Shareholder Recovery and Leverage

Daniel Kim*

December 3, 2018

Link to the Latest Version

Abstract

According to the absolute priority rule (APR), firm shareholders should recover nothing in default unless creditors are paid in full. However, historically, shareholders have sometimes received a positive payoff in default. In this paper, I develop a dynamic model to estimate shareholder recovery rate and examine its implications. A positive recovery rate makes shareholders more willing to default, which increases borrowing costs. In response, firms lower leverage ex-ante. This channel helps to match distributions of both leverage and default probabilities. Structural estimation reveals a dramatic change over time in the U.S. bankruptcy system: shareholder recovery rate increased from roughly zero to 29% around the Bankruptcy Reform Act of 1978, and has gradually decreased back to zero. Finally, I show that a positive shareholder recovery rate has a quantitatively large effect on leverage, default probabilities, firm value, and government tax revenue.

*The Wharton School, University of Pennsylvania. I am deeply indebted to my dissertation committee: Joao Gomes, Christian Opp, Nikolai Roussanov, Luke Taylor, and Amir Yaron for their insightful comments, guidance, and support. I would like to thank Sylvain Catherine, Sudheer Chava, Mehran Ebrahimian, Lorenzo Garlappi, Marco Grotteria, Kevin Kaiser, David Skeel, Lin Shen, Karin Thorburn, Wei Wang, Jinyuan Zhang, participants at Trans-Atlantic Doctoral Conference 2018, INSEAD-Wharton Doctoral Consortium, and Wharton PhD Finance seminar for their valuable comments. I would also like to thank the Rodney L. White Center for Financial Research and Jacobs Levy Equity Management Center for financial support on this project.

1. Introduction

In the United States, the absolute priority rule[1] states that shareholders should recover nothing in default unless creditors are paid in full. However, shareholders have received a positive payoff due to a sequence of historical events, notably the Bankruptcy Reform Act of 1978. Between 1970 and 2005, shareholders received a positive payoff in 30.3% of bankruptcy instances (Bharath, Panchapegesan and Werner, 2007). In this paper, I use U.S. data to study the economic consequences of a positive shareholder recovery rate. To that end, using a dynamic model, this paper structurally estimates shareholder recovery rate and conducts counterfactual analysis.

The key insight of the dynamic model is as follows. When shareholders expect to receive a positive payoff in default, they choose to strategically default sooner, which increases borrowing costs, reducing optimal leverage ex-ante. Shareholders would like to commit to zero recovery in default because this would enable them to take higher leverage ex-ante, which generates a greater tax shield benefit. Yet, due to the unique nature of the bankruptcy system in the United States, shareholders sometimes are able to recover some value ex-post, and thus the commitment to zero recovery is not credible. This commitment problem is amplified by allowing default to be costly even when shareholders receive a positive payoff by renegotiating with creditors. The costly default contrasts with model implications of Fan and Sundaresan (2000) and yet is realistic and consistent with empirical findings (Andrade and Kaplan, 1998). As default cost increases, borrowing costs, conditional on leverage, increase, reducing optimal leverage ex-ante. Taken together, this commitment problem can help explain the observed leverage, and thus addresses the "underleverage puzzle," which states that the "trade-off theory" produces counterfactually high leverage levels when given realistic default costs. (Miller, 1977; Graham, 2000)

How much does this commitment problem reduce leverage? I address this question by estimating the structural parameters of my model, targeting leverage and default probabilities. I am able to identify shareholder recovery rate and default cost in the following way. I define

[1] See the U.S. Bankruptcy Code §1129(b)(2)(B)(ii))

shareholder recovery rate as a fraction of remaining firm value before default cost is realized. Accordingly, shareholder recovery increases with shareholder recovery rate although it does not move with respect to changes in default costs. Thus, conditional on leverage, in making a strategic default decision, shareholders consider their recovery rate and yet do not consider default cost. This implies that conditional default probabilities increase with shareholder recovery rate but do not move with respect to changes to default cost. The difference in sensitivities of conditional default probabilities with respect to the two structural parameters helps to separately identify them. Then, I structurally estimate for the representative firm similar to Hennessy and Whited (2005, 2007).[2]

I document dramatic changes over time in the U.S. bankruptcy system. As Hackbarth, Haselmann and Schoenherr (2015) show, the Bankruptcy Reform Act of 1978 increased shareholders' bargaining power *vis-á-vis* creditors, and thus shareholder recovery rate inreased. In order to test this, similar to Hackbarth et al., I form two subperiods, 1975Q1-1978Q3 and 1981Q2-1984Q4. Between these two subperiods, I allow tax rates to vary in order to account for the other concurrent change: the Economic Recovery Tax Act of 1981. Consistent with Hackbarth et al.'s finding, my structural estimation shows that shareholder recovery rates statistically significantly increased from 0.1% to 29%, whereas default cost statistically insignificantly increased from 19.0% to 21.0%. In response to the change in shareholder recovery rates, firms optimally lowered leverage ex-ante by 32.0%. This shows that allowing a positive shareholder recovery rate better explains the empirically observed leverage than does the "trade-off theory." Due to lower leverage, default probabilities decreased by 62.5%, and credit spreads decreased by 5.4%. Because firms took less advantage of tax shield benefits, firm values decreased by 5.0% and government tax revenue, defined as a contingent claim to the future tax revenue, increased by 22.2%. Lastly, lower default probabilities, driven by a positive shareholder recovery, implied less frequent realization of deadweight cost. Thus, the sum of firm values and government tax revenue increased by 4.4%.

After a subsequent series of contractual innovations in the bankruptcy process (Skeel, 2003; Bharath, Panchapegesan and Werner, 2007), shareholders' bargaining power *vis-á-vis*

[2]In addition, in order to analyze how shareholder recovery rates vary across firms, I structurally estimate shareholder recovery rate for each subset of firms.

creditors steadily decreased, and thus shareholder recovery rate decreased. After accounting for changes in tax rates, my estimates for shareholder recovery rate show the consistent trend: 19.9% between 1985Q1 and 1994Q4; 3.8% between 1995Q1 and 2004Q4; and 0.97% between 2005Q1 and 2016Q4. On the other hand, default cost did not significantly change from one subperiod to the next.

Similar to the existing empirical literature on the capital structure, I also estimate model parameters based on the long sample period, 1970Q1-2016Q4. The implied shareholder recovery rate was 7.1% and the implied default cost was 17.3%. Compared to the counterfactual world where shareholder recovery rate is set to zero, firms' optimal leverage was 9.4% lower. Due to lower leverage, default probabilities were 8.1% lower, and credit spreads were 1.7% lower. Moreover, firm values were 1.5% lower, government tax revenue was 9.9% greater, and the sum of firm values and government tax revenue was 0.9% greater.

My empirical strategy complements existing literature that relies on natural experiment and direct measurement. Even though results from a natural experiment can be instructive, due to other concurrent changes, it is empirically challenging to tease out the impact of a positive shareholder recovery rate. For example, a seemingly ideal setting for a natural experiment is the Bankruptcy Reform Act of 1978. However, the Economic Recovery Tax Act of 1981 changed tax rates almost simultaneously and thus it is hard to disentangle the impact of shareholder recovery rate from the impact of tax rate. Moreover, it is empirically challenging to use a natural experiment by itself to estimate an unobservable parameter such as shareholders' expected recovery rate. Direct measurement analysis calculates a sample average of shareholder recovery rates among bankrupt firms. While instructive, these results may suffer from sample-selection bias because firms with lower shareholder recovery rates default more frequently. This paper bases estimates on a broad cross-section of firms, including both bankrupt and non-bankrupt firms, and thus is immune from the sample-selection bias. Using direct measurement analysis, literature estimates shareholder recovery rate to be between 0.4% and 7.6% (Eberhart, Moore and Roenfeldt, 1990; Franks and Torous, 1989; Betker, 1995; Bharath, Panchapegesan and Werner, 2007). Even before accounting for the sample-selection bias, this paper's structural estimate of 7.1% for shareholder recovery rate during 1970Q1-2016Q4 is in-line with direct measurement analysis' estimates.

Admittedly, a structural estimation has limitations. One limitation is that it is hard to account for heterogeneity across firms. This limitation makes it empirically challenging to structurally estimate the sample-selection bias.[3] Firm heterogeneity can arise due to multiple sources, such as heterogeneous shareholder recovery rates or heterogeneous model misspecification. Because the sample-selection bias arises due to heterogeneous shareholder recovery rates but not due to heterogeneous model misspecification, estimating the sample-selection bias requires identifying a portion of heterogeneity that arises only due to the former. Unfortunately, the structural estimation cannot distinguish between these two sources; thus, structural estimation for the sample-selection bias is significantly biased. Due to this limitation, I do not target the result of direct measurement analysis in the structural estimation. Moreover, the limitation implies that researchers might need to revisit the structural estimation of the sample-selection bias (Glover, 2016).

The rest of the paper is structured as follows. Immediately following the introduction is the literature review. Section 2 discusses in detail the sequence of events in the United States that allowed shareholders to receive a positive payoff. Section 3 develops the model and Section 4 discusses the estimation procedure. Section 5 presents my empirical results on model fit, parameter estimates, and economic consequences. Section 6 discusses robustness, and Section 7 concludes.

Literature Review First, there is growing literature on shareholder recovery rate in default. Shareholders can recover non-negative value in default because shareholders can threaten to exercise several options.[4] Credibility of these threats is best illustrated in Eastern Airlines' bankruptcy case in 1989 (Weiss and Wruck, 1998). Thus, creditors are forced to accept shareholders' renegotiating terms and this naturally allows shareholders to recoup non-zero residual value in default. Accordingly, using pre-2000 samples on defaulted firms, a

[3] The structural estimation for the representative firm properly addresses heterogeneity thanks to the law of large numbers.

[4] These include 1) an option to take risky actions (asset substitution), 2) an option to enter costly Chapter 11, 3) an option to delay the Chapter 11 process if entered and 4) an option not to preserve tax loss carryfowards (for asset sales).

number of empirical papers (Eberhart, Moore and Roenfeldt, 1990; Franks and Torous, 1989; Betker, 1995) document that shareholders recover 2.28% to 7.6% of the remaining firm value on average. However, a subsequent series of contractual innovations in the bankruptcy process (Skeel, 2003) decreased shareholder recovery rate ever since. Shareholders recover 0.4% of the remaining firm value on average in 2000Q1-2005Q4 period (Bharath, Panchapegesan and Werner, 2007). Although these results are instructive, their measures could potentially suffer from sample-selection bias in estimating population cross-sectional mean of shareholder recovery rates, whereas my structural estimation is immune from the bias. Moreover, consistent with documented time-series variation, my subperiods analysis (see Figure 4) yields a downward trend in shareholder recovery rate.

