Rating}_{it}$ obtained from the first stage procedure and γ_i and η_t are company and time fixed effects, respectively. Superscripts (1) and (2) represent unique coefficients in the first and second stages.

A difference between this and the analyses described in Section 5.1 is that I use a linear probability model here, rather than the conditional logit formulation. I do this to achieve a practical and tractable way of implementing the IV, which is not well defined for the conditional logit model. In unreported tests, I also verify that all results here are robust to an IV probit model.⁵⁰

To avoid over-fitting, I only consider industries for which I observe at least 10 distinct corporations in my sample, since much of the key variation in this framework is coming from the differences in industries' reactions to macroeconomic factors.⁵¹ Doing so leaves me with eight distinct industries.

There is some difference in the set of companies that I analyze in my primary models for each of the four types of violations.⁵² These differences also then manifest in some diversity of strengths of the first stage predictive power of this instrument. In order to obtain comparable results across different violation types, I use a "common denominator" set of companies for all of the analyses that use this instrument. Constructed as such, this proves to be a strong instrument, with a cluster-adjusted first stage F-stat of 11.05 on the instrument and a first stage R^2 value of 0.77.

5.3.1 Evaluating the Instrument and the Exclusion Restriction

The first stage F-stat demonstrates that the macroeconomic fluctuations have significant impacts on corporations' bankruptcy risks. But, macro conditions may also impact other firm characteristics, such as available funds or profitability. Thus, the IV cannot directly prove that it is the changes in bankruptcy risk, and not one of these other financial conditions, that account for changes in firms' illegal pollution.

⁵⁰This has the advantage of being a non-linear model suitable to binary outcomes. But, the probit has the disadvantage of not being able to address the incidental parameter estimation problems that come from estimating fixed effects.

⁵¹In practice, however, whether I include or exclude industries with small numbers of companies makes little impact on my coefficient estimates - perhaps not surprisingly given these small industries contribute few observations to my data overall.

⁵²Companies with no violations of a given type will not impact the coefficients, given the fixed effects, and thus drop from the analyses.

Instead, it shows that more general changes in the financial condition of firms drive changes in their likelihood of violating pollution laws. Nevertheless, given the results in Section 5.2 which show that financial features such as liquidity, leverage, and profitability do not drive pollution risk, the evidence would seem good that this IV does indeed establish that it is changes in bankruptcy risk, rather than some other financial factor, which are driving changes in firms' likelihoods of pollution violations.

Given this caveat, the IV likely satisfies the exclusion restriction that macroeconomic changes not influence firms' likelihood of committing pollution violations except through their impact on the financial stability of firms. There are two principal channels through which changes in macroeconomic conditions will impact a firm's bankruptcy risk. They could either reduce demand for the firm's products or increase costs to the firm of producing those products. In the event that macroeconomic conditions decrease demand for a firm's products, it will tend to reduce its production levels. Lower production, if anything, will almost certainly reduce the likelihood of pollution violations.⁵³

The other channel through which macroeconomic conditions would impact a firm's bankruptcy risk would be through increasing its costs. If a firm's costs rise, particularly if costs rise across an industry, which is what the IV models, then the price of the firm's products will also likely rise. This in turn will tend to depress demand for those products, again leading to a reduction in production levels.

In both of these cases, therefore, any violation of the exclusion restriction will serve to correlate drops in credit ratings with *decreases* in pollution violations. In other words, any bias that might enter into the IV would cause an underestimation of the effects of bankruptcy on pollution, and thus would in no way challenge the robustness of the results here.

5.3.2 Instrumental Variable Results

Table 5 presents the results of the IV analysis. Because the IV uses a linear probability model, the coefficient magnitudes are not directly comparable to earlier results from the logit model. Nevertheless, studying the signs of the coefficients and their relative significance still yields useful insights.

The first thing to note is that the instrument strongly confirms that corporations become more likely

⁵³Many violations occur when chemicals are emitted beyond permitted limits. These will drop as production decreases. Other violations may result from random accidents. The more a firm produces, the more opportunity for such accidents.

to be sanctioned for EPA-detected violations when their financial conditions are weakened by macroeconomic shocks. In fact, the coefficient in the IV model for EPA-detected violations is noticeably larger than for the corresponding naive linear probability model. The pattern of IV estimates being larger than naive ones is consistent throughout the four violation types in Table 5. If bias in the naive analyses is coming from an unobserved factor such as CEO strategies, this suggests that such bias is actually attenuating the effects of insolvency risk on likelihood of pollution violations. As I discuss above, a plausible explanation for this could be that skillful CEOs (who are more likely to steer their companies away from insolvency) recognize that EPA enforcement is set at sub-optimal levels and thus wisely (from the companies' perspectives) invest less in preventative measures.⁵⁴

There are additional interesting patterns in the IV results for the other violation types. For instance, the naive results for upgrade compliance and self-reported violations are statistically insignificant, mirroring the baseline logit analyses. But, the IV reveals more significant effects for both types of violations. Interestingly, the effect for reporting failure violations loses its significance for both the IV and naive analyses here, whereas there was a significant effect for that in the main conditional logit analyses.⁵⁵

5.4 Extension Analyses - Heterogeneity of Effects

Do different types of companies respond differently to the proximity of bankruptcy? In Section 5.2 I discuss one dimension of potential heterogeneity - that between public and private companies. The results from Table 3 and Table 4 show little differences in the coefficient estimates for the credit rating variable when considering either the full sample or the sample restricted to public companies. In unreported tests, I also confirm that there is no statistical significance to a formal interaction between an indicator for a company issuing public stock and the effect size of the credit rating variable.

The similarity between public and private companies may be relatively intuitive, given the composition of my sample. Although many companies in my sample do not issue public equity, they all issue public debt. As such, they are generally large corporations that will be likely to have structures of professional management between owners and operations. Unsecured creditors, such as bond holders,

⁵⁴A similar explanation could be that a relatively large tolerance for risk is optimal for financial performance.

⁵⁵Despite this coefficient losing its statistical significance, its sign remains consistent with earlier analyses and its magnitude considerable. The most likely explanation may be that while the IV can control for bias, it increases variance, yielding larger errors for a given point estimate.

will have relatively little ability to directly impact the operation of these firms. Thus, the firms' choices of funding may not be very influential for their operations. And, even where some of the private corporations may be owned by small numbers of individuals, those individuals are apt to be wealthy and sophisticated investors with the ability to achieve whatever their desired levels of diversification are.

I also consider whether corporations differ in their responses to bankruptcy risk based on size and the amount of secured debt they carry. To investigate this, I break my data up into several groups based on values of the size and secured debt characteristics. I then allow the credit rating in Equation 2 to take a unique value for each group of companies. Table 6 presents the results for company size. It shows little variation amongst companies of different sizes. Again though, it should be noted that all the corporations I consider are relatively large. Even a "small" company can have assets up to \$1 billion.

I next consider analyses for corporations with different amounts of secured debt. Since unsecured creditors will have their claims impaired in bankruptcy more than secured creditors, it is possible that firms with more unsecured debt may keep a more constant level of precautions even as they approach insolvency. At the same time, unsecured creditors, particularly bond holders, may have relatively little influence over the operations of large firms. Table 7 presents the results of these analyses. It does show some differences, with firms in the middle groups, having secured debt between 2 and 40% of their assets, showing positive coefficients in comparison to the base level firms with the most secured debt. This suggests smaller (less negative) effects of the credit rating variable for these firms, and is thus consistent with the notion that firms with more unsecured debt may be less sensitive to proximity to insolvency. Yet, the effects are not statistically significant, and firms with the least amount of secured debt show no difference from the firms with the most secured debt. Overall, these results do not present strong evidence in favor of heterogeneous effects based on the amount of secured debt firms carry.

5.5 Robustness Checks

I conclude my discussion of empirical results by considering robustness checks to address two potential concerns. One is that companies' actions may result in violations being reclassified from one of the types I consider to another. Suppose that a firm nearing bankruptcy commits a pollution violation.

