Efficient Bankruptcy, Bargaining Power, and AI Innovation

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Abstract

Using a large exogenous increase in bankruptcy court capacity in a triple-differences framework, I show that higher expected bankruptcy probability increases existing creditors' willingness to accept out-of-court debt restructuring proposed by moderately distressed firms. Firms' threat to file for bankruptcy becomes more credible with less congested courts, so the appeal of extrajudicial restructuring is higher when bankruptcy is more efficient. To establish bargaining power as the channel, I show that out-of-court restructurings do not respond to bankruptcy efficiency when the firm's CEO owns more than one percent of the firm's equity, likely because the bargaining power of these firms are impeded by their CEOs' high personal cost of bankruptcy. Exposure to the bankruptcy efficiency shock causes moderately distressed firms to hire more AI workers and produce more AI-related patents. These results suggest that a shift of bargaining power from creditors to debtors ameliorates two frictions: it reduces the overuse of costly bankruptcy (over out-of-court restructuring), and alleviates the underinvestment in broadly useful innovations.

JEL: G31, G32, G33, O30, O32

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Introduction

The bankruptcy system is crucial for reallocating assets to productive use. Efficient bankruptcy reduces the costs of failure, reinforcing the "safety net" of the innovation ecosystem. If a risky project and a safe project are equally attractive to a firm *ex ante*, improving bankruptcy efficiency would induce the firm to choose the risky project, whose downside payoff is steeper and more salvaged by the efficiency of the bankruptcy process. In this way, efficient bankruptcy encourages innovation not just for the small set of firms that actually go bankrupt, but also a larger number of firms considering innovative projects, for which the probability of future bankruptcy is positive.

The general equilibrium effect of efficient bankruptcy has another channel that is perhaps more subtle. Corporate loans are often syndicated and a collective action problem among syndicated lenders impedes efficient restructuring (e.g., write-down) of these loans. Restructuring the loan is efficient because a failure to restructure pushes the firm to the bankruptcy court, which is costly and undesirable for both the firm and its creditors. Notwithstanding their aversion to bankruptcy, each creditor has a free-riding incentive to wait for other creditors to take on the restructuring deal. This "holdout" problem creates extra traffic in the bankruptcy court, which could have been avoided if out-of-court restructurings are carried out more efficiently.

In the first part of this paper, I provide empirical evidence that efficient bankruptcy leads to more out-of-court restructurings. I leverage the theoretical insight of Donaldson et al. (2020) that higher expected bankruptcy probability increases creditors' willingness to accept out-of-court restructurings, because the seniority that they gain from restructuring is more valuable when bankruptcy is more likely. This mechanism generates a surprising result that bankruptcy and restructuring are substitutes in reality but complementary in expectation. I use the 2005 U.S. Bankruptcy Abuse Prevention and Consumer Protection Act (BAPCPA) as a natural experiment that provides exogenous variation to bankruptcy efficiency. In a triple-differences framework, I show that moderately distressed firms headquartered in high BAPCPA-exposure court districts report a large increase in out-of-court restructurings after the bankruptcy court reform. This result is consistent with the interpretation that higher bankruptcy efficiency increases the firm's willingness to file, which increases the value of seniority offered in out-of-court restructuring deals.

To further elucidate the complementarity between expected bankruptcy and restructuring, I exploit the heterogeneous degree to which the firm's bankruptcy propensity responds to bankruptcy efficiency. The identifying variation that I use comes from the CEO's personal cost of bankruptcy, which I measure with her equity ownership of the firm (Friend & Lang, 1988; Schoenherr & Starmans, 2022) . I show that in the sub-sample where CEOs own more than 1% of their firms' shares, higher bankruptcy efficiency does *not* lead to more out-of-court restructurings, unlike in the full sample and in the sub-sample where CEOs' ownership is less than 1%. Since filing for bankruptcy often brings deep discount to the firm's equity value, CEOs with higher equity ownership are subject to a greater personal cost of bankruptcy. Creditors of these firms anticipate the CEOs reluctance to file, so their willingness to restructure barely change.

The sub-sample results make clear that bankruptcy efficiency affects out-of-court restructuring via affecting the bargaining power that firms have over their creditors. Since the firm holds the option to incur a lose-lose scenario by filing for bankruptcy, it has high bargaining power over creditors for restructuring if it can credibly commit to the bankruptcy threat. If the firm obtains a more credible threat (e.g., due to higher bankruptcy efficiency), it gains bargaining power and restructure its debt. If it cannot credibly commit (e.g., due to CEO's high personal bankruptcy cost), it loses bargaining power and fails to restructure.

The second part of this paper relates bankruptcy efficiency to innovative outcomes. The bargaining power dynamic between firms and creditors matter because it affects the incentive to innovate for a broad set of firms *ex ante*. I work under the assumption that innovation produces positive externality and encouraging innovation is broadly beneficial. To make this assumption not too restrictive, I focus on innovation related to AI, which has shown great potential to bring productivity-improving transformation to a wide range of industries. When efficient bankruptcy increases the bargaining power of firms over their creditors, I show that firms more affected by the bankruptcy efficiency shock increase their leverage and hire more AI workers relative to firms less affected by the shock. I interpret these effects as evidence that firms increase risk-taking in attempts to produce innovative outcomes. I then show that firms more affected by the bankruptcy efficiency shock indeed produce more patents, particularly AI-related patents, and these patents receive more citations from follow-on patents.

Throughout the paper I use BAPCPA to generate exogenous variation in bankruptcy efficiency. The BAPCPA enactment in October 2005 considerably increases the cost for individual debtors to file for bankruptcy. The effect is immediate: filings submitted to the bankruptcy court dropped by nearly 40% in 2006 and by another 30% in 2007 (Iverson, 2018). Corporate debtors receive an indirect (and thus plausibly exogenous) benefit from the reform: since they share the bankruptcy courts with individual debtors, a sudden drop in individual bankruptcy filings essentially increases the bankruptcy courts' capacity to handle corporate bankruptcies. A straightforward evidence of increased bankruptcy efficiency following BAPCPA is in Müller (2022), which reports that the median recovery rate for corporate bankruptcy filers increased from 28% before BAPCPA to 70% in the first year after BAPCPA.

Conceptually, bankruptcy efficiency is not important to innovation in the partial equilibrium because the unconditional probability of bankruptcy is low. My focus on the bargaining power dynamic between firms and creditors introduces the rational expectation effects that lead to a broad response in out-of-court restructurings and innovation. These general equilibrium effects make the paper interesting but more importantly, the bargaining power dynamic that induces them elucidates the role of policy. A policy that directly targets bankruptcy efficiency (like the BAPCPA reform studied in this paper) is effective but costly, yet a policy that targets the *expectation* of bankruptcy efficiency is cheaper and potentially effective enough. This point is made in Donaldson et al. (2020) and more generally relevant to Bayesian persuasion à la Kamenica and Gentzkow (2011).