The second strand of literature that this paper relates to is on the underleverage puzzle. Using various approaches, a few papers (Altman, 1984; Andrade and Kaplan, 1998) estimate default cost to be between 10% and 20%. However, researchers find that the empirically observed default cost is too low to justify empirically observed leverage (Miller, 1977; Graham, 2000). In response to this concern, Almeida and Philippon (2007), Elkamhi, Ericsson and Parsons (2012), Ju et al. (2005), Bhamra, Kuehn and Strebulaev (2010), and Chen (2010) use various approaches to address the puzzle. More recently, Glover (2016) estimates population default cost to be much larger (45%) and attributes sample-selection bias as a possible reason behind the large discrepancy between his estimate and other empirical work. In an attempt to address the same puzzle, this paper uses shareholders' strategic default action driven by a positive shareholder recovery.

Similar to this paper, Morellec, Nikolov and Schurhoff (2012) allow shareholders to receive a positive payoff and obtain a number for shareholder recovery rate. They set liquidation cost to be 46%, assume the liquidation cost to be a bargaining surplus between creditors and shareholders, and assume that shareholders are as equally powerful as creditors are in bargaining. This implies that default is not costly when shareholders and creditors bargain and shareholders recover 23% in default. The gap between Morellec et al.'s estimate and the direct measurement analysis estimate is too large to be reconciled only by the sample-selection bias. This paper allows default to be costly, focuses on the commitment problem driven by shareholder recovery rate, and obtains a shareholder recovery rate that is more in line with the previously documented numbers, between 0.4% and 7.6%.

More recently, by using a model that forces firms to roll over a fixed fraction of debt, Reindl, Stoughton and Zechner (2017) estimate default cost to be 20%. Although Reindl et al.'s estimate is similar to mine, we differ in a few major areas. Most importantly, I allow shareholders to receive a positive payoff and this extension makes the model general enough to capture some types of debt covenants. Absent such an extension, as Reindl et al. argues, debt covenants could have prevented shareholders from strategically defaulting. Next, Reindl et al. argues that Glover's estimate is significantly upward biased due to a model misspecification in explaining leverage, and motivates the authors' choice not to match leverage. As discussed in Section 6.4.1, I show that the first-order reason behind Glover's large estimate is due to Glover's particular choice of estimation procedure, which is conducted at each firm level. Moreover, I show that the structural estimation procedure, which is used by Hennessy and Whited (2005, 2007), and used in this paper, suffers significantly less from a model misspecification problem and thus validates use of leverage as a matching moment. Lastly, I allow firms to optimally choose an upward refinancing point.

The third strand of literature that this paper relates to is as follows. Noting the importance of a positive shareholder recovery, Fan and Sundaresan (2000) model strategic interactions between creditors and shareholders and their model is adopted in a number of recent papers (Davydenko and Strebulaev, 2007; Garlappi, Shu and Yan, 2008; Garlappi and Yan, 2011; Morellec, Nikolov and Schurhoff, 2012; Hackbarth, Haselmann and Schoenherr, 2015; Boualam, Gomes and Ward, 2017). Yet, their models typically assume that firms do not incur any default cost in equilibrium, whereas my model allows firms to incur default cost.

Finally, Green (2018) studies how valuable a restrictive debt covenant is in reducing agency costs of debt. As the author focuses on refinancing, he models firms' default decision as random events. On the contrary, I take firms' strategic default decision more seriously and study how it impacts firms' financing. Although I do not explicitly model covenants in my model, a cash-flow-based covenant can be one-to-one matched with shareholder recovery rate and have the similar effect on firms' optimal leverage ex-ante (see Section 3.1 for more discussion). Corbae and D'Erasmo (2017) studies a welfare implication of an policy counterfactual (hybrid version of Chapter 7 and Chapter 11). Corbae et al. compares a policy counterfactual to the world where firms in default optimally choose between Chapter 7, which complies with APR yet comes with high default cost, and Chapter 11, which violates APR yet comes with low default cost. On the contrary, in this paper, firms are not given an option to choose between Chapter 7 and Chapter 11, and this paper studies a shareholder recovery's impact on the behavior of "average" firms.

2. Bankruptcy Law in the United States

In the United States, the bankruptcy code states that creditors should be paid in full before shareholders can receive anything in default. However, in practice, the bankruptcy process is a negotiated agreement involving both creditors and shareholders. Thus, the code merely serves as a guideline for the process rather than a requirement, and thus shareholders can receive a positive payoff even when creditors are not paid in full. In this section,[5] I briefly discuss the sequence of historical events in the United States that eventually allowed a positive shareholder recovery rate.

Prior to the nineteenth century, the bankruptcy system in the United States was administrative in nature: bankrupt firms were almost always liquidated, its shareholders did not recover any value and managers were let go. Consequently, APR always held and shareholders were never part of the bankruptcy process.

However, in the late nineteenth century, there was a dramatic turn of events due to a series of bankruptcies in the railroad industry. These bankruptcies prompted the courts to intervene and rescue them for the sake of public interest in an effective transportation system. The courts formed equity receivership to run the bankrupt firm. Equity receivership comprised old shareholders, old creditors and old managers. This is important because this was the first time that shareholders became a part of the bankruptcy process. The

[5] See Skeel (2001) for a more detailed discussion.

practice spread to other industries and persisted over time. The Bankruptcy Reform Act of 1978 formally gave more power to shareholders, leading to larger shareholder recovery rate. Although the bankruptcy laws did not significantly change since then, a subsequent series of contractual innovations in the bankruptcy process gradually decreased shareholder recovery rate over time.

It is important to note that a positive shareholder recovery is a byproduct of the courts' effort to *keep its business alive and pay creditors*, which is Chapter 11's stated objective. The bankruptcy process sometimes requires shareholders' help or consent and thus requires shareholders to be paid off at the expense of the creditors. Consequently, this effort leads to a positive shareholder recovery. In the rest of the document, through the lens of the model, developed in the next section, I test whether a positive shareholder recovery is implied by firm data, and if so, quantify its magnitude that is implied by firm data.

3. Model

I extend the workhorse dynamic capital structure model (Goldstein, Ju and Leland, 2001) as follows. Upon default, firms lose α , shareholders recover η, and creditors recover the remainder $1 - \eta - \alpha$ fraction of the remaining firm value.[6][7] If shareholders are subject to a higher tax rate than creditors are, firms have an incentive to issue debt to shield earnings from taxation. Such a tax shield benefit motive is the only reason that firms want to lever up in my model. To stay in a simple time-homogeneous setting, I consider callable debt contracts that are characterized by a perpetual flow of coupon payments. Shareholders of each firm make three types of corporate financing decisions: (1) when to default, (2) when to refinance, and (3) how much debt to issue upon refinancing. Shareholders exercise their default option if earnings drop below a certain earning level, called the default threshold. Shareholders exercise the refinancing option if earnings rise above a certain earning level, called the upward refinancing threshold. These features are shared with numerous other

[6] This naturally imposes a restriction that $\eta + \alpha <= 1$.

[7] Contrary to Leland (1994), the model allows shareholders to recover non-zero value. Contrary to Fan and Sundaresan (2000), firms can potentially incur default cost even when shareholders and creditors enter renegotiation. Here, I want to emphasize that the model does not rule out $\alpha = 0$ nor $\eta = 0$.

capital structure models.

3.1. Setup and Solution

In the model, a firm i's earnings growth depends on aggregate earnings shocks as well as idiosyncratic shocks specific to the firm. Before-tax earning, $X_{i,t}$, evolves according to

$$\frac{dX_{i,t}}{X_{i,t}} = \mu_i dt + b_i \sigma_A dW_t^A + \sigma_i^F dW_{i,t}^F$$

Firm i's expected earnings growth is given by μ_i. b_i is firm i's exposure to the aggregate earnings shocks generated by the Brownian motion W_t^A and σ_A is the volatility of aggregate earnings shocks. σ_i^F is the volatility generated by the firm-specific Brownian motion $W_{i,t}^F$. By assumption, $W_{i,t}^F$ is independent of W_t^A for all firms i.

The model is partial equilibrium, and thus the pricing kernel is exogenously set as:

$$\frac{d\Lambda_t}{\Lambda_t} = -rdt - \varphi_A dW_t^A$$

where r is the risk-free rate and φ_A is the market Sharpe ratio. Under the risk-neutral measure, the earnings process evolves according to:

$$\frac{dX_{i,t}}{X_{i,t}} = \hat{\mu}_i dt + \sigma_{i,X} d\hat{W}_{i,t}$$

where $\hat{W}_{i,t}$ is Brownian motion under the risk-neutral probability measure, $\hat{\mu}_i = \mu_i - b_i \sigma_A \varphi_A$ and $\sigma_{i,X} = \sqrt{(b_i \sigma_A)^2 + (\sigma_i^F)^2}$. In order to guarantee the convergence of the expected present value of $X_{i,t}$, I impose the usual regularity condition $r - \hat{\mu}_i > 0$. For notational convenience, I drop i in the rest of the document.

This paper uses $\tau_{cd} \equiv 1 - (1 - \tau_c)(1 - \tau_d)$ as an effective tax rate that shareholders pay on the corporate earnings where τ_c denotes tax on corporate earnings and τ_d denotes tax on equity distributions. $\tau_{cdi} \equiv \tau_{cd} - \tau_i$ denotes tax shield benefit rate, where τ_i denotes tax on interest income.

Now, I describe how debt value and equity value are derived. For given default threshold X_D and optimal policies (coupon C and upward refinancing point X_U), I use the contingent claims approach to solve for debt value $D(X)$ and equity value $E(X)$. The most relevant boundary conditions are as follows. (Please see the Appendix for more detail.)

$$D(X_D) = (1 - \alpha - \eta)\frac{(1 - \tau_{cd})X_D}{r - \hat{\mu}} \tag{1}$$

$$E(X_D) = \frac{\eta(1 - \tau_{cd})X_D}{r - \hat{\mu}} \tag{2}$$

The first boundary condition captures that creditors recover $1-\alpha-\eta$ fraction of the remaining unlevered firm value. The second boundary condition captures that shareholders recover η fraction of the remaining unlevered firm value.

The next step is to solve for an optimal coupon C, upward refinancing point X_U, and default threshold X_D. C and X_U are determined at time 0 (initial point or refinancing point) to maximize firm value minus debt issuance cost. Here, debt issuance cost is ϕ_D times the debt value.

$$[C, X_U] = \arg\max_{C^*, X_U^*} \left((1 - \phi_D)D(X_0; C^*, X_U^*) + E(X_0; C^*, X_U^*)\right) \tag{3}$$

subject to

$$\lim_{X_t \downarrow X_D} E^{'}(X_t) = \frac{\eta(1 - \tau_{cd})}{r - \hat{\mu}} \tag{4}$$

X_D is determined based on the above smooth pasting condition, Equation (4) (see the heuristic derivation of the smooth pasting condition in Appendix C.2).