The firm can either cover it up by tampering with its monitoring equipment and reports, or it can report it as a self-reported violation. If the firm conceals the violation, the EPA may detect it. Thus, the same violation may be more likely to be classified as EPA-detected for a firm near bankruptcy, but as self-reported for a firm far from bankruptcy. In this case, the fact that firms near bankruptcy show more EPA-detected violations may not mean that they are actually causing more harm.⁵⁶

To address this concern, I create a new metric for violations that equals one in the event a violation of any type occurs. Under this metric, if a firm's actions lead its harmful activities to be reclassified, the metric will be unaffected. Of course, the hope for firms that conceal violations is not that the violations will be reclassified, but that they will remain undetected. Any time that this occurs, it will result in data that show that firms near bankruptcy are actually *less* likely to commit violations (under this combined violation metric), because more of their violations would be going undetected. In other words, bias under this combined metric would tend to under-estimate the impact of bankruptcy risk.

The magnitude of effects for this combined indicator will be influenced by those for each of the individual violation types. Thus it is not directly comparable to any one of them alone. Nevertheless, its sign and statistical significance bear on concerns from reclassification of violations. For this combined violation metric, I obtain a coefficient of -0.034 ($p = 0.0013^{***}$) in the baseline logit model, and a coefficient of -0.085 ($p = 0.036^{**}$) for the IV. Thus, my results are robust to violation reclassification.

A second concern is that the EPA may be more likely to inspect firms that have had recent instances of pollution violations. Of course, even if the EPA does so, it does not necessarily mean that this will result in a bias that accentuates the role of bankruptcy risk. If the increased rate of inspection is less than firms' increased rate of pollution violations, the bias would actually run the opposite direction.

Nevertheless, to address this concern I perform the following series of tests for the EPA-detected violations. First, I count for each firm and in each quarter how many total violations it has previously been sanctioned for. I then include these counts as an explicit predictor in my model.⁵⁷ If the EPA is

⁵⁶Reporting failure violations could also be affected. If a firm fails to collect required data (e.g. due to reduced compliance personnel) or collects data indicating permit violations, the firm could submit a false report, potentially resulting in an EPA-detected violation if detected.

⁵⁷I omit this factor from my main models because of its potential to bias parameter estimates for my credit variable towards 0, though in practice any bias is minimal. Consider a firm that only changes credit rating once. Suppose that shortly after the firm's rating drops, it commits an EPA-detected violation. If the firm does not commit further violations (which is plausible given the median frequency is one per fourteen years), then cumulative violations will be essentially collinear with credit rating for the firm.

over-inspecting firms with past violations and such over-inspection is driving my results, then including this predictor should reduce or eliminate the measured effect of my credit rating variable. In fact, the measured coefficient for the credit rating variable under this specification is -0.0815 ($p = 0.006^{**}$), very close to the coefficient value when omitting this predictor.

As a second test, I remove all observations that occur within two years, four years, and six years following a pollution violation. As a violation fades further into the past, it becomes increasingly less likely to be determinative in influencing EPA inspection policy for a firm. The coefficient estimates for these three specifications, under the conditional logit model are -0.076^{**} , -0.072^* , and -0.070^* . These are all close to the original coefficient in the full data (-0.101). Statistical significance drops slightly in the models that remove four and six years of data, yet this is likely simply a result of shrinking sample size. Overall then, the evidence suggests no serious problems due to EPA inspection policies.

6 Policy Considerations

The results in this paper show that as a corporation's risk of bankruptcy increases, so too does the likelihood that its actions will harm third parties. Although this paper is the first to empirically document this phenomenon, its existence as a theoretical prediction is far from new. As such, numerous policy changes have already been suggested to address concerns it raises. Section 2 surveys these proposals. While each has advantages, they also come with large drawbacks. In particular, proposals such as restricting limited liability or priority for secured creditors, requiring firms to carry additional insurance, or requiring firms to operate with more capital, all require significant legislative changes. These may be unlikely to occur in the near future. Many proposals also could have drawbacks by upsetting core tenants of corporate law or being impractical to implement (Grundfest, 1992).

Many of these downsides can be sidestepped, however, through a relatively small change in the operation of regulators like the EPA that supervise activities with the potential to harm third parties. The reason that proximity to insolvency can lead to inefficiently low incentives to prevent harm to third parties is because the greater a firm's probability of insolvency, the lower the expected cost of any

sanctions to the owners of a firm.⁵⁸ We can represent the net deterrent effect of enforcement as:

$$\text{Net Deterrent Effect} = \text{Probability of Detection} \times \text{Expected Cost Given Detection} \quad (6)$$

Provided that penalties for harms to third parties are set efficiently for firms remote from bankruptcy, if expected penalties are lowered by the prospect of insolvency, incentives for inefficient care will result.

There is, however, a simple and easily implemented response that can ameliorate these incentive effects, at least for activities that are policed by agencies such as the EPA. Since the expected penalty given detection is less for firms near bankruptcy, an optimal deterrent can be re-established by increasing the probability that illegal harms will be detected. This will achieve for firms both near and far from insolvency at least roughly equal net expected costs of causing illegal harm to others.

This proposal is similar to the CAMELS system already used by federal banking regulators, in which banks near insolvency are monitored more closely. In that situation, the primary goal is in preventing losses to the FDIC insurance fund. For this proposal, by contrast, the goal is more broadly correcting the incentive effects that limited liability can have on firms' efforts to prevent harm to third parties. But, there are still many commonalities. Also, other authors have in the past suggested taking into account factors such as firm profitability and liquidity when deciding monitoring levels for regulated entities (Filer and Golbe, 2003; Earnhart and Segerson, 2012). But, discussions of the principal behind this proposal have been generally absent from the law and economics debate that addresses the implications of limited liability.⁵⁹ Additionally, this paper makes contributions to the policy discussion through its investigation of incentive effects for firm managers, not just owners, which have been the focus in the past. Finally, the policy analyses here addresses complexities that have not been prominently addressed in the prior literature, such as the implications of the priority of claims in bankruptcy and the implications if existing levels of enforcement for all firms are sub-optimal.

If a firm is near bankruptcy and any fines the EPA imposes for pre-bankruptcy violations⁶⁰ receive low priority in bankruptcy, would increasing the probability of those fines serve as an effective deterrent? It would, for several key reasons. First, consider the firm's owners. If the probability of detection goes up,

⁵⁸The analysis here is a straightforward extension of the notion that expected penalties from an action comprise the product of probability of sanction times cost conditional upon sanction, as discussed in Becker (1968); Wittman (1977).

⁵⁹See, e.g. the surveys of policy responses given in Shavell (2007); Allen and Kraakman (2016).

⁶⁰As stated in Section 3, I presume that once a receiver is appointed it will take efficient levels of care.

owners will be hurt because the fine will either reduce the profits they would have gained (if the firm stays solvent) or perhaps even push the firm into bankruptcy which otherwise it could have avoided.

Next, consider the firm's managers and the model for their incentives from Section 3. The managers' incentives in the simplest model are to minimize the probability of bankruptcy. If the probability of detection goes up, this will mean that there are more scenarios in which the firm would have escaped bankruptcy but for the imposition of the fine. More formally, it is evident from Equation 1 that as probability of detection rises, the amount of benefit the firm gets from not spending resources on the preventive measure must increase in order for it still to be optimal to neglect the efficient precaution.

To give a concrete example of management's incentives, consider the firm described in Section 3 whose probability of remaining solvent a year from now is 80% and for whom the probability of a violation being detected is 10%. Under this scenario, managers require that cost-savings from not taking the precaution increase their chances of remaining solvent by 8.9%. Suppose instead the probability of detection is 15%. Equation 1 indicates that managers would require that cost savings increase the chances of the firm remaining solvent by 14.1%. Thus, a 50% increase in the probability of detection here yields a 63% increase in the benefit managers must receive from not taking the precaution.

If managers have more complex incentives, such as to also improve the chances of a successful reorganization, the analysis remains much the same. Increasing the probability of detection will do little to reduce the likelihood of a successful reorganization, since that will depend on whether the firm as a whole has a positive value as a going concern, after discharging whatever claims cannot be paid. But, even where managers care about improving chances of a reorganization, their first preference is to avoid a bankruptcy altogether, and under this scenario, the same logic from above applies.