Three strands of literature are related. Gertner and Scharfstein (1991) establish that a collective action problem among creditors impedes restructuring, and that making the restructured debt more senior in bankruptcy than the original debt can overcome the free-riding problem. Donaldson et al. (2020) extend this result to a setting where bankruptcy is the firm's decision rather than a predetermined outcome, and derive the same result that bankruptcy and restructuring are complements in expectation. Empirical evidence of this complementarity is thin. I contribute to this literature by showing empirically in a triple-differences framework that a large exogenous increase in bankruptcy efficiency facilitates restructuring.

Iverson (2018) is among the first studies to analyze the impact of BAPCPA on corporate outcomes. BAPCPA increases credit supply to mortgage companies (Lewis, 2023), decreases bank loan losses (Heitz & Narayanamoorthy, 2021), increases the amount and duration of trade credit offered to firms (Costello, 2019), and narrows credit spread (Müller, 2022). BAPCPA increases firm leverage, particularly for firms with high employee bargaining power or union bargaining power (Chen et al., 2020; Halford et al., 2024). BAPCPA also increases derivative availability and usage by financially distressed airlines (Giambona & Wang, 2020). Both out-of-court restructurings and AI innovation are, to my knowledge, novel outcomes unexplored in this literature.

There is a large literature on the economics of AI. This paper abstracts from much of the debate on the distributive effects of AI and operates under the assumption that AI innovation produces positive externality because AI has shown great potential to broadly transform the economy. Babina et al. (2024) show that investment in AI leads to increased product innovation and growth in sales, employment, and market valuation for U.S. firms, with the growth concentrated among larger firms. These authors suggest that AI contributes to growth primarily as a prediction technology that reduces the cost to learn about promising projects and customer preferences, both of which help increasing the firm's product scope. While this study is among the first to relate AI innovation to bankruptcy efficiency shocks, the idea that corporate risk-taking responds to the bankruptcy environment are known since Jensen and Meckling (1976).

The paper proceeds as follows. Section 1 presents a theoretical framework that makes clear how bankruptcy efficiency affects out-of-court restructuring. Section 2 overviews the data used in my empirical study. Section 3 presents the triple-differences framework that sources the identifying variation of bankruptcy efficiency from the exogenous BAPCPA exposure. Section 4 reports empirical results on out-of-court restructurings, highlighting bargaining power as an important channel. Section 5 reports results on AI workers as a form of risk-taking that leads to AI innovation. Section 6 reports results on AI-related patent outcomes. Section 7 concludes.

1 A Theoretical Framework

The bankruptcy system is an important cornerstone of the economy. Given the amount of time and resources that a formal bankruptcy involves, the transaction cost of going bankrupt is almost certainly non-zero, and most likely large. By the Coase Theorem, large transaction costs imply that *ex ante* allocation of property rights greatly matter for the eventual allocative efficiency. In the case of bankruptcy, extrajudicial workouts that preemtively adjust property rights are therefore crucial for achieving the best allocative outcome.

In this section, I first set up a one-firm model, which highlights the firm's and the creditors' strategic decision between restructuring and bankruptcy. The key prediction from this model is that the creditors' willingness to accept out-of-court restructurings is increasing in the efficiency of the bankruptcy court. I then consider two extensions. In the first extension, I model maturity extension instead of debt reduction as the way that the firm restructures its debt. In the second extension, I consider a continuum of firms and endogenous court congestion. I show that multiple equilibria exist when bankruptcy court capacity is moderate, and discuss policies that can navigate towards the efficient, low-bankruptcy equilibrium.

1.1 The One-Firm Model

In the model, there are two dates, date 0 and date 1. At date 0, a single firm i has a risky asset with an uncertain payoff, denoted by $v \in [0, \bar{v}]$ to be realized at date 1. The payoff follows a cumulative distribution function denoted by $F(v)$. The firm has existing unsecured debt with a face value D_0, owed to a continuum of dispersed creditors. Both the creditors and the firm are risk-neutral and aim to maximize their expected payoff.

At date 1, if the firm's realized asset value v is insufficient to repay its debt, the firm may enter financial distress. When the firm files for bankruptcy, a fraction $(1 - \lambda)$ of the asset value is lost due to legal fees, administrative costs, and other inefficiencies. The remaining value available to the firm and its creditors is λv, where $\lambda \in (0, 1)$ is the parameter of bankruptcy efficiency. After settling the deadweight costs, the firm and its creditors split the residual value. Creditors receive a fraction θ of λv and the firm receives $(1 - \theta)$. The parameter θ measures the "creditor-friendliness" of the bankruptcy system. A timeline of the events is as follows:

1. At date 0, the firm decides whether to propose an out-of-court restructuring to creditors. If a restructuring is proposed, creditors individually decide whether to accept or reject the offer.

2. At date 1, the asset value v is realized. The firm decides whether to repay the debt, default, or file for bankruptcy.

1.1.1 The Firm's Problem

At date 1, asset value v is realized and the firm has two options. It can repay the debt, which yields the payoff $v - D$. It can also file for bankruptcy, which yields the payoff $(1-\theta)\,\lambda v$. The firm prefers filing for bankruptcy when $(1-\theta)\,\lambda v \geq v - D$. The bankruptcy filing threshold, denoted by $\hat{v}$, is given by a rearrangement of this inequality:

$$\hat{v} = \frac{D}{1-(1-\theta)\,\lambda}. \tag{1}$$

Since $\frac{D}{1-(1-\theta)\lambda} > D$, the bankruptcy threshold is higher than the insolvency threshold (at which $v = D$ and the firm has zero net assets). Therefore, for a range of asset value realization $v \in [D, \hat{v}]$, the firm files for bankruptcy even if it can repay the debt, as visualized in Figure 1. Voluntary bankruptcy is a manifestation of ex post inefficiency: the firm's optimal action reduces total welfare.

By the Coase Theorem, ex post inefficiency can be resolved by a proper ex ante reallocation of property rights, i.e., out-of-court restructuring. Restructuring at date 1 is never feasible since $\frac{D}{1-(1-\theta)\lambda} > D$ holds regardless of the value of D. The out-of-court restructuring has to be preemptive, i.e., it should take place before v is realized. At date 0, the firm can propose a debt restructuring to reduce its debt burden from D_0 to a lower amount $D < D_0$. To incentivize creditors to accept the restructuring, the firm gives the new debt higher seniority in the event of bankruptcy, so the restructured debt would have a higher payoff in bankruptcy to offset the lower payoff absent bankruptcy. If the creditors accept the preemptive extrajudicial restructuring, the bankruptcy court becomes a sideshow and its efficiency does not matter. I now move to the creditors' problem and discuss how a collective action problem hinders efficient restructuring and necessitates the role of bankruptcy efficiency.

1.1.2 The Creditors' Holdout

A key friction in the model is the collective action problem among creditors. I assume that the creditors are disperse and cannot coordinate their actions. As a result, creditors decide independently whether to accept the restructuring, taking other creditors' decisions as given. Each creditor has an incentive to reject the restructuring ("holdout"), hoping that other creditors would accept the restructuring and they get to be the free-rider in the restructuring deal.