Because the model is used to explain the data, it is important to discuss what η might potentially capture. In the model, shareholders recover only in default. In reality, prior to declaring bankruptcy, some shareholders can potentially enjoy benefits of control rights by, for example, opportunistically refinancing to change covenants (Green, 2018).[8] To the extent

[8]For example, fallen angel firms delay refinancing relative to always-junk firms because loose covenants allow shareholders to transfer wealth from creditors.

that shareholders' opportunistic behavior makes debt more costly and higher debt cost is internalized, shareholder recovery rate η in the model captures such benefits in addition to explicit ex-post recovery value.

When shareholders recover zero amount in default, shareholders might not be able to strategically default at the optimal default threshold due to debt covenants (Reindl, Stoughton and Zechner, 2017). Yet, when shareholders are allowed to receive a positive payoff in default, such debt covenants can be easily described with my current model and shareholders will behave as if shareholders strategically default. More specifically, let us consider a cash-flow-based covenant, which specifies that shareholders must default if the earnings-to-coupon ratio goes below a certain threshold, say $\bar{X}_{DC}$. Because strategic default threshold $X_{DC}(\eta)$ monotonically increases over η (as shown below in Equation (5)), I can find unique η that sets $X_{DC}(\eta) = \bar{X}_{DC}$. Such an implied η increases over $\bar{X}_{DC}$, and thus shows that a more restrictive covenant (or equivalently higher $\bar{X}_{DC}$) corresponds to larger η. As such, my model is general enough to capture cases with some types of debt covenants.

3.2. Key Economic Channels: Commitment Problem

In this subsection, I discuss key economic channels in three steps.

Let me explain the first step. In their decision to default, shareholders weigh the benefits of holding on to their control rights, all future dividends, and recovery value against the costs of honoring debt obligations while the firm is in financial distress. As shareholder recovery rate (η) increases, the trade-off shifts and leads to earlier exercise of the option to default. This intuition can be seen in a closed form for the normalized default threshold (X_{DC}):

$$X_{DC} = \frac{X_D}{C} = \frac{r-\hat{\mu}}{r}\frac{-\lambda_-}{1-\lambda_-}\frac{1}{1-\eta} \tag{5}$$

where λ_- is a negative solution to the characteristic equation.

On a related note, X_{DC} does not depend on default cost, α, yet depends on η. The intuition is as follows. I define shareholder recovery rate as a fraction of remaining firm value before default cost is realized. Accordingly, shareholder recovery rate does not move with respect to changes to default cost. Thus, conditional on leverage, in making a strategic default decision, shareholders account for their recovery rate and yet do not account for default cost. This implies that conditional default probabilities increase with shareholder recovery rate but default probabilities do not move with respect to changes to default cost. This intuition is a key mechanism in separately identifying α and η. Thus, I write this as a proposition below and refer back to it later:

Proposition 1 *Conditional on the leverage, default probabilities increase over shareholder recovery rate (η). Conditional on the leverage, default probabilities do not change over default cost (α).*

The second step is, conditional on the leverage, debt becomes more costly. In other words, as η increases, borrowing cost increases because creditors lose η to shareholders and X_{DC} is determined to maximize the equity value at the expense of the bond value. In the third step, firms internalize higher debt cost and optimally lower leverage ex-ante.

[INSERT FIGURE 1]

The aforementioned three-step intuition can be illustrated graphically as shown in Figure 1. Going from point A to B illustrates the first two steps, where firm value decreases due to shareholders' strategic default action. The last step is illustrated by going from point B to C where firms optimally lower leverage ex-ante, and thus firm values increase. Interestingly, as **Proposition** 7 proves, the increase in firm values from point B to C is not sufficient to offset the decrease in firm values from point A to B.

In the rest of this section, I show why costly default is important in my setting. In order to present the intuition with closed forms, I suppress upward refinancing and study terms for firm value minus debt issuance cost:

$$(1-\phi_D)D(X_t)+E(X_t)=\frac{1-\tau_{cd}}{r-\hat{\mu}}X_t+\frac{\tilde{\tau}_{cdi}C}{r}+Loss\left(\frac{X_t}{C\cdot X_{DC}}\right)^{\lambda_-} \tag{6}$$

where $\tilde{\tau}_{cdi} = (1-\tau_i)(1-\phi_D) - (1-\tau_{cd})$ and

$$Loss/C = -\frac{\tilde{\tau}_{cdi}}{r} - (\alpha + \phi_D(1-\alpha-\eta))\frac{(1-\tau_{cd})X_{DC}}{r-\hat{\mu}} < 0 \tag{7}$$

Here, $\frac{\tilde{\tau}_{cdi}C}{r}$ captures the tax shield benefit whereas $Loss\left(\frac{X_t}{C \cdot X_{DC}}\right)^{\lambda_-}$ captures expected firm-value loss. As η increases, firm values decrease because the expected firm-value loss increases due to larger X_{DC}. Firms' optimal policy, C, has to decrease to equate marginal cost and marginal benefit. It is important to note that η impacts firms' capital structure decision mainly through X_{DC}. Thus, if default cost (α) becomes zero, because ϕ_D is very small in magnitude, $(\alpha + \phi_D(1-\alpha-\eta))$ in Equation (7) becomes negligible, and thus $Loss$ term in Equation (6) becomes insensitive to η. Consequently, η's impact on the optimal leverage significantly decreases.

3.3. Leverage, Default Probability and Market Beta

In this subsection, I discuss how η and α relate to leverage, default probability, and market beta.

Higher α implies higher firm-value loss conditional on defaults and thus higher expected firm-value loss. This consequently implies lower optimal leverage. Higher η implies higher firm-value loss and higher default probability. Taken together, this implies higher expected firm-value loss and consequently implies lower optimal leverage.

Proposition 2 *Higher default cost (α) and higher shareholder recovery rate (η) lead to lower leverage.*

All proofs are in the Appendix. Let us now discuss how α and η relate to default probabilities. As α increases, optimal leverage decreases, and thus default probabilities decrease. Higher η implies higher default probabilities *and* higher firm-value loss conditional on defaults. If leverage decreases only to exactly offset the increase in default probabilities but not in firm-value loss, then marginal cost is larger than marginal benefit and thus it is not optimal.

Leverage has to further decrease and this exactly implies that default probabilities decrease over η.

Proposition 3 *Higher default cost (α) and higher shareholder recovery rate (η) lead to lower default probability.*

Because default probabilities and leverage change over η in the same direction as they do over α, I need an extra key economic channel to separately identify α and η. The structural estimation in this paper is akin to solving the system of two equations for two unknowns. The two unknowns correspond to shareholder recovery rate and default cost. Leverage specifies one equation in terms of two model parameters and default probability specifies the other equation in terms of the same two parameters. Figure 2 graphically illustrates the intuition. It shows locus of α and η that match a given leverage (solid line) and a given default probability (dashed line). A necessary condition for α and η to be point-identified is that both lines have different slopes.

[INSERT FIGURE 2]

The key driver for the aforementioned necessary condition is **Proposition** 1. The difference in sensitivities of conditional default probabilities with respect to the two model parameters helps to separately identify them in the system of two equations. **Proposition** 4 uses this intuition to prove the necessary condition.

Proposition 4 *Leverage and default probability help to separately identify default cost (α) and shareholder recovery rate (η).*

Lastly, let us discuss how market betas change over η. Upon default, higher η implies that shareholders recover a higher share of the unlevered firm value. Because unlevered firm value is less risky than equity, positive probability of receiving higher payout that is less risky in default implies lower market beta. Moreover, as firms actively lower their leverage, firms face smaller distress risk and thus market betas further decrease. This idea is consistent with empirical evidence that is documented in Garlappi, Shu and Yan (2008), Garlappi and Yan (2011) and Hackbarth, Haselmann and Schoenherr (2015).

Proposition 5 *Higher shareholder recovery rate (η) leads to lower market beta.*

4. Estimation

This section describes the data, aggregate parameters, estimator, and intuition behind the estimation method.

4.1. Data

4.1.1. Sample

I obtain panel data from CRSP and COMPUSTAT. I omit missing observations and all firms whose primary SIC classification is between 4900 and 4999 or between 6000 and 6999 since the model is inappropriate for regulated or financial firms. I follow Bharath and Shumway (2008) and Gomes, Grotteria and Wachter (2018) to construct quarterly distance-to-default (DD) default probability measures. The sample contains 246,090 firm-quarter observations, number of unique firms is 4,435 and spans from 1970Q1 to 2016Q4. Table 1 shows summary statistics for the panel data set that this paper attempts to match. Section D.1 describes data variable definitions.

[INSERT TABLE 1]

Market beta is 1.105 on average,[9] quarterly earnings growth rate is 0.6% on average, and leverage is 0.283 on average. Moments of quarterly DD default probability are important in identifying my key parameters. Thus, I validate DD default probability measures. Sample average for my constructed *quarterly* default probability is 0.27%. This is similar in magnitude to the realized *quarterly* bankruptcy frequencies that are reported at 0.27% based on the sample period between 1970 and 2014 (Chava and Jarrow, 2004; Chava, 2014; Alanis, Chava and Kumar, 2015) or 0.28% based on the sample period between 1970 and 2003 (Campbell, Hilscher and Szilagyi, 2008). I also validate my measure against Moody's Expected Default Frequencies (EDF) measures, which are widely used by financial institutions as a predictor

[9] Market beta is not 1 on average because this is an equal-weighted average.

of default probability and are used in several academic papers including Garlappi, Shu and Yan (2008) and Garlappi and Yan (2011). My measures and Moody's are significantly and positively correlated as rank correlation is 0.75 with p-value=0.00.

4.1.2. Tax Rates

Following Graham (2000), a few papers (Chen, 2010; Glover, 2016) set $\tau_c = 35\%$, $\tau_d = 12\%$ and $\tau_i = 29.6\%$. However, Graham's sample period covers only from 1980 to 1994. Because my sample spans from 1970 through 2016, it calls for more up-to-date tax rates. I construct panel data of the most up-to-date tax rates (τ_c, τ_i and τ_d) by closely following Graham (2000) (see Section D.1.3).

The tax rates used in this paper are $\tau_c = 28.21\%$, $\tau_d = 17.76\%$, and $\tau_i = 32.85\%$. Relative to what were used by a few papers, my τ_c is lower because it captures periods with low earnings growth and thus implies lower corporate tax rates. My τ_d is larger because the proportion of long-term capital gains that is taxable increased from 0.4 to 1 after 1987 and my sample captures more of post-1987 than Graham (2000) does. Lastly, my τ_i is slightly larger because it accounts for the fact that τ_i is larger in the pre-1988 period. In net, τ_{cdi} decreased from 13.20% to 10.20%.