Next, consider the firm's secured creditors. For them, the fact that the fine would be dischargeable is largely irrelevant, since their claims would have priority over the fines in any case. Despite this, their first preference is, like that of managers, to avoid all together. Although their claims are protected, the bankruptcy process will impose costs on them. Thus, just as for managers, increasing the probability of detection increases the probability that the firm will become bankrupt, and thus makes it worthwhile for secured creditors to exert what influence they have to push the firm towards taking efficient care.

Increased enforcement for firms near insolvency can have an additional benefit beyond raising the likelihood of detecting violations. It may also increase the speed at which violations are detected.⁶¹ To see how the speed of detection is relevant, even given a fixed probability of eventual detection, take an extreme example in which probability of detection is fixed at 100%. In one scenario, if a firm violates pollution laws, the violation will be detected with perfect probability in one year's time and a fine assessed. In the other scenario, the violation will be detected with perfect probability immediately. In the first situation, a firm near bankruptcy may have incentives to take inefficient care, since it might be judgment-proof by the time the fine is assessed. In the later scenario, however, the financially precarious firm will still act efficiently, provided the fine is set to match the harms the firm causes. With a certainty of immediate detection, there is no incentive for firm owners, creditors or managers to "gamble" and hope to profit from the cost savings of taking inefficient care.

This solution can be effective in addressing harms directly policed by agencies like the EPA that can shift monitoring resources. But, it does little for individuals who need to bring tort claims for harms.⁶²

Another challenge with this solution is that it, as I have presented it so far, rests upon the assumption that current levels of enforcement are at least roughly optimal. If one assumes that current EPA enforcement is sub-optimal, then it is no longer certain that the best use of agency resources will be to more frequently inspect facilities owned by companies with a higher risk of bankruptcy. If both low and high bankruptcy risk firms are monitored at a sub-optimal level, the question becomes where an added dollar of enforcement would have the largest marginal benefit.

There are, however, good reasons to believe that the marginal value of extra enforcement will frequently have the largest benefit for firms near insolvency. The basic intuition is that the size of a penalty loses its deterrent power for owners of a firm that can discharge some or all of that penalty in bankruptcy. But, for firms near bankruptcy, if a fine is imposed, it can significantly increase the likelihood of the firm becoming bankrupt. Thus, if the fine can wipe out most or all of a firm's profits and even assets, something which is more likely for a firm near insolvency, then that firm will respond more strongly to a higher probability of that fine than would a financially healthy firm for which the fine

⁶¹This would occur, for instance, if an enforcement action in any given month has a random probability.

⁶²In a few instances, individuals at an appreciable risk of harm from a specific corporation may be able to act based on these principles.

would be undesirable but not catastrophic. In the Appendix I present a simple theoretical model that formalizes these intuitions and demonstrates that there are a wide range of conditions under which overall enforcement levels are suboptimal but that the marginal value of added enforcement directed towards firms near insolvency is greater than that for financially sound firms.

It is important to note that these arguments above establish that additional enforcement directed towards firms with high risk of insolvency can frequently be optimal. They by no means establish that it is always so. This policy proposal should not therefore be interpreted as suggesting an iron-clad formula that locks administrative agencies in to a strategy that determines inspection intensity as a mechanistic function of firms' risk of bankruptcy. Instead, it more sensibly should be interpreted as suggesting that administrative agencies considering enforcement priorities should take into account, as one factor, whether firms have recently begun to experience unusual risk of insolvency.⁶³

Finally, I note that as with any policy change, this one is not apt to achieve a perfect optimum in one fell swoop. If, for instance, penalties for non-compliance are set at inefficiently low levels, then increasing penalties to more efficient levels could be an important prerequisite to getting maximum benefits from this proposal. Likewise, if total enforcement resources are vastly inadequate to meet enforcement needs, marginal improvements from this proposal may only make a small impact on a much larger problem. Thus, this proposal should be considered as one amongst many tools that can be used, ideally in concert with one another, to improve overall enforcement efficiency.

Despite these limitations, this proposal offers a relatively simple, easy to implement, and low cost response to what has been a thorny and much debated issue in corporate law for many decades now.

7 Conclusion

Corporate law has seen a prominent debate as to what extent limited liability creates incentives for firms near insolvency to take inefficiently low care to prevent harm to third parties. Despite the robustness of the theoretical debate, there has not been, prior to this paper, a direct empirical showing that bankruptcy risk is systematically associated with increased risk of harm to third parties. This paper

⁶³An agency could also design a randomized trial in which certain firms are notified that inspection policy will consider bankruptcy risk.

shows such a link, using as a case study violations of the Clean Water Act as enforced by the EPA.

None of my methods amount to randomly assigning limited liability to some firms but not others, or to randomly increasing bankruptcy risk, holding constant firms' other financial conditions. Nevertheless, I show that my results linking bankruptcy risk and harm to third parties cannot be explained by factors such as inability to pay for precautions, or firm managers' skill or risk preferences. As such, I contend the most plausible explanation is that bankruptcy risk drives risk of harm to third parties.

And, if increasing bankruptcy risk increases the risk of harm to third parties, I argue that limited liability must play a leading role in explaining this. This conclusion is bolstered by the fact that when bankruptcy risk has been studied as a predictor of harm to third parties in a context where there is a party (an insurance company) that will be liable for harms in excess of a firm's ability to pay, the association I observe, linking bankruptcy risk and harm to third parties, disappears (Feinstein, 1989).

In response to these findings, I offer a policy proposal that can help ameliorate many of the inefficiencies that come from owners and managers of firms near bankruptcy having incentives to take inadequate levels of care. Namely, I suggest that agencies such as the EPA, which are charged with monitoring corporations for violations of laws designed to protect third parties, should take into account the proximity of firms to insolvency when setting their monitoring levels. And, the EPA is just a single example. There are a wide number of administrative agencies to which this could be applicable - agencies such as the FTA, SEC, Federal Reserve, and others all provide crucial supervision of firms with significant risks of both insolvency and externalized harm to third parties. By developing enforcement policies based on the findings of this research, agencies such as these can create more efficient incentives for appropriate levels of care by firms throughout the economy.

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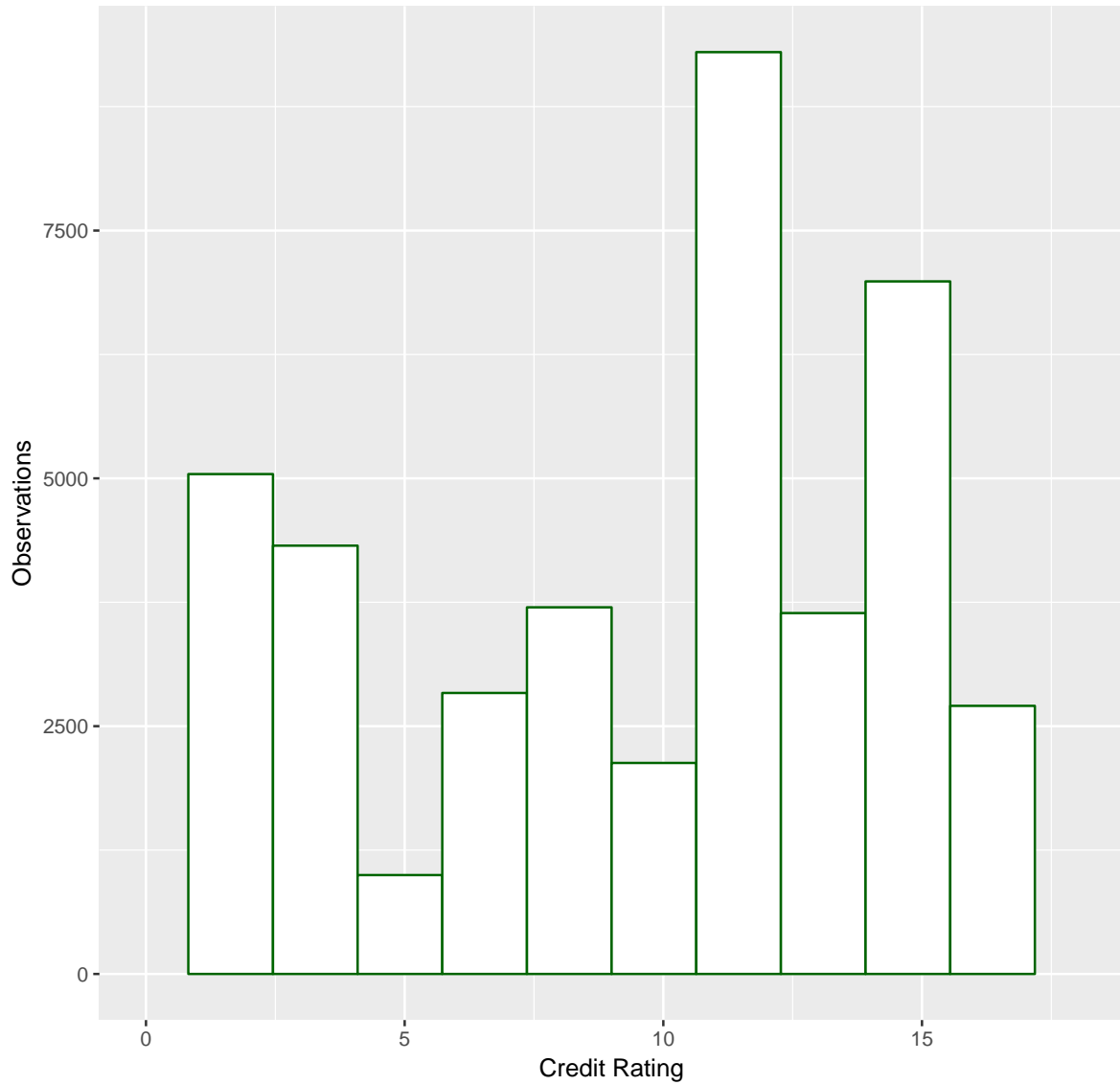