The no-coordination assumption simplifies the strategic interaction among creditors and reduce the game to a single creditor's maximization problem. From the creditor's perspective, she considers the most desirable scenario, where all other creditors accept the deal and she is the only free-rider. This scenario maximizes the probability that the firm remains solvent and she receives the full debt value D_0, and minimizes the probability that the firm goes bankrupt and she receives nothing due to being junior to other creditors. If she refuses the deal even in this most desirable scenario, other creditors would reach the same conclusion and restructuring becomes infeasible. If she accepts the deal in this scenario, under the assumption of no higher-level play, other creditors would again reach the same conclusion and everyone accepts the deal. Therefore,

Proposition 1. *When the firm offers a restructuring deal that is sufficiently appealing to one creditor under the most favorable circumstance, all creditors would accept the deal under the (correct) assumption that other creditors would do the same. Under this condition, a restructuring deal goes through if and only if it is compatible with the incentive of a single creditor.*

With this proposition, it is sufficient to examine a single creditor's decision problem. An individual creditor will accept the restructuring if their expected payoff from accepting is weakly higher than their payoff from rejecting, given that all other creditors accept. When she accepts the deal, she receives D if the firm does not go into bankruptcy, and receives $\theta\lambda v$ if the firm is bankrupt. Her expected payoff from accepting is

$$\text{Payoff}_{\text{accept}} = \underbrace{\left[1 - F\left(\hat{v}\left(D\right)\right)\right] D}_{\text{payoff if solvent}} + \underbrace{F\left(\hat{v}\left(D\right)\right) \mathbb{E}\left[\theta\lambda v \mid v < \hat{v}\left(D\right)\right]}_{\text{payoff if default}}.$$

If she rejects the offer, she retains the original unsecured debt with value D_0. Since all other creditors accept, she becomes the most junior creditor. When the firm stays solvent and repays all debts, she receives D_0. When the firm enters bankruptcy, she receives nothing because other creditors have seniority. The expected payoff from rejecting is

$$\text{Payoff}_{\text{reject}} = \underbrace{\left[1 - F\left(\hat{v}\left(D\right)\right)\right] D_0}_{\text{payoff if solvent}}.$$

The creditors incentive compatibility (IC) condition is

$$\left[1 - F\left(\hat{v}\left(D\right)\right)\right] D + F\left(\hat{v}\left(D\right)\right) \mathbb{E}\left[\theta\lambda v \mid v < \hat{v}\left(D\right)\right] \geq \left[1 - F\left(\hat{v}\left(D\right)\right)\right] D_0,$$

which can be rearranged as

$$\left(\left[1 - F\left(\hat{v}\left(D\right)\right)\right]\left(D - D_0\right)\right) + F\left(\hat{v}\left(D\right)\right) \mathbb{E}\left[\theta\lambda v \mid v < \hat{v}\left(D\right)\right] \geq 0. \tag{2}$$

It is useful to express the IC constraint (2) as the maximum debt reduction $D_0 - D$ that the creditors are willing to accept:

$$D_0 - D \leq \frac{F\left(\hat{v}\left(D\right)\right) \mathbb{E}\left[\theta\lambda v \mid v < \hat{v}\left(D\right)\right]}{1 - F\left(\hat{v}\left(D\right)\right)}.$$

Proposition 2. *For any D satisfying the inequality above, the restructuring is accepted by creditors and makes the firm strictly better off.*

To summarize, the feasibility of restructuring depends on:

1. **Probability of bankruptcy**: The higher $F\left(\hat{v}\left(D\right)\right)$ is, the more valuable seniority becomes, as there is a greater chance that priority in bankruptcy will matter.

2. **Bankruptcy costs**: Higher bankruptcy efficiency λ increase the value of seniority, as creditors can expect higher recoveries in bankruptcy.

1.2 Extension 1: Maturity Extension Instead of Write-down

An empirical regularity in the data is that in out-of-court restructuring, creditors often agree to extend the maturity of the loan, instead of writing down the value of the loan. Intuition suggests that the effect would be similar: if maturity extension lowers both the probability of bankruptcy and the creditor's recovery value in bankruptcy, it enters into the creditors' problem just like debt reduction in (2). As a result, there exists a maximum maturity extension that satisfies the creditors' IC constraint and provides a feasible Pareto improvement over bankrupting the firm.

To capture this intuition more formally, I extend my two-period model to a three-period model. In the empirical part of the paper, my measure of out-of-court restructuring will include both debt reduction (write-down of either principal or interest) and maturity extension.

The model now has three dates and the timeline is as follows:

1. At date 0, the firm decides whether to propose an out-of-court restructuring to creditors. If a restructuring is proposed, creditors individually decide whether to accept or reject the offer.
2. At date 1, the asset value v_1 is realized. If the restructuring is accepted, the firm repays nothing and continues its operation. If the restructuring is rejected, the firm decides whether to repay the debt at face value D_0 or file for bankruptcy.
3. At date T, the asset value v_T is realized. If the restructuring is accepted, the firm decides whether to repay the debt at face value D_0 or file for bankruptcy.

The payoffs at date 1 and date T are i.i.d. with the same support, $v_1,\ v_T \in [0, \bar{v}]$ and the same cumulative distribution $F(v)$. The one-period temporal discount factor is $\delta \in (0, 1)$, so the present value of the debt's face value is δD_0 if repaid at date 1, and $\delta^T D_0$ if repaid at date T. Since $\delta^T D_0 \leq \delta D_0$, the creditors would not agree to extend the maturity of the debt unless they are promised a higher recovery value when the debt defaults. The firm makes such an offer by granting the restructured debt higher seniority in bankruptcy.

An individual creditor's expected payoff when agreeing to a maturity extension at date 0 is

$$
\begin{aligned}
\text{Payoff}_{\text{accept}} &= \delta^T \mathbb{E}\left[\begin{cases} D_0 & \text{if } v_T \geq D_0, \\ \theta\lambda v_T & \text{if } v_T < D_0. \end{cases}\right] \\
&= \underbrace{\delta^T \left[1 - F\left(\hat{v}\left(D_0\right)\right)\right] D_0}_{\text{payoff if solvent}} + \underbrace{\delta^T F\left(\hat{v}\left(D_0\right)\right) \mathbb{E}\left[\theta\lambda v_T \mid v_T < \hat{v}\left(D_0\right)\right]}_{\text{payoff if default}}.
\end{aligned}
$$

If the creditor rejects the maturity extension, her expected payoff is

$$
\begin{aligned}
\text{Payoff}_{\text{reject}} &= \delta \mathbb{E}\left[\begin{cases} D_0 & \text{if } v_1 \geq D_0, \\ 0 & \text{if } v_1 < D_0. \end{cases}\right] \\
&= \underbrace{\delta \left[1 - F\left(\hat{v}\left(D_0\right)\right)\right] D_0.}_{\text{payoff if solvent}}
\end{aligned}
$$