4.2. Aggregate Parameters

Because I assume that aggregate variables do not change over time, I calibrate aggregate variables using the longest sample period available: 1947 through 2016. Table 2 summarizes calibrated values for aggregate parameters and the corresponding data sources. For quarterly aggregate earnings growth volatility (σ_A), I use log growth rates based on the quarterly aggregate earnings data from National Income and Product Accounts (NIPA) Table 1.14. For real risk-free rate (r), I subtract realized inflation rate from the nominal three-month Treasury bill rate.[10] Lastly, I use quarterly market Sharpe ratio and debt issue cost (ϕ_D) that are reported in Chen (2010) and Altinkilic and Hansen (2000) respectively.

[10] Using the expected inflation rate (Bansal, Kiku and Yaron, 2012) yields very similar value for r.

[INSERT TABLE 2]

4.3. Estimator

I estimate the model using a two-step process. I first set μ to the sample mean of earnings growths, which is 0.60%. Then, I estimate the remaining four parameters by using the simulated method of moments (SMM), which chooses parameter estimates that minimize the distance between moments generated by the model and their data analogs. The following subsection defines matched moments and explains how they identify the four parameters. The four parameters are η and α, which characterize the default process, and b and σ^F, which characterize earning. Appendix A contains additional details on the SMM estimator.

4.4. Identification and Selection of Moments, and Heterogeneity

In a structural estimation, proper moment selection is crucial to identify a unique set of model parameters that make the model fit the data as closely as possible. To that end, moments' predicted values need to be differently sensitive to the model parameters, and there should be a sufficient number of moments. I match eight moments to identify the four parameters.

Before defining the moments, I address the issue of firm heterogeneity. Model parameters vary across firms, and it is undoubtedly important to account for cross-sectional distribution of model parameters as shown by Glover (2016). However, it is empirically challenging to estimate cross-sectional distribution especially when the model is misspecified (see Section 6.4). Similar to Hennessy and Whited (2005, 2007), the structural estimation used in this paper addresses firm heterogeneity in the data by removing firm fixed effects and estimates for the representative firm. Consequently, this allows me to match time-series variation of moments.

Now, I define the moments. The eight matched moments are the mean of market beta, the variance of earnings growth, leverage's three moments (mean, variance and skewness) and default probability's three moments (mean, variance and skewness).[11] One additional candidate for moments, in identifying η, are statistical moments of shareholder recovery rates among defaulted firms, which are documented by Eberhart, Moore and Roenfeldt (1990), Franks and Torous (1989), Betker (1995), and Bharath, Panchapegesan and Werner (2007). In matching these moments, it is crucial to address sample-selection bias. Unfortunately, the magnitude of sample-selection bias is very sensitive to cross-sectional distribution of η. Because it is empirically challenging to estimate cross-sectional distribution of η (see Section 6.4), I decided not to match those moments.

Next, in order to explain how the identification works, I discuss how each parameter is identified by the aforementioned eight moments. Table 3 tabulates how much each moment changes over parameters and supports the description below. Each moment depends on all model parameters, but I explain the moments that are the most important for identifying each parameter.

[INSERT TABLE 3]

Time-series mean, volatility and skewness of leverage and the same statistical moments of default probabilities help to identify η. This is illustrated by Figure 3. The figure illustrates two firms that face the same sequence of earnings (top panel). Two firms have the identical model parameter numbers except for η. The middle panel illustrates that $\eta = 0$ firm has larger leverage than $\eta \neq 0$ firm on average (consistent with **Proposition** 2). Lower target leverage, driven by larger η, makes leverage less sensitive to sequence of subsequent earnings growth shocks and thus decreases time-series volatility of leverage.

Moreover, larger η incentivizes firms to upward refinance less frequently. Because upward refinancing makes it more probable to default, larger expected firm-value loss, driven by larger η, incentivizes firms to upward refinance *less* frequently. Similar to debt issuance cost (see Leary and Roberts (2005) for empirical support), shareholder recovery rate makes firms' leverage more persistent over time. Consequently, leverage decreases on average and becomes

[11] Another relevant moment to match is the credit spread. Yet, I decided not to match the credit spread due to its data limitation. Firms' debt frequently consists of heterogeneous instruments, and market prices for most of these are less readily available than aforementioned data. Nonetheless, I study its sensitivity to key parameters.

less volatile. As firms reduce their target leverage and stay below its target leverage longer, time-series distribution becomes more positively skewed. Although default probabilities are similarly related to η as leverage is related to η, default probabilities are not as sensitive to η as leverage is due to the opposing force from shareholders' strategic default action (see Table 3). As illustrated in Figure 3, $\eta = 0$ firm upward refinances at time 84 whereas $\eta \neq 0$ firm does not upward refinance until its earnings reach a higher threshold at time 154. Because $\eta = 0$ firm increases its leverage earlier, a series of negative shocks between time 90 and 140 keep its leverage much higher and more volatile than $\eta \neq 0$ firm's. This leads to more significant jumps in default probability for $\eta = 0$ (bottom panel).

[INSERT FIGURE 3]

In addition, market beta helps to identify η. η is negatively related to market beta. This relation is consistent with empirical findings reported in Garlappi, Shu and Yan (2008), Garlappi and Yan (2011), and Hackbarth, Haselmann and Schoenherr (2015).

Similar to η, time-series mean, volatility and skewness of leverage and the same statistical moments of default probabilities help to identify α. Higher α makes leverage lower on average, less volatile and more positively skewed and thus default probability lower on average, less volatile and more positively skewed.

Most importantly, I discuss how α and η are separately identified. Conditional on leverage, shareholders' strategic default implies that default probabilities increase over η. Due to the commitment problem, however, optimal leverage decreases and, consequently, default probabilities decrease over η. Thus, default probabilities are less negatively related to η than they would be without the opposing force driven by shareholders' strategic default. However, because shareholders' strategic default action does not depend on α, default probabilities are much more negatively related to α. I illustrate this by calculating the implied slopes of two curves shown in Figure 2. Using numbers reported in Table 3, the slope of solid blue curve is $-\frac{\partial E(Lev)/\partial \eta}{\partial E(Lev)/\partial \alpha} = -\frac{-0.317}{-0.603} = -0.53$, whereas the slope of dashed red curve is $-\frac{\partial E(DP)/\partial \eta}{\partial E(DP)/\partial \alpha} = -\frac{-0.081}{-0.530} = -0.15$. Two curves have different slopes, and thus satisfy a necessary condition for α and η to be point-identified.

Lastly, let us discuss how the remaining two parameters are identified. Larger b implies higher exposure to the systematic risk. This naturally translates to larger mean of market beta. Larger b also implies lower risk-neutral earnings growth rate, which implies lower equity value. This translates to larger mean, higher volatility and smaller skewness of leverage. Larger b also implies higher volatility of earnings growth rate and thus implies larger mean and higher volatility of default probability. σ_F is naturally identified by the earnings growth rate volatility. Moreover, larger σ^F translates to higher volatility of default probability and implies higher volatility of equity value, and thus higher volatility of leverage. Lastly, as σ^F increases, the probability of reaching the default threshold during the next period increases and thus the mean of default probability increases.

5. Empirical Results

In this section, I present main structural estimation results and discuss their implications.

5.1. Main Results

Table 4 summarizes model fit. The first and the second rows show data moments and standard errors, respectively. The third row shows model-implied moments. The last two rows show difference between data and model-implied moments and t-statistics.

[INSERT TABLE 4]

As shown, all the moments are matched well as none of the differences between data and model-implied moments are statistically significantly different from zero. Especially, I want to highlight two main matching moments. Data sample mean of leverage is 0.283, whereas the model counterpart is 0.283. The difference between the data leverage and model-implied leverage is statistically insignificant. Data sample mean of quarterly default probability is 0.3%, whereas the model counterpart is 0.4%. Again, the difference between the data default probability and model-implied default probability is statistically insignificant.

Table 5 summarizes the parameter estimates. Shareholders' recovery rate (η) is estimated to be 7.1% and α is estimated to be 17.3%. Most interestingly, η is statistically different from zero, thus a natural null hypothesis that $\eta = 0$ is rejected at 1% significance level. This number is in line with the empirically observed counterpart, between 0.4% and 7.6% (Eberhart, Moore and Roenfeldt, 1990; Franks and Torous, 1989; Betker, 1995; Bharath, Panchapegesan and Werner, 2007), and thus strongly validates my estimates (see Section 6.4.3 for more careful validation of my estimates). Another interpretation of results is that average firms expect to enter the Chapter 11 in default and expect shareholders to recover a non-negative amount. If average firms expect to enter the Chapter 7 in default, then the implied η should have been 0, but this is statistically significantly rejected. This is consistent with an empirical observation that most publicly listed firms that are declaring bankruptcy file for the Chapter 11 rather than the Chapter 7.[12] Moreover, default cost (α) is expected to be statistically significantly positive even when shareholders and creditors are expected to renegotiate in default. Lastly, if $\eta = 0$ is imposed in the structural estimation, α is estimated to be 22.7%. This illustrates how allowing a positive shareholder recovery helps to obtain default cost, which is more in line with the empirically observed counterpart, between 10% and 20% (Altman, 1984; Andrade and Kaplan, 1998),[13] and thus strongly validates my estimates.

[INSERT TABLE 5]

5.2. Credit Spread, Firm Value, and Government Tax Revenue

In this section, I discuss how η qualitatively relates to credit spreads, firm values and government tax revenue. Then, I quantify such relations in the subsequent sections.

5.2.1. Credit Spread

Conditional on leverage, larger η can be thought of as wealth transfer from creditors to shareholders. As this is disadvantageous to creditors, credit spreads increase. However, as

[12]According to www.bankruptcydata.com, more than 90% of U.S. public firms file under Chapter 11.
[13]Morellec, Nikolov and Schurhoff (2008, 2012) cite Gilson, John and Lang (1990) to argue that α is small (0%-5%) when shareholders and creditors renegotiate. However, Gilson's measure does not include indirect cost and thus is not an appropriate measure in my context.

firms lower leverage in response, their default risk decreases, and thus credit spreads decrease. Such a commitment problem is strong enough that credit spreads decrease over η in net.

Proposition 6 *Higher shareholder recovery rate (η) leads to lower credit spread.*

In the literature, there is no empirical consensus on how η impacts credit spreads. Davydenko and Strebulaev (2007) find the relation to be positive yet economically small in magnitude. Based on cross-country data, Davydenko and Franks (2008) do not find any positive correlation between η and credit spreads. Hackbarth, Haselmann and Schoenherr (2015) find that credit spreads increased after η supposedly increased due to the Bankruptcy Reform Act of 1978. Yet, I argue that the increase in credit spreads was not due to the increase in η but due to the concurrent decrease in personal income tax rates (τ_i). Section 6.1 lists more detail on quantitative analysis of the Bankruptcy Reform Act of 1978.