Figure 1. Distribution of Observed Credit Scores Over Sample Period. See Table 1 for translations between numeric and alphabetic credit ratings.

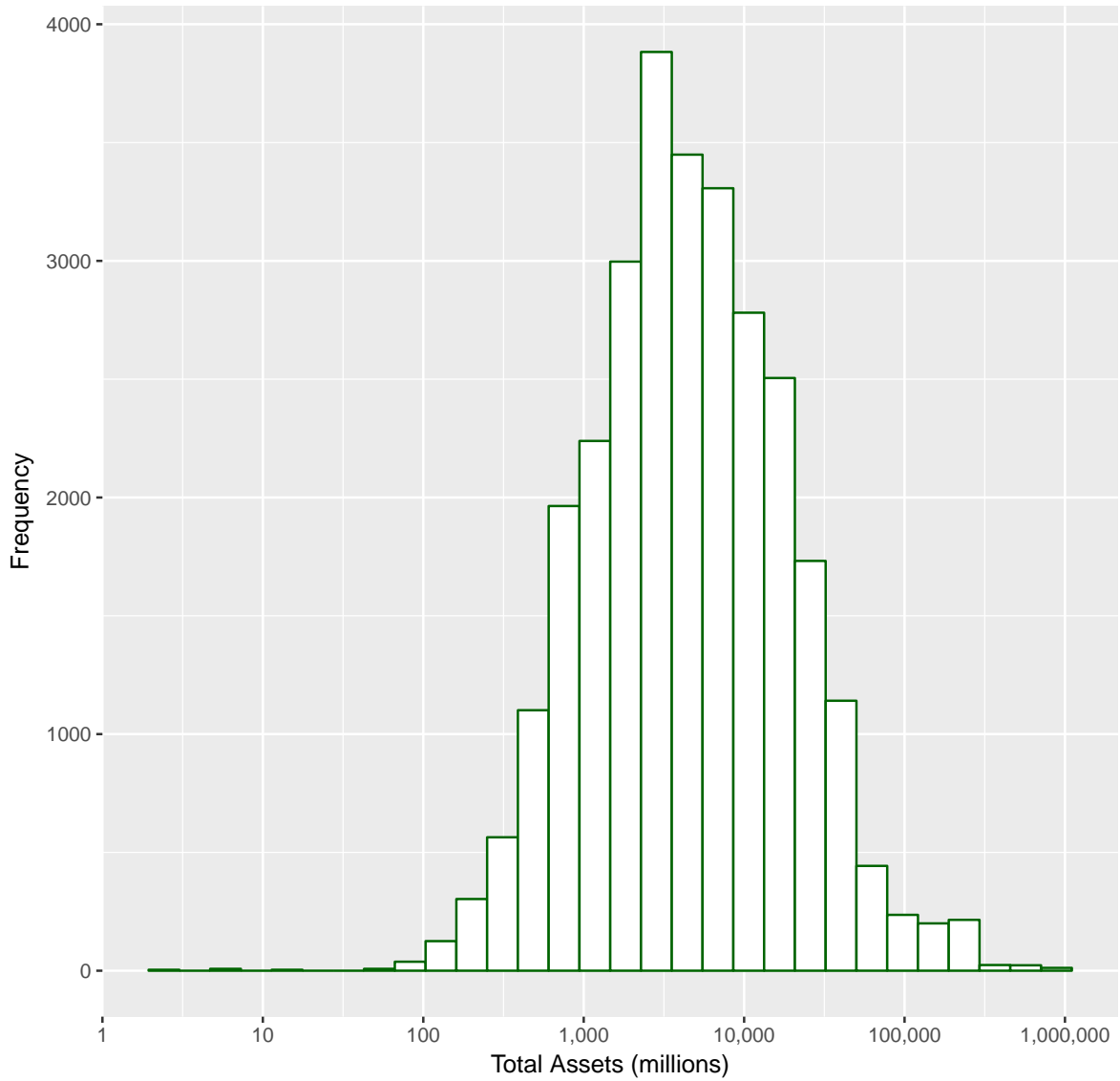


Figure 2. Distribution of Company Sizes by Total Assets. This plots the distribution of total assets amongst the company-quarter observations in this study. Thus, as companies change asset sizes throughout the course of the study they will be reflected in different portions of the depicted distribution. Data for total asset sizes comes from Compustat and is available for approximately 50% of the observations in the sample.