The creditor's IC constraint is $\text{Payoff}_{\text{accept}} \geq \text{Payoff}_{\text{reject}}$. She is incentivized to accept the maturity extension in exchange for seniority in bankruptcy, essentially trading some repayment in the solvent state for a higher recovery value in the default state. The creditor will agree to restructuring if

$$
\left(\delta^T - \delta\right) \left[1 - F\left(\hat{v}\left(D_0\right)\right)\right] D_0 + \delta^T F\left(\hat{v}\left(D_0\right)\right) \mathbb{E}\left[\theta\lambda v_T \mid v_T < \hat{v}\left(D_0\right)\right] \geq 0. \tag{3}
$$

It is also useful to express the IC constraint (3) as the concession that the creditors are willing to make. In this extension, the concession is in the form of maturity extension $T - 1$:

$$
T - 1 \leq \frac{\ln\left\{\left[1 - F\left(\hat{v}\left(D_0\right)\right)\right] D_0\right\} - \ln\left\{\left[1 - F\left(\hat{v}\left(D_0\right)\right)\right] D_0 + F\left(\hat{v}\left(D_0\right)\right) \mathbb{E}\left[\theta\lambda v_T \mid v_T < \hat{v}\left(D_0\right)\right]\right\}}{\ln\left(\delta\right)}.
$$

I make two observations to connect to intuition. First, as δ gets close to one, $\ln(\delta)$ approaches zero from below and the RHS of the equation goes to positive infinity. This means that the firm can propose a longer maturity extension if the discount rate is low. Second, when the expected bankruptcy recovery value $\mathbb{E}\left[\theta\lambda v_2 \mid v_2 < \hat{v}(D_0)\right]$ or the expected probability of bankruptcy $F(\hat{v}(D_0))$ is high, the maximum feasible maturity extension is also higher. This is because creditors value the seniority in bankruptcy more when bankruptcy is more likely and when they can potentially recover more from it. Since seniority is offered in exchange for maturity extension, more valuable seniority trades for longer maturity extension.

1.3 Extension 2: Many Firms and Court Congestion

In this section, I extend the model to allow court congestion to affect bankruptcy efficiency λ. Court congestion is closely related to the bankruptcy reform (BAPCPA) that I use for empirical identification. Modeling court congestion is also one way to present policymakers in the model. Since beliefs about court congestion create multiple equilibria, policies about court capacity matter for financial stability.

Suppose there is a continuum of identical firms, each facing the condition described in the baseline model. By the law of large numbers, the fraction of firms that file for bankruptcy is identical to each firm's probability to file for bankruptcy $F(\hat{v})$. Let κ denote the capacity of the bankruptcy court. When the total number of bankruptcy filings is $F(\hat{v}) \leq \kappa$, the courts are not congested and bankruptcy efficiency is high. When $F(\hat{v}) > \kappa$, court is congested and the bankruptcy efficiency is low. The bankruptcy efficiency parameter λ now depends on the aggregate filing rate:

$$\lambda = \begin{cases} \lambda_H & \text{if } F(\hat{v}) \leq \kappa, \\ \lambda_L & \text{if } F(\hat{v}) > \kappa. \end{cases}$$

Each firm anticipates the impact of its own restructuring and bankruptcy decisions on the aggregate filing rate and, consequently, on bankruptcy costs.

Proposition 3. *Two equilibrium values of λ exist, and the firms' expectations about λ are self-fulfilling, if the following inequality holds:*

$$\hat{v}(D_H, \lambda = \lambda_H) < F^{-1}(\kappa) < \hat{v}(D_L, \lambda = \lambda_L), \tag{4}$$

where D_H and D_L are the restructured debt levels corresponding to λ_H and λ_L.

The intuition is that, when bankruptcy court capacity κ is moderate, beliefs that $\lambda = \lambda_L$ make creditors perceive bankruptcy to be costly and unlikely. Creditors then assign a low value to seniority in bankruptcy and have low incentive to accept the restructuring deal, leading to high level of debt $D = D_L$. Highly indebted firms are more likely to end up in bankruptcy court and congest it. With congested courts, the aggregate bankruptcy efficency $\lambda = \lambda_L$ is consistent with individual creditors' beliefs, which constitutes an equilibrium. Beliefs that $\lambda = \lambda_H$ are self-fulfilling for the same reason.

Policies can break the first inequality in (4) by raising court capacity κ (and lowering $F^{-1}(\kappa)$) so much that $\hat{v}(D_H, \lambda = \lambda_H) < F^{-1}(\kappa)$ no longer holds, and the only rational expectation equilibrium is one in which $D = D_H$ and court is not congested. However, actually raising court capacity in this way is costly and the court would seem underutilized *ex post*, since creditors rationally restructure out of court and effectively lower the likelihood of bankruptcy. A credible pledge of capacity increase is cheaper and equally effective, since a successful coordination on the $D = D_H$ obsoletes the need for actual capacity slack. In the empirical section, I show that an increase in bankruptcy court capacity lead to increases in out-of-court restructurings that are an order of magnitude larger, which implies equilibrium jumps modeled in this extension.

2 Data

2.1 The bankruptcy efficiency shock

Building on Iverson (2018) and Müller (2022), I exploit the exogenous shock on bankruptcy court capacity following the passage of the Bankruptcy Abuse Prevention and Consumer Protection Act (BAPCPA) in 2005. BAPCPA reduces bankruptcy courts' caseload by considerably increasing the cost of bankruptcy filing for individual debtors. Since BAPCPA almost exclusively targets individual debtors, its effect on court capacity is largely orthogonal to corporate debtors. Court districts vary in their exposure to the BAPCPA shock: some districts handle more non-business bankruptcies than others before BAPCPA, so they enjoy a larger increase in their bankruptcy court capacity after BAPCPA shuns individual debtors.

BAPCPA is intended to prevent *individual* debtors from abusing the bankruptcy system to evade liabilities. *Corporate* debtors are subject to minimal regulatory changes, but since they share the bankruptcy court with individual debtors, they benefit from reduced case backlog and lower wait time to bring a case to court. Because efficient bankruptcy for corporate debtors is not the forefront goal of BAPCPA, it is more plausible that this policy shock is exogenous and not a result of endogenous developments earlier in time.

2.2 Out-of-court restructuring data

I construct a dataset of extrajudicial workouts that includes workouts proposed by both distressed and non-distressed firms, so it extends the data on distressed restructurings (e.g., Demiroglu and James, 2015; Gilson et al., 1990). This is necessary in my setup because my triple-difference strategy intends to compare "troubled" workouts proposed by distressed firms to normal workouts in less adverse conditions, and show that BAPCPA affects the frequency of workouts more when bankruptcy looms large. In the dataset, I determine the materiality of debt workout plans by considering whether it brings major or minor modifications to previous loan agreements.

The data on out-of-court loan restructurings come from Refinitiv LoanConnector Dealscan. A well-known issue of the legacy Dealscan data is that loan contract amendments are frequently treated as new loan contracts, making such amendments difficult to track (Campello et al., 2019; Roberts, 2015). One major improvement in the new Dealscan data (launched May 2020) is that it correctly groups loan contract origination and subsequent amendments under the same deal identifier, so researchers can consistently track the change of a loan contract over time (Wharton Research Data Services, 2021).