5.2.2. Firm Value and Government Tax Revenue

Higher η leads to lower default probabilities and thus lower expected firm-value loss. Simultaneously, lower leverage and less frequent refinancing, driven by higher η, decrease the tax shield benefit. As default probabilities are small in magnitude, the latter channel more than offsets the former channel. In net, firm values decrease over η.

Proposition 7 *Higher shareholder recovery rate (η) leads to lower firm value.*

As η increases, firms decrease their leverage and upward refinance less often. Both of these lead to less usage of the tax shield benefit and thus the government collects more taxes. In order to quantify how much government tax revenue increases, I assume that government tax revenue is a contingent claim to the future tax revenue (see the Appendix for the derivation).

Proposition 8 *Higher shareholder recovery rate (η) leads to larger government tax revenue.*

Let us make one more assumption to study η's impact on the entire economy: the entire economy consists of firms and the government. In the model, there are two sources of deadweight cost, default cost and debt issuance cost. Larger η leads to smaller default probabilities and thus less frequent realizations of default cost. Moreover, larger η leads to less frequent realization of debt issuance cost as larger η makes refinancing less frequent. Taken together, larger η implies less frequent realization of deadweight cost, and consequently larger value for the entire economy (see Section C.6 for the mathematical derivation).

5.3. The Effect of Positive Shareholders' Recovery Rate

Column (1) of Table 6 summarizes the counterfactual world when shareholders recover zero amount in default ($\eta = 0$). Under column (2), I allow shareholders to recover non-zero amount in default, yet I force firms to keep the same optimal policies (coupon, C, and refinancing point, X_U) as under (1). This exercise helps to quantify how much expected firm-value loss increases, conditional on the firms' optimal policies. Upon default, firms lose $\alpha\frac{(1-\tau_{cd})X_D}{r-\hat{\mu}}$, where $\frac{(1-\tau_{cd})X_D}{r-\hat{\mu}}$ is the unlevered firm value in default. Firm-value loss increases as X_D increases from 0.077 to 0.083. Simultaneously, default probabilities increase from 0.388% to 0.436%. Taken together, expected firm-value loss increases by 21.3% even when default cost α does not change. Lastly, consistent with a few papers such as Davydenko and Strebulaev (2007), credit spreads increase. Now, under (3), I allow firms to internalize higher borrowing cost and to re-choose their optimal policies. Higher borrowing costs force firms to borrow less, and thus default probabilities decrease, market betas decrease and credit spreads decrease.

In sum, as we allow for a positive shareholder recovery (i.e. comparing column (1) and (3)), leverages decrease by 9.4% and default probabilities decrease by 8.1%. Market betas decrease by 20.5% and this is qualitatively consistent with Garlappi, Shu and Yan (2008), Garlappi and Yan (2011), and Hackbarth, Haselmann and Schoenherr (2015)'s empirical finding. Moreover, credit spreads decrease by 1.7% (see Appendix E for the discussion on its magnitude).

Interestingly, firm values decrease by 1.5% as firms lose tax shield benefit. Positive η

decreases the net leverage benefit (defined as a difference between levered firm value and unlevered firm value) by 14.2%. As firms take less advantage of tax shield benefits, the government collects more taxes. That amounts to a 9.9% increase in government tax revenue. Lastly, the sum of firm values and government tax revenue increases by 0.9%.

6. Robustness

This section reports how estimates for shareholder recovery rate changed over time and over different subsets of firms. I discuss how firm heterogeneity might affect estimates for shareholder recovery rate. Lastly, I discuss how estimates would change when I use a different assumption in the model.

6.1. Bankruptcy Reform Act of 1978

The Bankruptcy Reform Act of 1978 (BRA) is the most important act that shaped the nature of the modern U.S. bankruptcy system (see Appendix F for more institutional details). Through the lens of my model, I test how much this act changed default cost, α, and shareholder recovery rate, η.

Similar to Hackbarth, Haselmann and Schoenherr (2015), I construct two subperiods: 1975Q1-1978Q3 and 1981Q2-1984Q4. A period between 1978Q4-1981Q1 is removed because, as Hackbarth argues, the market was still learning of BRA's true impact. In order to focus on the impact that BRA had on η and α, I assume that only η and α changed over these two subperiods and assume that the other model parameters did not change. In order to account for shifts in firms' optimal decisions driven by changes in tax rates, I allow tax rates to vary across these two periods. More specifically, in each subperiod, I set the tax rate to the panel-wide average of firm-quarter tax rates. For the pre-event subperiod, tax shield benefit rate (τ_{cdi}^{pre}) is set to 11.28%. For the post-event subperiod, tax shield benefit rate (τ_{cdi}^{post}) is set to 18.95%. τ_{cdi} changed over these two subperiods because the Economic Recovery Tax Act of 1981 significantly decreased the personal tax rate on interest income (τ_i).[14]

[14]One caveat to note here is that data on corporate marginal tax rates (τ_c) are not available for pre-1980

Similar to the main structural estimation (Section 4.3), I first estimate μ by using the entire sample. Then, I structurally estimate six parameters by matching sixteen moments. Six parameters include b, σ^F, η for the pre-event subperiod (η^{pre}), η for the post-event subperiod (η^{post}), α for the pre-event subperiod (α^{pre}), and α for post-event subperiod (α^{post}). Sixteen moments include eight moments (mean of market beta, variance of earnings growth, three moments of leverage and three moments of default probability) from the pre-event subperiod and the same eight moments from the post-event subperiod.

[INSERT TABLE 7]

Table 7 summarizes parameter estimates. Consistent with the literature's qualitative argument, η statistically significantly increased (t-statistics is 11.4). Decrease in market betas, leverages and default probabilities combined with the concurrent decrease in tax rates have contributed to a significant increase in estimated η. More interestingly, the current paper quantifies such an increase: η increased from 0.1% to 29.0%. Moreover, $\eta^{pre} = 0.1\%$ is consistent with Hackbarth et al.'s argument that the impact of BRA was unclear leading up to 1978. In addition, α increased, although not statistically significantly, from 19.0% to 20.1%.

Over these two subperiods, three parameter values have changed: η, α and tax rates. In order to study impacts of each change, I conduct a counterfactual analysis by turning on each change in sequence. Table 8 summarizes such results.

[INSERT TABLE 8]

When only η changed from 0.1% to 29.0% (comparison between (1) and (2) columns), leverages decrease by 35.8%, market betas decrease by 11.5% and credit spreads decrease by 6.6%. A slight increase in α (comparison between (2) and (3) columns) further decreases leverage, market betas and credit spreads. Yet, the concurrent change in tax rates (comparison between (3) and (4) columns) mutes the aforementioned changes. In net, leverages decrease by 14.0%, market betas decrease by 5.1% and credit spreads increase by 7.2%. Here, I want to highlight that an empirically observed increase in credit spreads, which Hackbarth,

and τ_c used for firms in the pre-event subperiod are imputed as described in Section D.1.3. However, I do not believe that this imputation causes an increase in τ_{cdi} as the Economic Recovery Tax Act of 1981 targeted only individual income tax rates.

Haselmann and Schoenherr (2015) documents, is not due to the change in the bankruptcy code but rather due to the change in the tax code. Lastly, the rise in η (comparison between (1) and (2)) decreases firm values by 6.6% and increases government tax revenue by 36.9%. Yet, after accounting for all the changes, including tax rates, firm values increase by 6.0% and government tax revenue decreases by 39.1%.

6.2. Evolution of Shareholders' Recovery Rate

Even though bankruptcy law has not significantly changed since BRA was passed, Skeel (2003) conjectured that contractual innovations in the bankruptcy process steadily decreased shareholder recovery rate. In support for Skeel's conjecture, Bharath, Panchapegesan and Werner (2007) documents an empirical evidence: among firms that defaulted between 2000 and 2005, shareholders only recovered 0.4% on average. Bharath et al. attributes such a time-series decline in shareholder recovery rate to contractual innovations, such as debtor-in-possession financing and key employee retention plans.

In order to test whether this is reflected in firm data, I structurally estimate shareholder recovery rate and other model parameters for more recent periods. I first divided post-1985 era into three subperiods: 1985Q1-1994Q4, 1995Q1-2004Q4, and 2005Q1-2016Q4. I estimate model parameters for each subperiod independently from the others. Figure 4 graphically illustrates subperiod results. For completeness, the figure also illustrates pre-1985 estimates, which were discussed in Section 6.1. Consistent with Skeel's conjecture and Bharath et al.'s empirical finding, shareholder recovery rate steadily decreased over time. Shareholders' recovery rate decreased from 19.9% during 1985Q1-1994Q4 to 0.97% during 2005Q1-2016Q4. On the contrary, default costs slightly increased, yet the increase is not statistically significant.

The time-series changes in shareholder recovery rates and default costs are driven jointly by various moving parts. Keeping other parameters constant, the time-series decrease in tax shield benefit rate implies time-series decrease in leverage and time-series decrease in default probability over 1985Q1-2016Q4. Absent the change in tax shield benefit rate, leverage and default probabilities would have actually increased, under which case Figure 5 illustrates how α and η are identified. As leverages and default probabilities increase, solid line (locus of α and η match a leverage) shifts downward and dashed line (locus of α and η that match a default probability) shifts downward. As shown, η significantly decreases yet α slightly increases. The time-series increase in volatility of default probabilities and leverages further help to identify significant decrease in η and modest increase in α.

Finally, this result helps to alleviate a possible concern that my structural estimates might be picking up other alternative economic factors that influence leverage. Those alternative factors are, but certainly not limited to, business cycle variation (Chen, 2010) or agency costs (Morellec, Nikolov and Schurhoff, 2012). However, there is no clear explanation on why either of these alternative factors shows the time-series trend that is shown in Figure 4, and thus puts more weight on my economic story: shareholder recovery rate.

6.3. Empirical Proxies for Shareholders' Recovery Rate

The results so far quantify how much shareholders expect to recover in default for the representative firm. Now, I explore how these values vary over firms with different characteristics. Based on empirical proxies for shareholder recovery rate, discussed below, I construct a subset of firms and estimate model parameters for each subset independently from others. Then, I conduct counterfactual analysis in each subset to quantify economic impacts of a positive shareholder recovery rate.

I first discuss empirical proxies for shareholder recovery rate that I use to construct subsets. Due to lack of guidance on proxies' validity, the literature uses a wide range of measures. Unfortunately, in many cases, these empirical measures simultaneously proxy other unobservable firm characteristics, and thus its validities can be ambiguous. This subsection studies two commonly used proxies, firm size and intangible assets. I use total asset (Compustat: AT) to measure firm size. I use two separate measures to proxy intangible assets: normalized R&D expense (Compustat: XRD/AT) and Intangibility proposed by Peters and Taylor (2016).