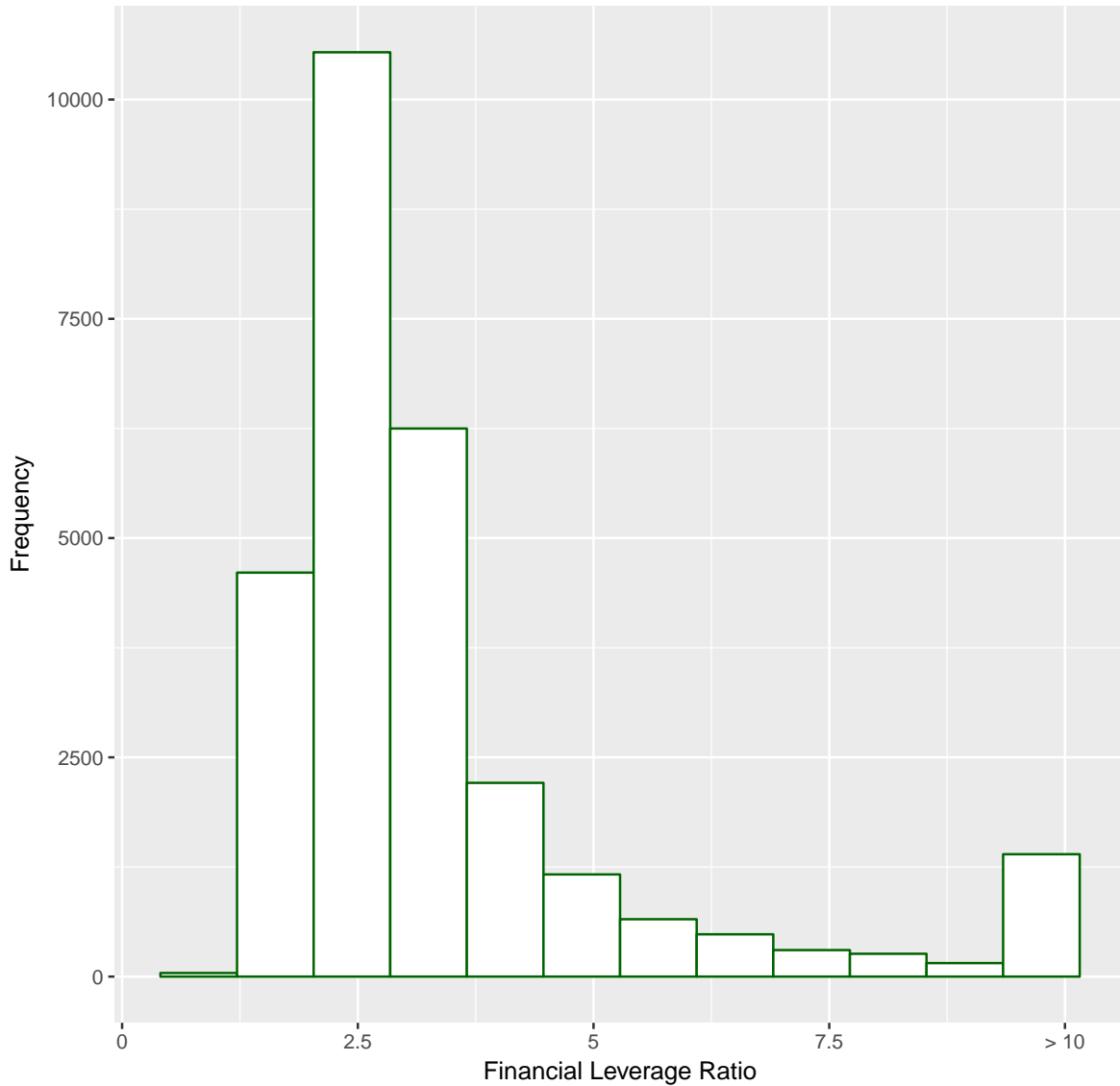


Figure 3. Distribution of Financial Leverage Ratios. This plot considers the financial leverage ratio, defined as $\frac{\text{Assets}}{\text{Assets}-\text{Liabilities}}$. As with Figure 2, each company-quarter observation contributes one point to the distribution depicted here, so companies may appear in different places in this distribution at different points in the sample period as their leverage ratios change. Data for calculating leverage ratios comes from Compustat and is available for approximately 50% of the observations in the sample.

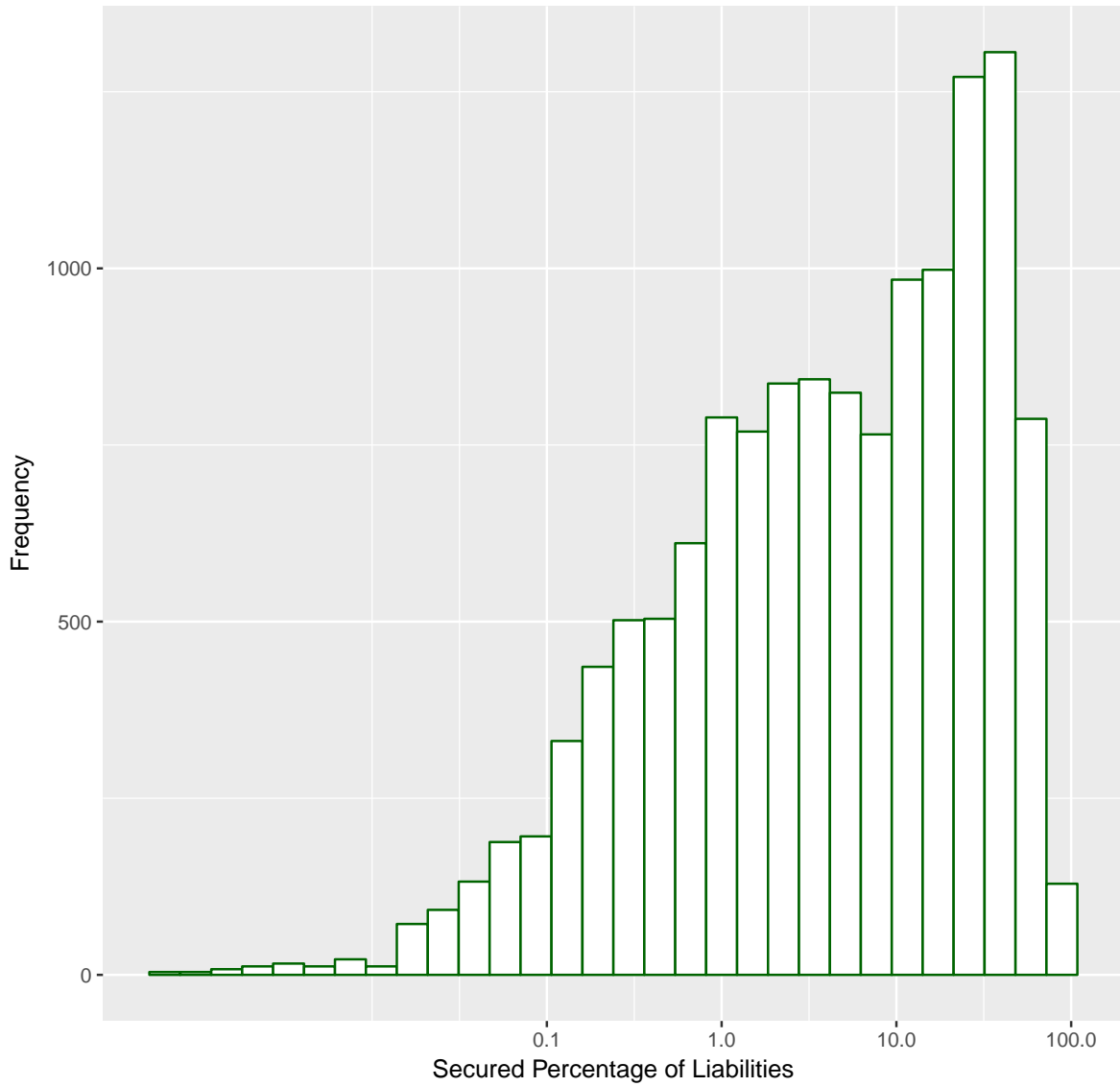


Figure 4. Secured Debt as a Percentage of Total Liabilities. Each company-quarter observation contributes one point to the distribution depicted here, so companies may appear in different places in this distribution at different points in the sample period as their leverage ratios change. Data for calculating leverage ratios comes from Compustat and is available for approximately 50% of the companies in the sample.