Following Gilson et al. (1990) and Demiroglu and James (2015), I define out-of-court restructurings as loan contract amendments in which the creditors agree to reduce principal payments, reduce interest payments, or extend debt maturity. Exchanging debt claims for equity are included in these authors' measures but not mine, since equity has lower priority in bankruptcy and cannot be compatible with creditors' incentive in the setup that I consider. All three types of amendments that I classify as restructurings are deemed significant by the U.S. Internal Revenue Service (IRS) and capital gains resulting from these modifications are subject to capital gain taxes (Campello et al., 2019).

2.3 Management bankruptcy cost data

I follow Schoenherr and Starmans (2022) to construct three proxies of management bankruptcy cost. Intuitively, when debtor's management has a higher personal cost of bankruptcy, the threat to file a Chapter 11 bankruptcy is less credible. For example, a owner-manager in a family firm would perceive the bankruptcy to be more costly than a professional manager. For the family firm manager, her personal cost of bankruptcy is higher, and her threat to file is less credible due to a higher degree of self sabotage.

The intuition closely captures my measurements of management bankruptcy cost. The measure is CEO ownership, defined as the fraction of the firm owned by the CEO and her family. When CEO owns a larger fraction of the firm, her personal wealth is more sensitive to the bankruptcy-induced decline of the firm's equity value. If bargaining power dynamics are indeed the key driver of the BAPCPA effect, the effect should have significant heterogeneity in the cross section of firms sorted by the manager's personal bankruptcy cost, which reflects the credibility of their threat to file.

I define CEO_high_stake$_{it}$ as an indicator function that takes one if the CEO of firm i owns more than one percent of the firm in year t. The data on CEOs' equity stake are from the Thomson Reuters Insiders Database, which consolidates publicly available information from Form 3, 4, and 5 that corporate insiders, including CEOs, must file to disclose changes in their equity holdings. The data on outstanding shares of public firms are from Compustat (item `csho`).

2.4 AI worker data

The empirical challenge of identifying AI workers is overcome by Babina et al. (2024) using resume-level data from Cognism.[1] Babina et al. (2024) develop an AI-relatedness score for skills that workers list in their resumes, and classify a worker as an AI worker if their job title and description contain the most AI-related skills (e.g., "senior *machine learning* developer"). For a firm in a given year, the AI worker share is measured as the number of AI workers divided by the total number of workers. The AI worker share represents a firm's risky investment in AI-related human capital. If efficient bankruptcy encourages AI innovation, the BAPCPA beneficiaries should engage in more risky human capital investment and has higher growth of AI worker shares.

2.5 AI output data

For AI output data, I use the Artificial Intelligence Patent Dataset by the US Patent and Trademark Office, which covers AI patent activities in the period from 1976 to 2023. The Artificial Intelligence Patent Dataset identifies AI-related content within 15.4 million U.S. patent documents published from 1976 to 2023. It incorporates recent advancements in patent landscaping, including the integration of BERT for Patents into the machine learning architecture.

I aggregate the patent-level data to the firm-year-level data by (1) counting the number of patents created by an inventor in a year and (2) summing the number of subsequent citations received by those patents. When assigning a patent to a firm-year cell, I use the patent 's *application* year and not the *grant* year (Moretti, 2021).

[1] Cognism is an industry data provider that covers more than 64% of full-time US employment as of 2018. While the Cognism data slightly overrepresents high-skill workers, it remains overall representative of the US workforce and aligns well with the Burning Glass job postings data, another source of worker data commonly used in the literature.

2.6 Assembly of the sample

I assemble the sample in the following way. For restructuring regressions, I start with U.S. firms that have at least one outstanding loan in the DealScan dataset at the end of 2003, i.e., right before the beginning of my sample. I exclude firms if all their outstanding loans mature before BAPCPA comes into effect because these firms have no outstanding loan to restructure after the reform. I exclude financial and utility borrowers to focus on industrial firms that are not heavily restricted by regulations. I study these firms' restructuring decisions by building a firm-year panel that straddles the BAPCPA enactment in October 2005. The two-year pre-treatment period is from 2004 to 2005, and the two-year post-treatment period is from 2006 to 2007. The Global Financial Crisis in 2008 is not included in the sample to minimize the degree to which it distorts the results.

For regressions that study longer-term outcome variables, I keep the pre-treatment sample period unchanged, but extends the post-treatment sample period to allow longer-term outcomes evolve. Fixing the pre-treatment period allows me to align with previous literature regarding the definition of court district-level exposure to BAPCPA, which is measured from pre-reform non-business bankruptcy shares. Results on longer-term outcomes are not sensitive to the exact number of years included in the post-treatment period, which I make precise later in the results section.

Several crosswalks are used to assemble the sample with different datasets. To associate loan restructurings in Dealscan with Compustat firms, I utilize the crosswalk between old and new Dealscan data provided by Refinitiv, and the linking table between legacy Dealscan and Compustat provided by Chava and Roberts (2008).[2] To associate court district-level BAPCPA shock to Compustat firms, I use the corporate headquarter data sourced from EDGAR filings and compiled by the University of Notre Dame.[3] The crosswalk to associate patent data and AI worker data to Compustat firms are provided by Kogan et al. (2017) and Babina et al. (2024) respectively.

[2]Refinitiv provide old-new Dealscan crosswalks at both loan level and company level. I retain matches derived from both methods.

[3]https://sraf.nd.edu/sec-edgar-data/10-x-header-data/. I use firms' headquarter location at the end of 2003, i.e., before the start of my sample, which is not feasible if I use Compustat headquarter data because the latter only keeps the most current headquarter information.

3 Econometric framework

The triple-difference regression is

$$
\begin{aligned}
Y_{it} \;=\; & \beta_1 \times \text{Post}_t + \beta_2 \times \text{Exposure}_i + \beta_3 \times \text{Distress}_i + \\
& \beta_4 \times (\text{Post}_t \times \text{Exposure}_i) + \beta_5 \times (\text{Post}_t \times \text{Distress}_i) + \\
& \beta_6 \times (\text{Exposure}_i \times \text{Distress}_i) + \beta_7 \times (\text{Post}_t \times \text{Exposure}_i \times \text{Distress}_i) + \\
& \text{FE}^{firm} + \text{FE}^{district \times year} + \epsilon.
\end{aligned}
$$

Post_t, Exposure_i, Distress_i, $\text{Exposure}_i \times \text{Distress}_i$, $\text{Post}_t \times \text{Exposure}_i$ are subsumed by fixed effects, yielding the regression

$$
\begin{aligned}
Y_{it} \;=\; & \beta_5 \times (\text{Post}_t \times \text{Distress}_i) + \\
& \beta_7 \times (\text{Post}_t \times \text{Exposure}_i \times \text{Distress}_i) + \\
& \text{FE}^{firm} + \text{FE}^{district \times year} + \epsilon. \qquad (5)
\end{aligned}
$$

Various financial distress measures have been used in the literature. Leverage-based proxies are well known and available for a large set of firms. However, high leverage does not directly correspond to high distress (see, for example, Almeida and Campello (2007) on asset tangibility as a moderator). On the other hand, accounting scores such as those developed by Ohlson (1980) and Altman (1968) are derived directly from bankruptcy cases, but they are sensitive to calibrated parameters.