For a given empirical proxy, I form two subsets. In order to make sure that firms do not move from one subset to the other over time, I perform the following procedure. At each quarter, I calculate the proxy's cross-sectional median, and I temporarily allocate a firm with proxy value greater than the median to High-subset and a firm with proxy value smaller than the median to Low-subset. This generates a time-series of subsets for a given firm. Then, I allocate the firm's entire time-series data to one subset that the firm spends the most time in.

Across different subsets, I allow tax rates to vary but keep other aggregate variables constant. Table 9's first panel summarizes tax shield benefit rates and other matching moments. For example, low-R&D firms' tax shield benefit rate is much larger than high-R&D firms' because high-R&D firms have higher expenses.

Next, I structurally estimate model parameters for each subset independently. Table 9's middle panel summarizes estimates for default cost (α) and shareholder recovery rate (η) for different subsets. First, I find that estimates for η increase over firm size. This result is consistent with the literature's use of η as a positive proxy. Citing more frequent occurrences of a positive shareholder recovery rate[15] in larger firms, Garlappi, Shu and Yan (2008) Garlappi and Yan (2011), and Hackbarth, Haselmann and Schoenherr (2015) use firm size as a positive proxy for η. They argue that small firms usually have a higher concentration of bond ownership. So, close monitoring by concentrated creditors severely decreases η.

Second, although η increases over R&D, the increase is not statistically significantly different from 0, and thus casts doubt on this literature's (Garlappi, Shu and Yan, 2008; Garlappi and Yan, 2011; Hackbarth, Haselmann and Schoenherr, 2015)'s use of R&D as a negative proxy for η. They use it as a negative proxy because firms with high R&D are more likely to face liquidity shortages (Opler and Titman, 1994) during financial crises, thus are more likely to forgo intangible investment opportunities that shareholders value (Lyandres and Zhdanov, 2013). Firms' urgent need for liquidity effectively acts as cash-flow-based covenants, and thus high intangibility puts shareholders at a disadvantage *vis-á-vis* creditors and implies low η. However, η can increase over R&D because some R&D investments are more valuable under shareholders' possession, which increases shareholders' bargaining

[15] Please see Weiss (1990), Betker (1995), and Franks and Torous (1994) for more detail.

power *vis-á-vis* creditors. Due to these offsetting forces, R&D might not be a good empirical proxy for η as evident in my estimates. A similar result holds for the other empirical proxy: intangibility.

Third, the results show that both R&D and intangibility are strong positive proxies for α. Consistent with some findings (Reindl, Stoughton and Zechner, 2017), this variable captures how non-transferable a firm's asset might be in default and thus is positively related to α.

Lastly, interestingly, the estimates imply that firm size is a strong positive proxy for α and this is inconsistent with some previous findings (Reindl, Stoughton and Zechner, 2017). If the same tax rates were used for both small and big firms, as was done in other studies, then small firms' α would have been larger than big firms' because small firms' leverage is smaller than big firms'. Yet, as shown in Table 9, big firms face much larger tax shield benefit rates (almost 3 times) than small firms do. Thus, through the lens of my model, it implies that big firms have to face larger α than small firms do. This finding illustrates the importance of using appropriate tax rates in estimating α and η for each subset.

Using these estimates, I do a counterfactual analysis for each subset of firms. Allowing η to be positive can have different implications on each subset because different subsets have different α, η and tax shield benefit rates. Table 9's last panel summarizes such counterfactual analysis results.

[INSERT TABLE 9]

For example, I focus on firms sorted by R&D. η for high-R&D firms is larger than that for low-R&D firms and thus allowing η to be positive should have larger economic consequences on high-R&D firms. High-R&D firms have larger α and thus reinforces the commitment problem that positive η plays. Thus, high-R&D's leverages and default probabilities decrease significantly more (17.1% and 24.0%, respectively) than low-R&D's (7.3% and 4.4%, respectively). However, these do not necessarily translate to lower dollar amount of tax shield benefit for high-R&D firms. Because high-R&D firms face a lower tax shield benefit rate than low-R&D firms, high-R&D firms face lower firm value loss than low-R&D firms despite that high-R&D firms reduce their leverage more. Accordingly, the percentage increase in government tax collection is larger for low-R&D firms than it is for high-R&D firms.

6.4. Firm Heterogeneity: Monte Carlo Simulations

As emphasized by Glover (2016), cross-sectional distribution of model parameters is important to consider, especially in estimating default cost and shareholder recovery rate. Although I agree with its importance, it is empirically challenging to estimate the cross-sectional distribution. Below, I first discuss how model misspecification at the firm level makes it empirically challenging to estimate the cross-sectional distribution. Then, I illustrate that estimating for the representative firms does not suffer from model misspecification problem. Lastly, I quantify sample-selection bias and validate bias-adjusted estimates.

To quantitatively analyze the aforementioned three points, it is the most ideal to know population cross-sectional distribution of model parameters. Thus, the most suitable way to analyze this is through a Monte Carlo simulation. In order to illustrate how my analysis is sensitive to different data-generating process (DGP), I create two simulated panel data (see Appendix B for details). Both DGPs are calibrated to resemble data on a few aspects, including population cross-sectional mean of model parameters, which are set almost equal to those reported in Table 5. In both simulated data set, firm heterogeneity arises due to heterogeneous model misspecification, heterogeneous model parameters or different realizations of earnings. The only difference between these two DGPs is as follows. I create the first simulated panel data set by randomly drawing α and η from truncated normal PDF. I create the second simulated panel data set by randomly drawing α and η from truncated exponential PDF. Panel A in Table 10 shows population cross-sectional mean of shareholder recovery rate for both DGPs.

6.4.1. Firm-Level Estimation

Glover (2016) estimates the population default cost to be 45% even though default cost among population conditional on defaults is 25%, and Glover attributed the large discrepancy to sample-selection bias. Even though I qualitatively agree with existence of sample-selection bias, I want to illustrate that Glover's particular choice of estimation method might have significantly upward biased its estimate of the sample-selection bias.

As long as the estimation procedure cannot distinguish between different sources of heterogeneity, estimated cross-sectional distribution of model parameters are biased by model misspecification. In order to illustrate my point, I study firm-level estimation, used by Glover, which cannot distinguish between different sources of heterogeneity. Due to small time-series data, the law of large numbers cannot help to "fix" the model misspecification problem, and consequently firm-level estimates are biased. Firm-level estimates are upward biased because both model-implied functions for leverage and default probability are convex functions in default cost, α, and shareholder recovery rate, η. Consequently, cross-sectional average of firm-level estimates are significantly upward biased. Panel B.1 in Table 10 reports estimation bias for both set of simulated panel data.

[INSERT TABLE 10]

6.4.2. Numerical Validation of Structural Estimation

Similar to Hennessy and Whited (2005, 2007), this paper structurally estimates for the representative firm. This subsection numerically shows that the structural estimation procedure used in this paper properly uncovers population cross-sectional mean of model parameters. The results are summarized in Panel B.2 in Table 10. As shown, the structural estimation procedure's estimate biases are small for both simulated panel data, yet not zero due to finite-sample bias. Thanks to the law of large numbers, estimating for the representative firm always yields lower bias than firm-level estimates as long as the model is nonlinear in model parameters.

6.4.3. Sample-Selection Bias and Validation of Estimates

Many earlier papers attempt to estimate η and α by examining defaulted firms. Thus, it seems natural to check my estimates against realized counterparts documented in those papers. However, as noted by Glover (2016), sample-selection bias can be large because firms with small η and/or small α tend to default more frequently. Thus, the sample average of η (α) conditional on defaults can be smaller than the unconditional sample average of η (α).

I quantify sample-selection bias and report results in Panel C in Table 10. Population cross-sectional mean of α and η is almost identical for both simulated data. Yet, cross-sectional distributions of α and η, which follow the normal distribution, have smaller mass on small values than those that follow exponential distribution. Thus, the magnitude of sample-selection bias should be smaller under the first specification. Consistent with the intuition, sample-selection bias is 5.5% for α and 2.3% for η using the first simulated data set, whereas sample-selection bias is 8.3% for α and 3.3% for η using the second simulated data set. As illustrated, the magnitude of sample-selection bias heavily depends on η and α's cross-sectional distribution.

Nonetheless, I use these bias-adjusted numbers to validate my estimates. Among defaulted firms, direct measurement literature estimate shareholder recovery rate after default cost is realized. Thus, the comparable number is the sample average of $\frac{\eta}{1-\alpha}$. The value is 5.4% under the first simulated data and 4.2% under the second simulated data. Both numbers are in line with empirically observed counterpart between 0.4% and 7.6%. Bias-adjusted default cost is 11.9% under the first simulated data and 9.1% under the second simulated data. Both numbers are in line with the empirically observed counterpart between 10% and 20%. This external validation exercise strongly validates my results. Lastly, I check if the parameter estimates imply a reasonable value for creditors' recovery rate. According to Moody's Ultimate Recovery Database announcement in April 2017, the median recovery for corporate bonds was 36% between 1987 and 2016. The model counterparts[16] are 25.4% using the first simulated data and 27.9% using the second simulated data. The discrepancy in creditors' recovery rate could arise due to different sample period.

[16] I define creditors' recovery rate as

$$\frac{(1-\alpha^r-\eta^r)(D(X_D)+E(X_D))}{D(X_0)}$$

where the numerator represents the creditor's realized recovery value and the denominator represents what creditors are owed.

6.5. Uncertainty in Shareholders' Recovery Rate

In this subsection, I study how uncertainty in shareholder recovery rate could impact firms' optimal leverage ex-ante.

I assume that shareholder recovery rate, η, is drawn once, immediately after firms decide on its initial leverage. One reasonable conjecture is that uncertainty in η decreases the commitment problem played by positive η because its power seems to have subsided due to its uncertainty. However, the opposite can happen for the following reason. Expected firm-value loss is a convex function in η (because X_{DC} is proportional to $\frac{1}{1-\eta}$ as shown in Equation (5)). Thus, the average of high η's optimal leverage and low η's is smaller than medium η's leverage. On a related note, as long as $\eta = 1$ event happens with some positive probability, expected firm-value loss becomes infinity (again, because X_{DC} is proportional to $\frac{1}{1-\eta}$ as shown in Equation (5)) and firms optimally choose zero leverage ex-ante. Thus, introducing uncertainty in η can allow us to match the empirically observed leverage even with lower magnitude of η.