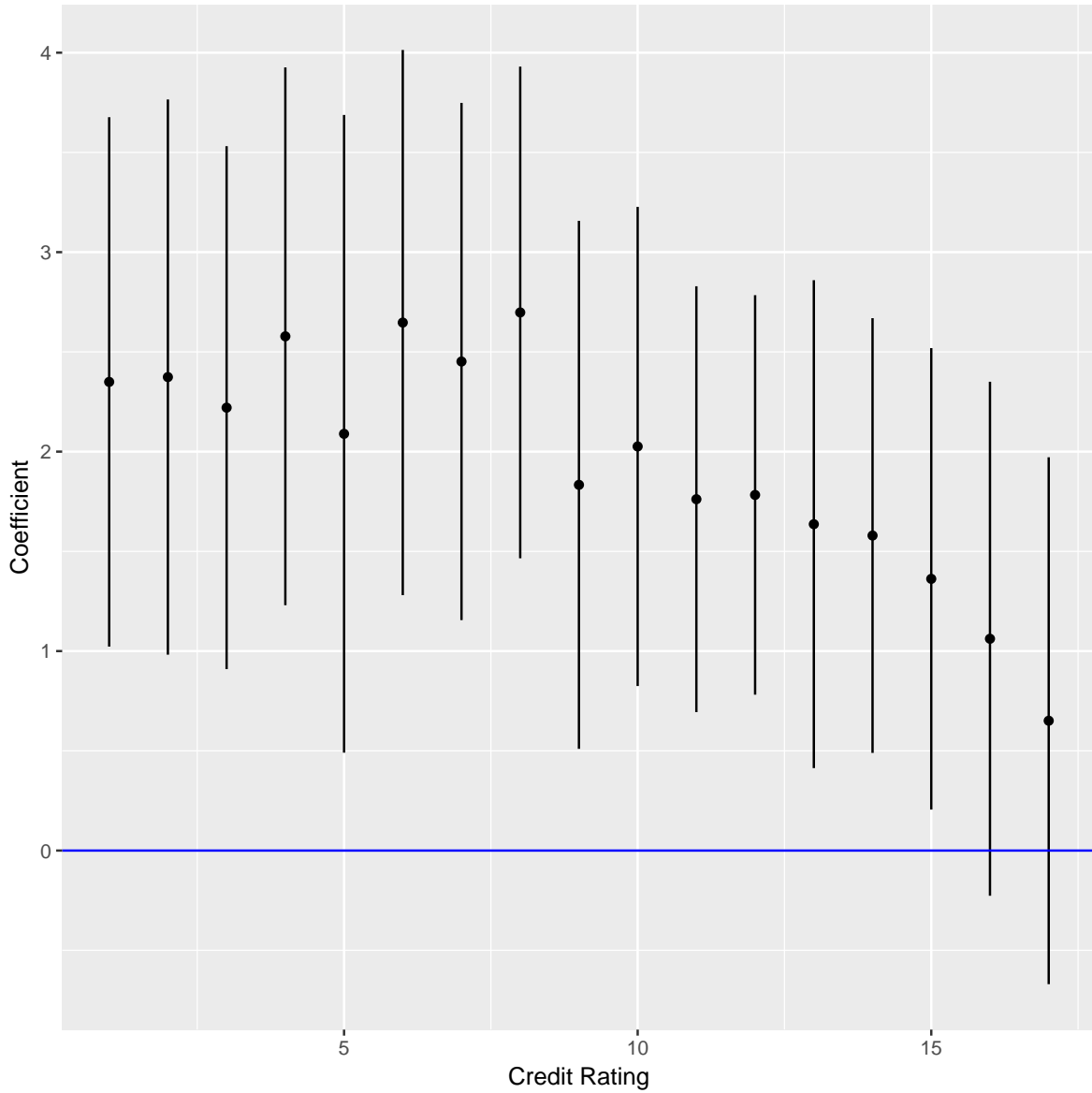


Figure 5. EPA-Detected Pollution Violations. This plots the coefficient estimates for each of the separate credit ratings, along with the associated 95% confidence intervals, from fitting a conditional logistic regression to predict the probability of an EPA-detected pollution violation as a function of credit rating plus company and quarter fixed effects. The base value for the factors is set to the highest credit rating, such that the fitted coefficient estimates represent default probabilities relative to that of the base level. Confidence intervals are calculated using robust standard errors clustered at the company level.

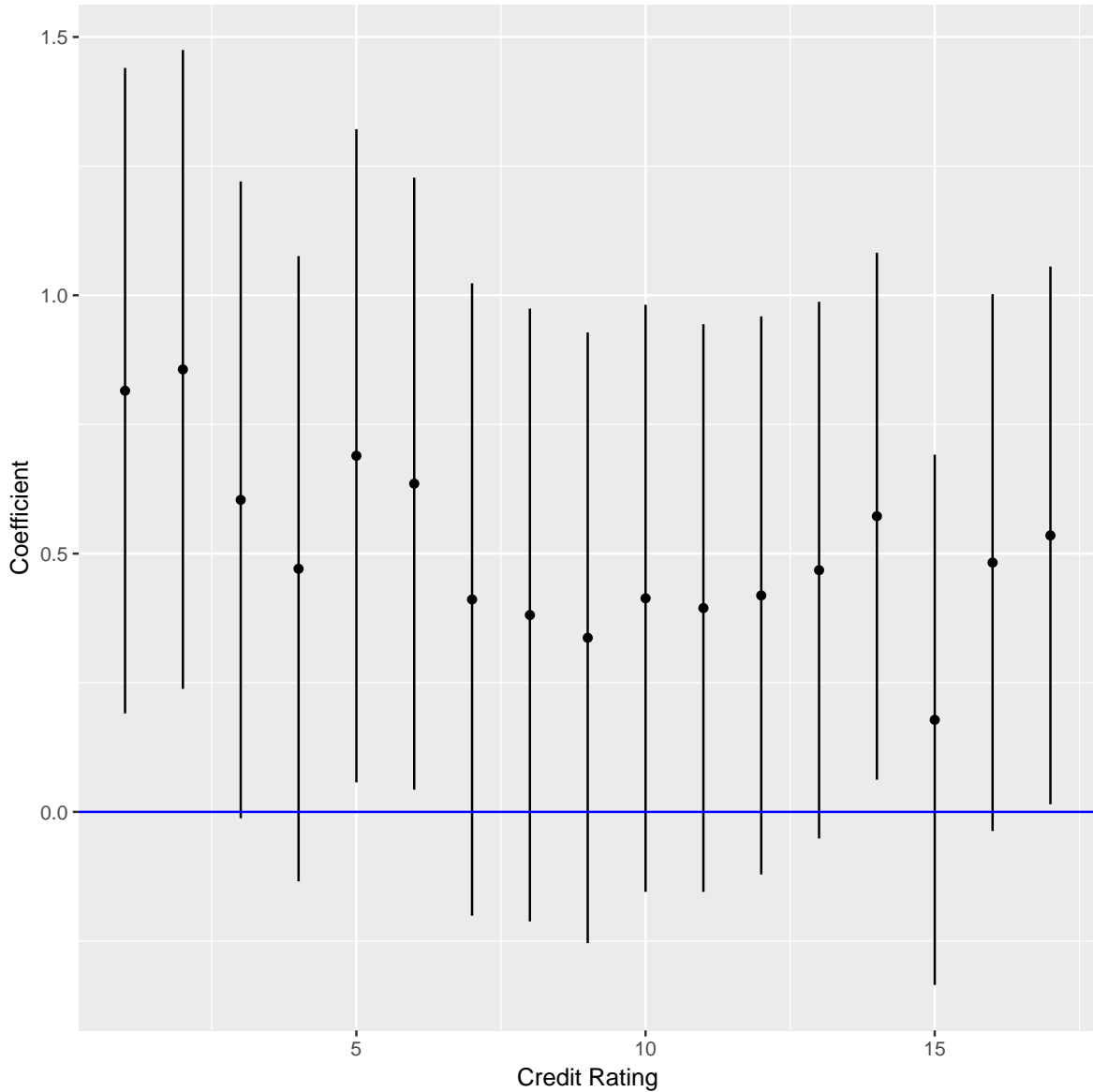


Figure 6. Reporting Failure Pollution Violations. This plots the coefficient estimates for each of the separate credit ratings, along with the associated 95% confidence intervals, from fitting a conditional logistic regression to predict the probability of a reporting failure pollution violation as a function of credit rating plus company and quarter fixed effects. The base value for the factors is set to the highest credit rating, such that the fitted coefficient estimates represent default probabilities relative to that of the base level. Confidence intervals are calculated using robust standard errors clustered at the company level.

Table 1

S&P Corporate Credit Risk Data - Summary Statistics. This table lists the different corporate credit ratings from the S&P agency that appear in the Mergent FISD database I access for this study. For each rating, I give the numerical equivalent that I use in my empirical models, as well as the number of company-quarter observations in my data for which the given credit rating applies. This table also lists the percentages of bonds with the given default rating that have gone on to default within a 1-year and 5-year time horizon, based on historical data from 1981 to 2015. S&P does not report separate statistics for its three lowest ratings (CCC-, CCC, and CCC+), so the default rates for bonds with each of these are reported as the same, even though a CCC- rating is indeed considered to be higher risk than a CCC+ rating. Source: "2015 Annual Global Corporate Default Study And Rating Transitions."

Rating	Numeric Equivalent	Observations	1-Year Default Rate	5-Year Default Rate
SD	1	3774	Imminent/Partial	NA
CCC-	2	3859	27.22	46.99
CCC	3	3363	27.22	46.99
CCC+	4	2857	27.22	46.99
B-	5	1742	8.74	27.82
B	6	2339	5.59	21.61
B+	7	1989	2.51	16.15
BB-	8	2688	1.22	10.52
BB	9	2165	0.76	7.68
BB+	10	2585	0.49	4.51
BBB-	11	4344	0.36	3.44
BBB	12	7379	0.23	1.67
BBB+	13	5129	0.15	1.26
A-	14	4896	0.09	0.68
A	15	5360	0.07	0.57
A+	16	2917	0.06	0.52
AA-	17	1612	0.03	0.38
AA	18	1266	0.02	0.38

Table 2

EPA Pollution Violations - Summary Statistics. The statistics in this table are calculated as follows. I start by considering each company, the number of years that it appears in the data, and the total number of violations I observe for it. I then divide that total number violations by the number of observed years, for each company, giving me an annual violation rate for each company. Then, for each type of violation, I calculate the 25th, 50th, and 75th percentiles of the annual rates of pollution amongst each set of relevant companies.