I define Distress_i to be agnostic about the optimal measure. Distress_i takes one if in the pre-treatment period (two years from 2003 to 2004), firm i falls within the interquartile range of all three distress proxies: market leverage, O-score, and Z-score.[4] Firms in the interquartile range of

[4] Market leverage is calculated from Compustat: $(\texttt{dltt} + \texttt{dlc})/(\texttt{me} + \texttt{dlc} + \texttt{dltt})$. O-score and Z-score follow the calculation in Ohlson (1980) and Altman (1968), respectively.

all three measures are likely not too safe for bankruptcy reform to bite, nor too deep in trouble that filing for bankruptcy is a forgone conclusion. Such moderately distressed firms are most likely to be affected by BAPCPA on outcomes including extrajudicial restructurings, risk-taking behaviors, and innovation.

For most of the empirical analyses, my outcome variables are discrete (e.g., counts of out-of-court restructurings and counts of patents) and I run a pseudo-Possion regression with fixed effects following the recommendation of Cohn et al. (2022). The number of observations reported in sub-sample regressions may not add up to the number of observations in full-sample regressions, because separated observations Correia et al. (2019) are excluded in a way that is particular to the actual sample used.

4 Restructurings

In low exposure districts, court congestion does not vary substantially before and after BAPCPA, and workout gap just widens at the average rate (as a result of the looming 2008 financial crisis). In high exposure districts, the workout gap narrows because non-distressed firms are catching up in their workout rates, due to higher expected bankruptcy probability forcing more lenders back to the negotiation table.

The results presented in Table 1 examine the impact of the 2005 BAPCPA on the frequency of out-of-court loan restructurings. These restructurings involve major modifications to existing loan agreements, such as reductions in principal or interest payments, debt-for-equity swaps, or extensions of debt maturity. Using a triple-differences framework, I compare financially distressed firms to non-distressed firms, court districts with high BAPCPA exposure to those with low exposure, and the periods before BAPCPA to periods after BAPCPA. The key variable of interest is the triple interaction term ($\text{Post}_t \times \text{Exposure}_i \times \text{Distress}_i$), which captures the differential effect of BAPCPA on distressed firms in districts more exposed to the reform.

Columns (2) to (5) of Table 1 vary the measures of financial distress used. $\text{Distress}_i = 1$ if firm i is in the interquartile range of distress, measured by market leverage in column (2), Ohlson's O-score in column (3), and Altman's Z-score in column (4). The coefficients on the triple interaction term are consistently positive and statistically significant at the 5% level. In column (5), $\text{Distress}_i = 1$ indicates that firm i is in the interquartile range of all three measures. I proceed with this composite measure going forward. With this distress measure, an one-standard-deviation increase in BAPCPA exposure (i.e., 12 percentage points increase in nonbusiness court caseload) leads to 2.1 more restructurings per year after BAPCPA implementation for moderately distressed firms.

The magnitude of the increase in out-of-court restructurings following BAPCPA is noteworthy. My sample includes firms that have at least one outstanding loan when BAPCPA is implemented. For these firms in the four years from 2004 to 2007, out-of-court restructuring occurs on average 0.53 time per year. Therefore, 2.1 more restructurings per year after BAPCPA implementation for moderately distressed firms represents a 300% increase from the sample average. While I do not provide a quantitative estimate on BAPCPA's effect on bankruptcy efficiency, Müller (2022) estimates that an one-standard-deviation increase in BAPCPA exposure leads to an 19.8% increase in bankruptcy recovery values (6.5 percentage points from the sample average of 32.86%; see Table A5 therein). Therefore, a back-of-envelope calculation suggests that BAPCPA's effect on out-of-court restructurings is an order of magnitude larger than its effect on in-court recovery values.

What drives such spikes in restructurings? The court congestion model in Section 1.3 suggests equilibrium jump as one possible explanation. Proposition 3 states that for moderate levels of bankruptcy capacity, creditors' beliefs about court congestion are self-fulfilling, and a small perturbation in their beliefs can lead to large changes in bankruptcy filings when the belief perturbation make creditors switch to coordinate on another equilibrium. BAPCPA can be understood as one such (not necessarily small) perturbation that makes creditors move towards the low-bankruptcy equilibrium, in which restructurings occur much more often.

Overall, results in this section support the prediction that higher bankruptcy efficiency enhances the credibility of firms' threats to file for bankruptcy. With more efficient courts, bankruptcy becomes less costly for both debtors and creditors, but both parties would still prefer to avoid the court if possible. The first-best of extrajudicial workout is not achieved before BAPCPA due to the holdout problem among creditors. The effect of BAPCPA is to increase the debtor's willingness to file, so creditors are discouraged from playing the dangerous game of holding out. To avoid formal bankruptcy, creditors become more willing to negotiate and agree to out-of-court debt restructurings. This shift in bargaining dynamics facilitates moderately distressed firms' efforts to reorganize their debts without resorting to formal bankruptcy proceedings.

4.1 Heterogeneity: bargaining power

To analyze if bargaining power is indeed the channel underlying the effect of BAPCPA on out-of-court restructurings, I repeat regression 5 on two subsamples, one containing firms with likely higher bargaining power and one containing firms with likely lower bargaining power. Specifically, I split the sample based on a proxy for management's personal cost of bankruptcy: whether the CEO owns more than 1% of the firm's shares. Using CEO ownership to proxy for the manager's personal bankruptcy cost is introduced by Friend and Lang (1988) and more recently seen in Schoenherr and Starmans (2022). When CEO owns a large fraction of her firm, her threat to bankrupt the firm is less credible, so her bargaining power against the creditors should not vary as much with bankruptcy efficiency. This is the empirical prediction that I test and report in Table 2.

Column (1) of Table 2 replicates the column (5) of Table 1 to ease comparison. In column (2), I examine firms with higher CEO ownership and thus low bargaining power. I find that among firms in which CEOs own 1% or more, the BAPCPA effect on restructurings becomes statistically insignificant, which I interpret as evidence of CEOs' high personal bankruptcy cost weakening their bargaining power. In contrast, when I fit regression 5 on the sample of firms with low CEO ownership, the effect of BAPCPA on restructurings is estimated to be around 60% larger than the full-sample estimate. These low-stake CEOs are less affected personally by the potential bankruptcy, so they can utilize the threat to file more effectively. Taken together, the findings in Table 2 suggest that bargaining power dynamics are important in leveraging the benefits of increased bankruptcy court efficiency.