What does this mean for my η estimate? If uncertainty in η truly exists in the real world, because the current model does not account for uncertainty, η reported in Table 5 is an upper bound for the population cross-sectional mean of η. Although this is a very interesting extension, quantitative analysis of the role of uncertainty in η is beyond the scope of this paper and I will leave this for later study.

7. Conclusion

According to the absolute priority rule (APR), shareholders should recover nothing in default unless creditors are paid in full. However, in practice, shareholders do receive a positive payoff in default even if creditors are not paid in full. In this paper, I develop a dynamic tradeoff model to examine the importance of a positive shareholder recovery rate. Consistent with existing empirical findings, I allow default to be costly even when shareholders recover a positive amount as a renegotiation outcome with creditors. A positive recovery makes shareholders more willing to default, which increases borrowing costs. In response, firms optimally reduce leverage ex-ante. This channel helps to match distributions of both leverage and default probability.

A structural estimation of the model yields a default cost of 17.3% and a shareholder recovery rate of 7.1%. Counterfactual analysis reveals that allowing a positive shareholder recovery rate decreases the leverage by 9.4%. Consequently, default probabilities decrease by 8.1%, market betas decrease by 20.5% and credit spreads decrease by 1.7%. As firms lose the tax shield benefit, firm values decrease by 1.5% and government tax revenue increases by 9.9%. Lastly, lower default probability, driven by a positive shareholder recovery, implies less frequent realization of deadweight cost. Thus, the sum of firm values and government tax revenue increases by 0.9%. Even though this paper does not do complete welfare analysis, these findings can still be used to shed some light on an important bankruptcy policy question as this paper highlights its consequences. Additionally, subperiod analysis reveals that shareholder recovery rate increased immediately after the Bankruptcy Reform Act was passed in 1978, and a shareholder recovery rate has steadily decreased ever since. Consistent with the empirical literature, my subset estimates show that firm size is a good positive proxy for shareholder recovery rate.

Table 1: Summary Statistics

This table reports the summary statistics for my sample of firm data. The sample contains 246,090 firm-quarter observations, number of unique firms is 4,435 and spans from 1970Q1 to 2016Q4. Market beta is calculated based on a rolling window of 24 months of monthly returns. Earnings growth is $\tilde{e}_{i,t+1} = \log\left(\frac{\sum_{j=0}^{K} OIADPQ_{i,t+1-j}}{\sum_{j=0}^{K} OIADPQ_{i,t-j}} - 1\right)$ where K is set to 8 and $OIADPQ$ is operating income after depreciation. Default probabilities are constructed by following distance-to-default model (Bharath and Shumway, 2008). Leverage is defined as $\frac{DLTTQ+DLCQ}{DLTTQ+DLCQ+ME}$ where $DLTTQ$, $DLCQ$ and ME are long-term debt, short-term debt and market equity, respectively.

	Market beta	Earnings Growth	Default Probability	Leverage
Mean	1.105	0.0060	0.0027	0.283
Median	1.050	0.0144	0.0000	0.231
Standard dev	0.858	0.3018	0.0437	0.225
Skewness	0.763	-0.9793	19.2656	0.815
Minimum	-12.771	-8.3713	0.0000	0.000
Max	15.278	8.0986	1.0000	0.999
Number of obs	246,090	246,090	246,090	246,090

Table 2: Aggregate Parameters Values

This table reports values used for aggregate parameters and their data sources. Quarterly aggregate earnings growth volatility (σ_A) and quarterly real risk-free rate (r) are calibrated based on the sample period from 1947Q1 through 2016Q4. A value for market Sharpe ratio is obtained from Chen (2010) and a value for proportional debt issuance cost is obtained from Altinkilic and Hansen (2000).

	Description	Value	Source
σ_A	Quarterly aggr earnings growth vol	0.052	NIPA
r	Quarterly real risk-free rate	0.0016	FRED
φ_A	Quarterly market Sharpe ratio	0.165	Chen (2010)
ϕ_D	Prop' debt issuance cost	0.015	Altinkilic and Hansen (2000)

Table 3: Sensitivity of Moments to Parameters

This table shows the local sensitivity of model-implied moments (in columns) with respect to model parameters (in rows). To make the sensitivities comparable across parameters and moments, the sensitivities are normalized as $\frac{\partial \text{ moment}}{\partial \text{ parameter}} \times \frac{\text{parameter's standard error}}{\text{moments' standard error}}$. Local sensitivities are calculated around the estimates that are reported in Table 5. From left to right, moments are mean of market beta ($E(\beta)$), variance of earnings growth ($var(EG)$), mean of leverage ($E(Lev)$), variance of leverage ($var(Lev)$), skewness of leverage ($skew(Lev)$), mean of default probability ($E(DP)$), variance of default probability ($var(DP)$) and skewness of default probability ($skew(DP)$). Parameter definitions are as follows. b is earnings growth beta, σ^F is volatility of firm-specific earnings growth shock, η is shareholder recovery rate and α is default cost.

	$E(\beta)$	$var(EG)$	$E(Lev)$	$var(Lev)$	$skew(Lev)$	$E(DP)$	$var(DP)$	$skew(DP)$
b	0.837	0.015	0.275	0.312	−0.204	0.235	0.202	−0.088
σ^F	0.003	0.215	−0.006	0.280	0.154	0.280	0.251	−0.107
η	−0.208	0.000	−0.317	−0.655	0.027	−0.081	−0.072	0.030
α	−0.276	0.001	−0.603	−0.733	0.465	−0.530	−0.452	0.196

Table 4: Model Fit

This table shows how well the model fits the eight moments targeted in the SMM estimation. The first and the second rows show data moments and standard errors respectively. The third row shows model-implied moments. The last two rows show the difference between data and model-implied moments and t-statistics. From left to right, moments are mean of market beta ($E(\beta)$), variance of earnings growth ($var(EG)$), mean of leverage ($E(Lev)$), variance of leverage ($var(Lev)$), skewness of leverage ($skew(Lev)$), mean of default probability ($E(DP)$), variance of default probability ($var(DP)$) and skewness of default probability ($skew(DP)$).

	$E(\beta)$	$var(EG)$	$E(Lev)$	$var(Lev)$	$skew(Lev)$	$E(DP)$	$var(DP)$	$skew(DP)$
Data	1.105	0.078	0.283	0.019	0.451	0.003	0.002	16.869
Std. Err.	(0.036)	(0.010)	(0.012)	(0.003)	(0.155)	(0.001)	(0.000)	(3.960)
Model	1.100	0.060	0.283	0.018	0.736	0.004	0.002	16.068
Difference	0.005	0.018	-0.001	0.001	-0.285	-0.001	0.000	0.801
t-stat	0.151	1.786	-0.041	0.251	-1.839	-1.662	-0.689	0.202

Table 5: Parameter Estimates

This table reports the model's parameter estimates from the simulated method of moments (SMM). Here, I cluster by industries to account for apparent correlation between firms in the same industry. I use 17 industry definitions from Kenneth French's website. This clustering strategy also accounts for time-series autocorrelation within firms. This is more conservative than clustering by firms. Parameter definitions are as follows. b is earnings growth beta, σ^F is volatility of firm-specific earnings growth shock, η is shareholder recovery rate and α is default cost.

	b	σ^F	η	α
Estimate	0.816	0.244	0.071	0.173
Standard Error	(0.019)	(0.002)	(0.009)	(0.010)

Table 6: The Effect of Positive Shareholders' Recovery Rate

This table illustrates the effect of a positive shareholder recovery rate. The first column reports values for the counterfactual world where shareholders are expected to recover nothing in default. The second column allows shareholders to recover non-zero amount in default yet forces firms to keep the same optimal policies (coupon, C, and refinancing point, X_U) as under the first column. This exercise helps to quantify how much expected firm-value loss increases, conditional on the firms' optimal policies. The third column summarizes the data-matched world where shareholders are expected to recover 7.1% in default. The first three rows are coupon, default threshold and upward refinancing boundary, all scaled by initial earnings level. The fourth row shows panel-wide average of leverage. The fifth row shows panel-wide average of default probabilities. The sixth row shows panel-wide average of market betas. The last row shows panel-wide average of credit spreads.

	(1)	(2)	(3)
	$\eta = 0$	$\eta = 7.1\%$	$\eta = 7.1\%$
Coupon (C)	1.145	1.145	1.006
Upward Refinancing Point (X_U)	3.882	3.882	3.918
Default Threshold (X_D)	0.077	0.083	0.073
Leverage	0.314	0.306	0.285
Default Probability (%)	0.388	0.436	0.356
Market-beta	1.386	1.132	1.102
Credit Spread (BP)	194	201	191

Table 7: Robustness — Bankruptcy Reform Act of 1978

This table reports the model's parameter estimates from the simulated method of moments (SMM). These estimates help to test how the Bankruptcy Reform Act of 1978 changed shareholder recovery rate (η) and default cost (α). Similarly to the baseline parameter estimates, I cluster by industries to account for apparent correlation between firms in the same industry. I use 17 industry definitions from Kenneth French's website. This clustering strategy also accounts for time-series autocorrelation within firms. This is more conservative than clustering by firms. Parameter definitions are as follows. b is earnings growth beta, σ^F is volatility of firm-specific earnings growth shock, η^{pre} is η for the pre-event subperiod (1975Q1-1978Q3) and η^{post} is η for the post-event subperiod (1981Q2-1984Q4), α^{pre} is α for the pre-event subperiod (1975Q1-1978Q3) and α^{post} is α for the post-event subperiod (1981Q2-1984Q4).

	b	σ^F	η^{pre}	η^{post}	α^{pre}	α^{post}
Estimate	0.812	0.220	0.001	0.290	0.190	0.210
Standard Error	(0.012)	(0.002)	(0.019)	(0.017)	(0.008)	(0.032)

Table 8: Robustness — Analysis of Bankruptcy Reform Act of 1978

This table illustrates the effect of the Bankruptcy Reform Act of 1978. The first column summarizes the model-implied moments when $\tau_{cdi} = 11.28\%$, $\eta = 0.1\%$ and $\alpha = 19.0\%$. The second column shows the model-implied moments when $\tau_{cdi} = 11.28\%$, $\eta = 29.0\%$ and $\alpha = 19.0\%$. The third column shows the model-implied moments when $\tau_{cdi} = 11.28\%$, $\eta = 29.0\%$ and $\alpha = 21.0\%$. The fourth column shows the model-implied moments when $\tau_{cdi} = 18.95\%$, $\eta = 29.0\%$ and $\alpha = 21.0\%$.