	Upgrade Compliance Violation	Self- Reported Violation	Missing Compliance Report	EPA- Detected Violation	All Violations
Number of Companies with ≥ 1 Violation	268	225	507	199	627
Total Violations Detected	989	1324	6268	581	9162
Violations Per Company Per Year:					
25th Percentile	0.07	0.07	0.16	0.04	0.15
50th Percentile	0.13	0.15	0.43	0.07	0.42
75th Percentile	0.23	0.43	0.98	0.15	1.1

Table 3

Conditional Logit - Baseline Results. This table presents the baseline results from Equation 2 which represents the probability of a firm being sanctioned by the EPA for one of four different types of pollution violations. Each analysis uses a full set of company and time fixed effects as well as a firm's credit rating to model the probability of an EPA sanction. AUC measures the area under the receiver operator characteristic as a measure of goodness of fit.

	(Upgrade Compliance)	(Self-Reported)	(Reporting Failure)	(EPA-Detected)
Credit Rating	-0.017 (0.028)	-0.017 (0.021)	-0.029 ** (0.013)	-0.101 *** (0.033)
Observations	19710	16808	35088	14255
AUC	0.828	0.833	0.86	0.826
Company FEs	yes	yes	yes	yes
Quarter FEs	yes	yes	yes	yes

Robust standard errors in parentheses, clustered at company level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4
Conditional Logit - Additional Predictors.

	(Other Predictors Only)	(Credit-Rating Only)	(All Predictors)
Panel A: Upgrade Compliance			
Credit Rating		-0.061 (0.039)	-0.057 (0.04)
Current Ratio	-0.068 (0.111)		-0.062 (0.112)
Stock Return	-0.137 (0.14)		-0.123 (0.131)
Gross Profits	-0.299 (0.967)		-0.17 (0.947)
Leverage Ratio	-0.002 (0.001)		-0.001 (0.002)
Observations	8742	8742	8742
AUC	0.845	0.846	0.846
Panel B: Self-Reported			
Credit Rating		0.019 (0.032)	0.014 (0.031)
Current Ratio	-0.074 (0.125)		-0.077 (0.122)
Stock Return	0.285 ** (0.145)		0.277 ** (0.138)
Gross Profits	-0.13 (0.962)		-0.147 (0.974)
Leverage Ratio	0.001 (0.001)		0.001 (0.001)
Observations	7749	7749	7749
AUC	0.847	0.845	0.847
Panel C: Reporting Failure			
Credit Rating		-0.039 * (0.021)	-0.037 * (0.022)
Current Ratio	0.015 (0.072)		0.016 (0.07)
Stock Return	-0.024 (0.051)		-0.009 (0.05)
Gross Profits	-0.452 (0.323)		-0.4 (0.312)
Leverage Ratio	0.001 (0.001)		0.001 (0.001)
Observations	15523	15523	15523
AUC	0.871	0.871	0.871
Panel D: EPA-Detected			
Credit Rating		-0.094 ** (0.043)	-0.1 ** (0.043)
Current Ratio	-0.144 (0.204)		-0.156 (0.188)
Stock Return	-0.019 (0.126)		-0.02 (0.124)
Gross Profits	1.216 (0.851)		1.482 * (0.88)
Leverage Ratio	-0.008 (0.006)		-0.006 (0.005)
Observations	6857	6857	6857
AUC	0.851	0.85	0.852
Company FEs	yes	yes	yes
Quarter FEs	yes	yes	yes

Robust standard errors in parentheses, clustered at company level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5

Instrumental Variable Formulation - Linear Probability Model. This table presents results for the IV formulation given in Equation 4. I use a linear probability model here, rather than a conditional logit, because the latter is not well defined in the instrumental variables context. The IV uses exogenous variation in macroeconomic factors to predict corporate credit ratings and represents the probability of pollution violations as a function of these predicted credit ratings. All models here contain a full set of company and time fixed effects.

	Upgrade Compliance		Self-Reported		Reporting Failure		EPA-Detected	
	(OLS)	(IV)	(OLS)	(IV)	(OLS)	(IV)	(OLS)	(IV)
Credit Rating	-0.002 (0.001)	-0.019 * (0.01)	-0.002 (0.001)	-0.045 ** (0.019)	-0.003 (0.003)	-0.043 (0.036)	-0.003 *** (0.001)	-0.025 ** (0.013)
Observations	12185	12185	12185	12185	12185	12185	12185	12185
Company FEs	yes	yes	yes	yes	yes	yes	yes	yes
Quarter FEs	yes	yes	yes	yes	yes	yes	yes	yes

Robust standard errors in parentheses, clustered at company level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6

Conditional Logit - Heterogeneous Effects by Corporation Size Group. This variation on the baseline analysis allows for the effect of a firm's proximity to insolvency, as measured by its credit rating, to vary based on the size of a firm, measured by its total assets. The size groups of small, medium, and large correspond to maximum assets of \$1 billion, \$5 billion, and \$1 trillion respectively, with groupings chosen to achieve roughly equal numbers of companies in each. The analyses here contain a full set of company and time fixed effects, as well as a unique constant term for each company size group, whose coefficients are insignificant and not reported here.

	(Upgrade Compliance)	(Self-Reported)	(Reporting Failure)	(EPA-Detected)
Credit Rating × Size = Small				
Credit Rating × Size = Medium	-0.052 (0.072)	0.049 (0.081)	0.063 (0.039)	0.045 (0.069)
Credit Rating × Size = Large	-0.047 (0.078)	0.005 (0.08)	0.1 *** (0.036)	-0.009 (0.079)
Observations	11157	10086	20656	9418
AUC	0.839	0.849	0.87	0.846
Company FEs	yes	yes	yes	yes
Quarter FEs	yes	yes	yes	yes

Robust standard errors in parentheses, clustered at company level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7

Conditional Logit - Heterogeneous Effects by Secured Percent Group. This variation on the baseline analysis allows for the effect of a firm's proximity to insolvency, as measured by its credit rating, to vary based on the percentage of its total liabilities that are comprised of secured debt. The goal is to investigate whether unsecured creditors act as a constraining force on a firm's tendency to reduce precautions to prevent harm to third parties as the firm approaches insolvency. The analyses here contain a full set of company and time fixed effects, as well as a unique constant term for each secured percent group, whose coefficients are insignificant and not reported here.

	(Upgrade Compliance)	(Self-Reported)	(Reporting Failure)	(EPA-Detected)
Credit Rating × Secured % ∈ [0, 2)	-0.086 (0.08)	0.038 (0.068)	0.031 (0.041)	0.011 (0.093)
Credit Rating × Secured % ∈ [2, 20)	-0.108 (0.077)	0.04 (0.078)	0.019 (0.045)	0.073 (0.098)
Credit Rating × Secured % ∈ [20, 40)	-0.099 (0.078)	-0.016 (0.074)	0.035 (0.046)	0.074 (0.098)
Credit Rating × Secured % ∈ [40, 100]				
Observations	11157	10086	20656	9418
AUC	0.842	0.85	0.87	0.85
Company FEs	yes	yes	yes	yes
Quarter FEs	yes	yes	yes	yes

Robust standard errors in parentheses, clustered at company level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix A - Modeling Efficient Deterrence

A.1 Model Setup

In this appendix, I present a simple model to demonstrate how there are a wide range of plausible circumstances under which the following three conditions hold:

- (a) Enforcement levels are suboptimal
- (b) Firms closer to bankruptcy are more likely to violate pollution laws on account of their proximity to bankruptcy
- (c) A marginal increase in enforcement resources directed towards firms near bankruptcy will have a larger marginal deterrent effect than the same increase in enforcement resources directed towards firms farther from bankruptcy.

The purpose of this model is to show that the policy proposal I make in Section 6 will frequently improve social efficiency, even when current enforcement levels are sub-optimal.