5 AI Workers

The previous section reports the impact of efficient bankruptcy on the bargaining power dynamics between debtors and creditors, and relate the increased debtor bargaining power to higher occurrence of out-of-court restructurings. In this section, I provide evidence that the ease of out-of-court restructuring increases the risk-taking incentive of firms.

I work with the premise that prior to the BAPCPA reform, firms are indifferent to some investment opportunities with different level of risk. For example, in the context of AI, the firm may be indifferent to a safe project that produces a new batch of old products, and a risky project that produces a batch of new products that incorporate AI. The bankruptcy reform improves the payoff of the risky project in this investment opportunity set, but leaves the payoff of the safe project unchanged. As a result, firms find it optimal to take up the risky project after the reform.

I examine a specific form of risk-taking that is particularly relevant for AI innovation: the investment in AI-related human capital. The scarcity of workers with AI skills are one of the most important barriers to AI adoption (Babina et al., 2024). Since AI skills are unique and have limited outside use, hiring AI workers represent a form of risky investment that is not well captured by common risk-taking measures such as R&D investment and capital expenditure.[5]

I use the long-differences regression to measure the impact of BPACPA on AI investment growth. AI development is a slow moving technological process and the long-difference regression is standard in this setting (e.g., Acemoglu & Restrepo, 2020). For each firm, I define its post-BAPCPA growth of AI worker share as the difference between its AI worker share in 2006, the first full year that BAPCPA is effective, and its AI worker share in 2018, the last year in which the AI worker data of Babina et al. (2024) is considered complete.[6] My results are similar if I study decadal differences from 2006 to 2016, use the entire (and potentially noisier) time series up to 2021, or set the starting value of AI worker share to zero in 2006 for all firms. The robustness to these choices is consistent

[5] I refer to Babina et al. (2024) for an example of the uniqueness of AI skills. In their classification, "Microsoft Cognitive Toolkit" has an AI-relatedness score of 0.975, whereas the much more transferrable skill of "Microsoft Office" has an AI-relatedness score of 0.003.

[6] Their data end in 2021, but the authors suggest excluding the last three years to account for the lag it takes for workers to update their resumes.

with the conventional wisdom that AI innovation sees its most rapid growth in the early 2010s; the results below are likely driven by firm's AI worker hiring decision during that period.

The long-differences regression is

$$\begin{aligned} \Delta\text{AI worker share}_i &= \gamma_1 \times \text{Exposure}_i \times \text{Distress}_i + \gamma_2 \times \text{Distress}_i \\ &\quad + \text{Controls} + \text{FE}^{industry} + \text{FE}^{district} + \epsilon. \end{aligned} \tag{6}$$

Similar to the triple-differences regression (5), the standalone term of Exposure_i is subsumed by court district fixed effects. Unlike the triple-differences regression, there is no Post_t variable since the long-differences regression sample starts in 2006, i.e., after BAPCPA is already enacted. Conceptually, the long-differences regression (6) operates as if all firms have zero pre-BAPCPA AI worker growth, so the Post variable is omitted and the triple-difference regression collapses to a dual-difference regression that includes only Exposure_i and Distress_i.

Table 4 reports the regression results. In column (1), regression (6) is run on a sample that includes all firms. In column (2), I exclude firms in the technology sector from the sample to ensure that the effect is not solely driven by technology firms hiring AI workers. In both specifications, the coefficient on the interaction term, $\text{Exposure} \times \text{Distress}_i$, is positive and statistically significant at conventional levels. These results suggest that part of the increased risk-taking encouraged by BAPCPA manifests in greater investments in cutting-edge technologies, as indicated by the higher share of AI workers. This finding supports the notion that efficient bankruptcy processes can serve as a catalyst for innovation in the corporate sector, encouraging firms to pursue more ambitious and potentially transformative projects.

5.1 Other risk-taking measures

In addition to AI-specific risk-taking, I also examine the effect of efficient bankruptcy on general risk-taking by firms. I measure general risk-taking with financial leverage and earnings volatility.

Leverage is constructed from Compustat items $(\texttt{dltt}+\texttt{dlc})/\texttt{at}$. Earnings volatility is the standard deviation of either ROA (`niq/atq`) or ROE (`niq/ceqq`) over the prior eight quarters. My prediction is that after BAPCPA, moderately distressed firms in high-BAPCPA-exposure districts have higher leverage and earnings volatility relative to firms less affected by BAPCPA, either due to their financial distress level or due to their court districts' low exposure to the reform.

I run regression (5) with these risk-taking outcomes and report the results in Table 3. In the leverage regression in column (1), the coefficient on the triple interaction term ($\text{Post}_t \times \text{Exposure}_i \times \text{Distress}_i$) is positive and statistically significant at the 5% level. This indicates that moderately distressed firms in high-exposure districts increased their leverage following the reform. Columns (2) and (3) report earnings volatility regression results. Earnings are scaled by total assets in column (2) and by total common equity in column (3). In both specifications the triple-differences estimate are positive, indicating increased variability in earnings for firms more exposed to BAPCPA. Statistical significance is marginal regardless of the scaling variable, so the effects vary even within the set of firms I define as highly exposed to the reform. Taken together, the results in Table 3 suggest that by improving the efficiency of the bankruptcy process and granting corporate debtors more bargaining power, BAPCPA has encouraged corporate risk-taking.

6 Innovation

The previous two sections provide evidence that higher bankruptcy efficiency leads to more efficient out-of-court restructurings and higher incentive for firms to take risks in AI, i.e., by hiring more AI workers. To complete the analysis, in this section I examine whether higher bankruptcy efficiency encourages AI innovation.

Does bankruptcy efficiency matter for the most recent epoch of technological change? I again run regression (5), this time with four innovation outcomes, and report the results in Table 5. These four outcomes are AI patent counts, general patent counts, the number of citations received by the AI patents, and the number of citations received by the general patents. The results in Table 5 demonstrate a positive impact of efficient bankruptcy on patent output for financially distressed firms in districts more exposed to the reform. The coefficients on the triple interaction term ($\text{Post}_t \times \text{Exposure}_i \times \text{Distress}_i$) are positive across all four columns, indicating that distressed firms in high-BAPCPA-exposure districts increased their patent production and received more patent citations following the reform.

While the estimated impact on general patents is positive, it lacks statistical significance at conventional levels. In contrast, the effect on AI patents and their citations is not only larger in magnitude but also statistically significant at the 5% level. One interpretation of this disparity in effects between general and AI patents is that the impact of BAPCPA on innovation was particularly pronounced in developing emerging technologies that involve higher uncertainty and risk, such as AI. The higher prominence of AI innovation effects relative to general innovation effects corroborates the higher prominence of AI risk-taking relative to general risk-taking. Since AI skills are unique and less transferable than general skills, the firms that increase risk-taking by hiring more AI workers are essentially targeting AI-related innovation. These AI innovative firms are likely the drivers of the innovation effect observed in my setup.