Consider a firm deciding whether to take a socially efficient, legally mandated precaution. The cost of the precaution is C . The firm starts with assets A . After one period, the firm will realize a net profit on its assets of $R \in \{H, L\}$ with probability $\{P_H, (1 - P_H)\}$. In the event the firm does not take the precaution, it will be detected with P_D . In that event it is assigned a fine of F at the end of the period. For simplicity, assume that the probability of detection is independent of the probability of the firm realizing high or low net profits.

The firm will have an incentive to not take the precaution whenever doing so increases its expected profits. But, rather than the firm deterministically making this decision, assume instead that the firm's likelihood of not taking the precaution increases proportionally with the amount its profits increase from not taking the precaution. That is, if avoiding the precaution gives only a small net benefit to the firm, it will still have a high likelihood of taking the precaution. This might be due to an inherent preference by firm owners to conform to social norms, *ceteris paribus*. It may be from a risk-aversion of the firm owner. It may be from an uncertainty of the firm owner in the probability or severity of the fine, or some other similar consideration.

As a natural corollary, assume that there is some upper bound beyond which additional expected profits will no longer increase the probability of not taking the precautionary measure. This could be because the probability of not taking the precaution has risen to one. Or it could be the probability has risen high enough that it is only concern for social norms, etc. that remains to motivate the owners to take the precaution.⁶⁴

Given these considerations, a firm's value at the end of the period (A_{final}) will depend on its starting assets, minus the cost of the precaution (if the firm takes the precaution), plus the return on its assets, minus the cost of the fine, if it is assessed. The return on the firm's assets can then be represented as:

$$\text{Return} := \frac{A_{\text{final}} - A}{A}$$

The firm will accordingly have the following expected returns depending on the its choice of compliance:

$$\begin{aligned} \mathbf{E}[\text{Return} \mid \text{Compliance}] &= \max \left\{ 0, \frac{A + P_H H + (1 - P_U)L - C}{A} \right\} \\ \mathbf{E}[\text{Return} \mid \text{No Compliance}] &= \max \left\{ 0, \frac{A + P_H H + (1 - P_U)L - P_D F}{A} \right\} \end{aligned}$$

Firms will comply or not based on the expected excess returns of noncompliance, that is:

$$\text{Excess Returns of Non-compliance} := \mathbf{E}[\text{Return} \mid \text{No Compliance}] - \mathbf{E}[\text{Return} \mid \text{Compliance}]$$

If this quantity is negative, then it will never be profitable for the firm to avoid taking the precaution. But, if it is positive, then the firm will have a positive probability of choosing not to take the precaution. Note that because the precaution is defined as socially efficient, any positive probability of choosing not to take the precaution represents a social inefficiency.⁶⁵

⁶⁴This assumption of proportional but bounded increase in probability of non-compliance is by no means necessary - other functional forms linking expected profits from non-compliance to probability of non-compliance could easily be devised, but this serves to create a simple exposition for this model.

⁶⁵The social inefficiency from not taking the precaution might or might not be outweighed by the costs of enforcement in order to increase

A.2 Judgment Proof and Non-Judgment Proof Firms

For simplicity, consider the two following specific cases of this general scenario.

Firm 1: The Non-Judgment Proof Firm

This is a firm that will not be bankrupted by the fine in any circumstances. That is, $F < A_1 + L$, where A_1 represents Firm 1's assets. The expected return in the event of non-compliance is:

$$E[\text{Return} \mid \text{No Compliance}] = \frac{A_1 + P_H H + (1 - P_H)L - P_D F}{A_1}$$

The expected return in the event of compliance is:

$$E[\text{Return} \mid \text{Compliance}] = \frac{A_1 + P_H H + (1 - P_H)L - C}{A_1}$$

Thus, the “excess returns” of non-compliance for the non-judgment proof firm are simply:

$$\frac{C - P_D F}{A_1}$$

This is relatively intuitive then: the non-judgment proof firm will find it profitable to comply whenever the expected cost of the fine ($P_D F$) is greater than the cost of the compliance measure (C).

We also see that the increase in marginal deterrence from increasing probability of detection is proportional to the ratio of the fine to the firm's total assets, that is:

$$\frac{\partial}{\partial P_D} \text{Excess Return from Noncompliance} = -\frac{F}{A_1}$$

Intuitively, the larger the fine, the larger the marginal effect of increasing the probability of detection.

Firm 2: The Judgment Proof Firm

Next, consider a firm such that $F > A_2 + H$, where A_2 represents Firm 2's assets. Thus, this firm will be bankrupted if it does not comply and it is assessed a fine for its compliance failure. In this case, the firm owners will get a return of zero in the event that a fine is assessed, as their net assets will go to zero. Thus, the expected return for the non-complying judgment-proof firm is:

$$0 * P_D + \frac{(1 - P_D)[A_2 + P_H H + (1 - P_H)L]}{A_2}$$

The expected return from the complying judgment-proof firm is:

$$\frac{A_2 + P_H H + (1 - P_H)L - C}{A_2}$$

Thus, the “excess returns” of non-compliance for the judgment-proof firm are:

$$\frac{C - P_D [A_2 + P_H H + (1 - P_H)L]}{A_2}$$

Rather than losing F in the event of the fine, as for Firm 1, for Firm 2, the max fine cannot go beyond its total assets, since it is judgment proof. Thus, this firm's expected losses from not complying are given by the probability of detection, P_D , times its expected assets given non-compliance ($A_2 + P_H H + (1 - P_H)L$).

The increase in marginal deterrent in this situation from increasing enforcement probability, P_D is:

the firm's incentive to take the efficient precaution. As will become clear, enforcement costs factor only tangentially into this model, through the evaluation of where a marginal dollar of enforcement expenditures will have the greatest effect.

$$\frac{\partial}{\partial P_D} \text{Excess Return from Noncompliance} = -\frac{A_2 + P_H H + (1 - P_H)L}{A_2}$$

In other words, the marginal deterrence from increasing the probability of detection for the judgment proof firm is proportional to the amount of profits the judgment proof firm would make if it did not comply and was not detected. As a firm with low net asset values, but still the potential to make an appreciable amount of money, the judgment proof firm stands to reap large profits if the random realizations in this model go its way. But, those large profits will be foreclosed upon completely if the firm violates the mandated safety requirement and is caught doing so. The foreclosure of those large potential returns on its upside thus has the potential to make the firm responsive to increases in the probability of detection.

A.3 Increases in Marginal Deterrence by Increasing Monitoring for Firms Near Insolvency

What remains to be established are the specific conditions set forth above, namely that there are plausible circumstances such that the three conditions given in Section A.1 are satisfied. Since the precaution is efficient by definition, sub-optimal deterrence occurs whenever there is a positive probability that firms will not comply. We satisfy conditions (a) and (b) whenever:

$$\frac{C - P_D [A_2 + P_H H + (1 - P_H)L]}{A_2} > \frac{C - P_D F}{A_1} > 0$$

We satisfy condition (c) whenever:

$$\frac{A_2 + P_H H + (1 - P_H)L}{A_2} > \frac{F}{A_1}$$

Lastly, we ensure that Firm 1 is indeed not judgment proof via $F < A_1 + L$ and that Firm 2 is judgment proof (in the event of a fine) via $F > A_2 + H$.

There are many more free parameters here than constraints, and they are easily met under a wide range of configurations. To give a particular example, let $A_1 = 10$, $A_2 = 3$, $H = 2$, $L = -1$, $P_H = 0.5$, $P_D = 0.1$, $F = 6$, and $C = 2$. Under these configurations, Firm 2, the judgment proof firm, has an increase in expected profits from not complying of 0.55, and Firm 1, the non-judgment proof firm, has an increase in expected profits from not complying of 0.14. In other words, both firms find it profitable to not comply, but the judgment proof firm has a stronger incentive not to do so, since it profits more by. Similarly, the marginal deterrent effect from increasing detection probability is -1.17 for the judgment proof firm, whereas it is -0.6 for the non-judgment proof firm.

The basic intuition behind this model and its results is relatively clear. The firm near bankruptcy is sub-optimally deterred because it is unresponsive to the size of the fine. But, because the fine, if assessed, would wipe out all profits the firm would make otherwise, the judgment proof firm is still relatively responsive to changes in the probability of detection, and in many cases, more so than the firm further from bankruptcy.