7 Concluding Remarks

If one actor (call him the saboteur) has an option to incur common deadweight cost to all actors, himself included, he can manipulate other actors' expectations about this sabotage, for example, by making a fake announcement that he will commit to it. Since announcement is cheap and sometimes effective, the saboteur captures some manipulation rent without actually sabotaging anyone. However, this announcement is often not convincing, and when he fails to convince he has to resort to actual sabotage. Policy should intervene to avoid such manipulation failure.

A social planner often has a costly option to endorse the saboteur's threat, so the threat becomes more credible and the actual sabotage occurs less often. Very similar to the saboteur, the social planner can announce her endorsement and manipulate expectations, without actually paying a cost to commit to it. Since the social planner internalizes all deadweight cost and the saboteur just his portion of it, there is always room for social planners to step in with policy (or announcements about it). This paper empirically demonstrates the effectiveness of one such policy in the setting of the U.S. corporate bankruptcy system.

The observation that a more credible actor (like the social planner in the example) also internalizes a larger fraction of the externalities is not universal. It is common that citizens do not trust the social planner in their government, and their trust is placed on someone who does not internalize much of the externalities. Uncorrected externalities harm the market economy and further displaces trust. In this way trust becomes a state variable that growth researchers should keep track of. More specifically, if credibility can be redistributed, it should be directed towards those that internalize a larger share of externalities. This proposition challenges the current iteration of representative governments, which tilts voting power towards beneficiaries of those uncorrected externalities. Such representative reallocation reinforces the growth trajectory and is only virtuous when the initial allocation (or subsequent exogenous reallocation) is reasonably efficient.

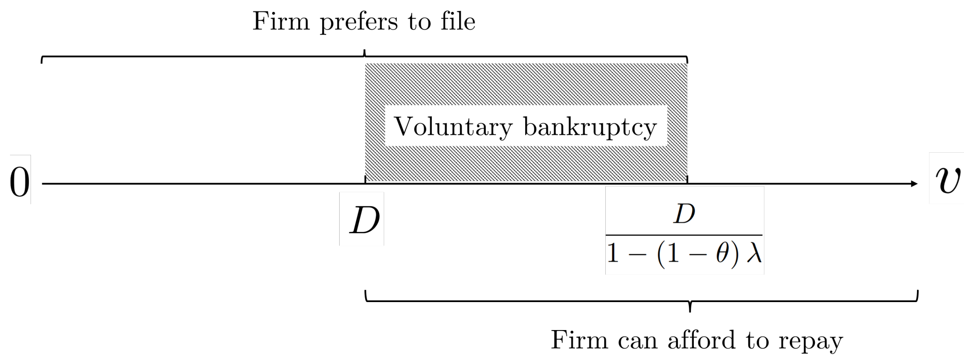

Figure 1: *Regions of Voluntary Bankruptcy.*

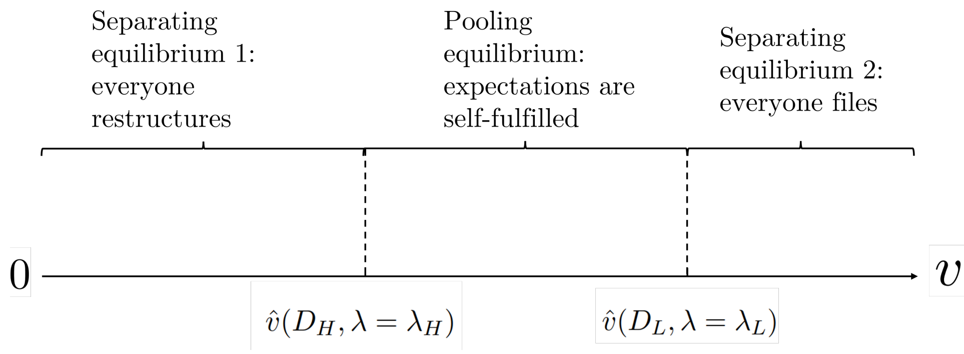

Figure 2: *Regions of Voluntary Bankruptcy.*

	DiD	Triple-differences			
	(1) DiD	(2) Leverage	(3) O-score	(4) Z-score	(5) Composite
Post × BAPCPA exposure	2.878*				
	(1.705)				
Post × BAPCPA exposure × Distress		11.813**	13.978**	18.035**	17.479**
		(2.183)	(1.986)	(2.503)	(2.490)
Post × Distress		−8.425**	−10.206*	−14.668**	−12.698**
		(−1.999)	(−1.917)	(−2.533)	(−2.354)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Industry by year FE	Yes	-	-	-	-
District by year FE	-	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Mean of DV	0.47	0.52	0.53	0.53	0.53
N	539	408	267	271	267

Table 1: *BAPCPA and Loan Restructurings*. Standard errors are clustered at the firm level. t-statistics are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1) Full sample	(2) Low bargaining power	(3) High bargaining power
Post × BAPCPA exposure × Distress	17.479**	−5.700	28.643***
	(2.490)	(−0.324)	(3.139)
Post × Distress	−12.698**	6.147	−21.545***
	(−2.354)	(0.460)	(−3.069)
Firm-level controls	Yes	Yes	Yes
District by year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Mean of DV	0.53	0.66	0.52
N	267	62	126

Table 2: *Restructuring is Most Affected by BAPCPA when Manager Bargaining Power is High.* Standard errors are clustered at the firm level. t-statistics are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1) Leverage	(2) ROA volatility	(3) ROE volatility
Post × BAPCPA exposure × Distress	0.134**	0.088	0.853*
	(1.978)	(1.411)	(1.907)
Post × Distress	−0.117**	−0.064	−0.645*
	(−2.225)	(−1.327)	(−1.859)
Firm-level controls	Yes	Yes	Yes
Industry by year FE	Yes	Yes	Yes
District by year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Mean of DV	0.20	0.05	0.28
N	5,983	5,989	5,989

Table 3: *BAPCPA and Corporate Risk-taking.* Standard errors are clustered at the firm level. t-statistics are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1) All firms	(2) Excl. Tech firms
BAPCPA exposure × Distress	0.002*	0.001**
	(1.685)	(2.152)
distress	−0.001*	−0.001**
	(−1.784)	(−2.275)
Firm-level controls	Yes	Yes
Industry FE	Yes	Yes
Court district FE	Yes	Yes
Mean of DV	0.00	0.00
N	794	627

Table 4: *BAPCPA and AI Workers.* Standard errors are clustered at the district level. t-statistics are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1) TotalPatent	(2) AIPatent	(3) TotalPatentCite	(4) AIPatentCite
Post × BAPCPA exposure × Distress	0.727	4.607**	1.072	8.805**
	(1.182)	(2.190)	(1.592)	(1.989)
Post × Distress	−0.623	−3.771**	−0.874	−6.753**
	(−1.292)	(−2.212)	(−1.633)	(−1.961)
Firm-level controls	Yes	Yes	Yes	Yes
Industry by year FE	Yes	Yes	Yes	Yes
District by year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Mean of DV	34.40	10.42	388.97	109.74
N	7,451	3,232	7,242	2,985

Table 5: *BAPCPA and AI Outputs*. Standard errors are clustered at the firm level. t-statistics are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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