	(1)	(2)	(3)	(4)
τ_{cdi}		11.28%		18.95%
η	0.001	0.290	0.290	0.290
α	0.190	0.190	0.210	0.210
Leverage	0.297	0.190	0.180	0.255
Market beta	1.094	0.968	0.958	1.038
Credit spread	216	202	197	232

Table 9: Robustness — Subset Based on Empirical Proxies for Shareholders' Recovery Rate

This table reports results for subset analysis. For each proxy (size, R&D, or intangibility), I form two subsets. At each quarter, I calculate the proxy's cross-sectional median, and I temporarily allocate a firm with proxy value greater than the median to High-subset and a firm with proxy value smaller than the median to Low-subset. This generates a time-series of subsets for a given firm. Then, I allocate the firm's entire time-series data to one subset that the firm spends the most time in. The first panel reports summary statistics for each subset. The second panel reports estimates for shareholder recovery rate (η) and default cost (α) and standard errors (in parentheses) for each subset. The last panel quantifies economic consequences of allowing shareholders to recover a positive amount in default. It reports percent changes on leverage, default probability, firm value and government tax revenue.

	Size		R&D		Intangibility	
	Small	Big	Low	High	Low	High
Summary Statistics						
Tax Shield Benefit Rate	0.048	0.132	0.112	0.063	0.105	0.098
Leverage	0.273	0.287	0.240	0.181	0.315	0.240
Default Prob	0.201	0.291	0.142	0.087	0.326	0.179
Estimates						
Shareholders' Recovery Rate (η)	0.015	0.122	0.071	0.101	0.061	0.073
	(0.008)	(0.009)	(0.009)	(0.043)	(0.008)	(0.014)
Default Cost (α)	0.105	0.242	0.131	0.150	0.174	0.21
	(0.004)	(0.028)	(0.010)	(0.022)	(0.006)	(0.012)
Economic Consequences: $\eta = 0 \Rightarrow \eta \neq 0$						
%Δ Leverage	-2.6	-14.6	-7.3	-17.1	-8.2	-11.0
%Δ Default Prob	-4.3	-12.2	-4.4	-24.0	-7.3	-13.7
%Δ Firm Value	-0.1	-4.0	-2.0	-1.1	-1.2	-1.2
%Δ Tax Revenue	0.6	79	146.4	11.2	7.5	7.5

Table 10: Robustness — Firm Heterogeneity

This table illustrates how firm-level heterogeneity can impact structural estimates. For illustration, I simulate two sets of panel data sets that feature firm heterogeneity due to variety of sources: heterogeneous model parameters (α, η), heterogeneous model misspecification and idiosyncratic shocks. The first simulated data set assumes truncated normal distribution for model parameters and the table's first column summarizes such results. The second simulated data set assumes truncated exponential distribution for cross-sectional distribution of model parameters and the table's second column summarizes such results (see Appendix Section B for more detail). Panel A summarizes population cross-sectional mean of heterogeneous model parameters. Panel B reports estimates for population cross-sectional mean using different structural estimation procedures. Panel C reports conditional mean in default, and quantifies sample-selection bias.

	Truncated Normal		Truncated Exponential	
Panel A. Population Cross-sectional Mean of Heterogeneous Model Parameters				
α_i	17.4%		17.0%	
η_i	7.1%		7.0%	
Panel B. Estimates Using Different Estimation Procedures				
		estimation bias		estimation bias
	B.1 Firm-Level Structural Estimation (Glover (2016))			
α	19.6%	2.2%	19.7%	2.7%
η	21.1%	14.0%	22.4%	15.4%
	B.2 Structural Estimation Used in the Current Paper			
α	17.7%	0.3%	16.3%	0.7%
η	7.4%	0.3%	6.5%	0.5%
Panel C. Conditional Mean Upon Default				
		selection bias		selection bias
α	11.9%	5.5%	8.4%	8.6%
η	4.8%	2.3%	3.4%	3.6%

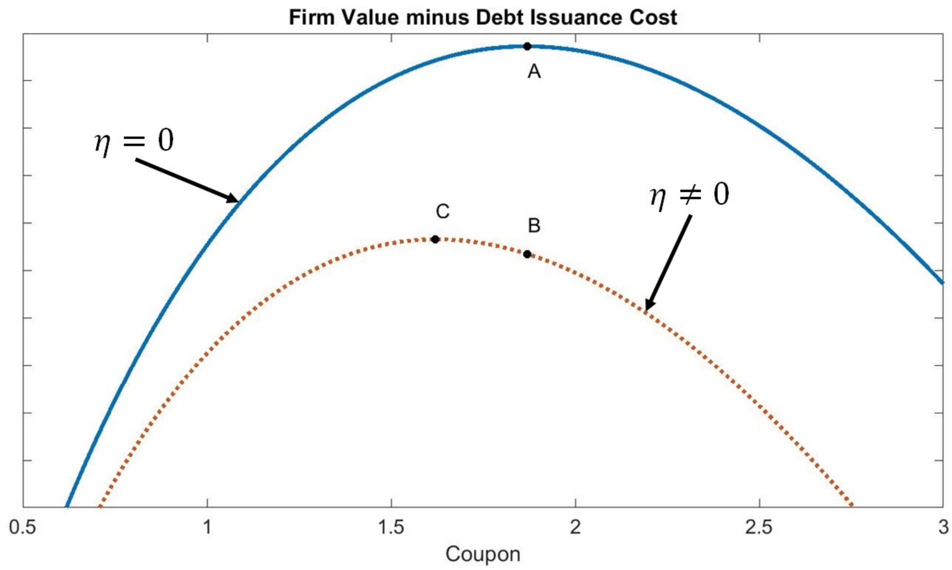

Figure 1: Illustration of the Trade-off Theory

This figure illustrates the Trade-off theory. Solid line illustrates the Trade-off theory when $\eta = 0$. Dashed line illustrates the Trade-off theory when $\eta \neq 0$. $A \rightarrow B$ illustrates an economic intuition that the firm value decreases due to shareholders' strategic default action. $B \rightarrow C$ illustrates that firms actively de-lever to optimize firm value minus debt issuance cost and illustrates a commitment problem.

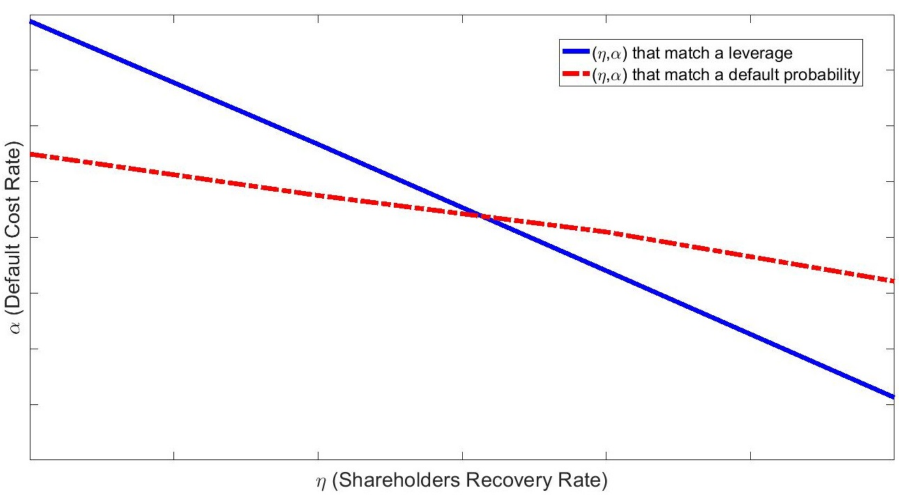

Figure 2: Identification of η and α

This figure illustrates how η and α are separately identified. Solid line is the locus of α and η that match a given leverage. Dashed line is the locus of α and η that match a given default probability.

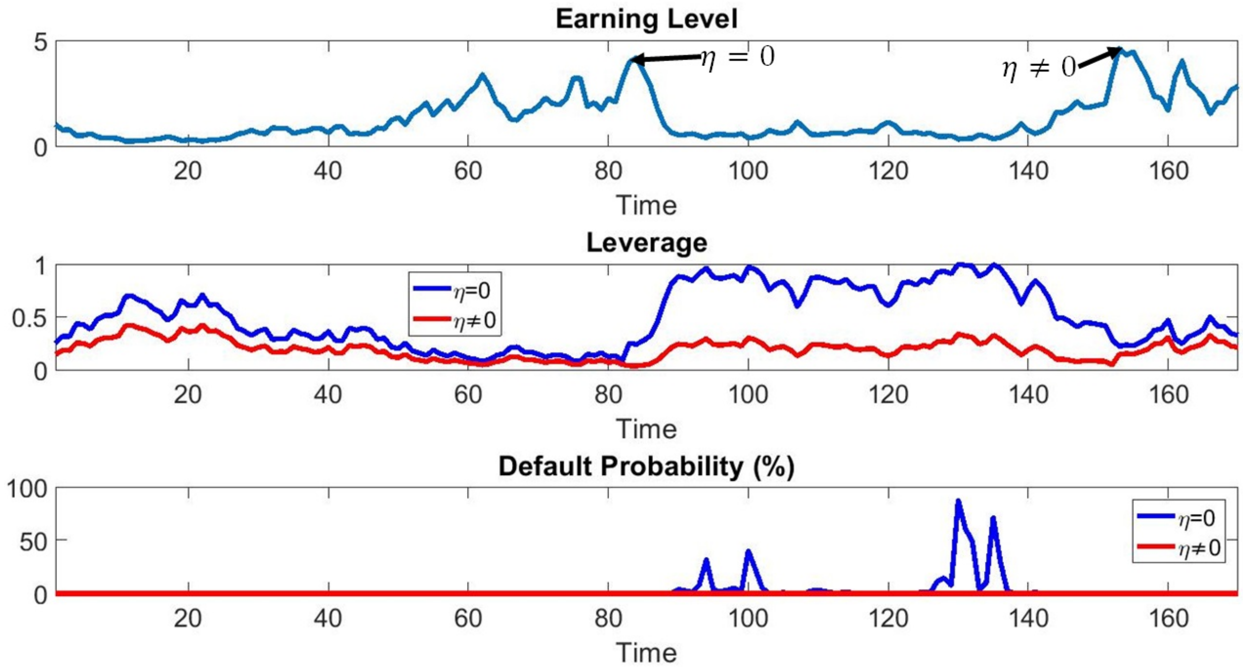

Figure 3: Time-Series Variation of Leverage and Default Probabilities

This figure illustrates how shareholder recovery rate (η) impacts time-series variation of leverage and default probabilities. Two firms have the same model parameters except for η: blue firm's η is zero, whereas red firm's η is non-zero. Both firms face the same sequence of earnings that are shown in the top panel. Middle panel shows time-series of leverage for both firms. Blue firm's leverage is larger than red firm's on average. Moreover, blue firm upward refinances earlier at time 84 than red firm does. Consequently, blue firm' leverage is more volatile and more positively skewed. Similar patterns are observed in the sequence of default probabilities (bottom panel).

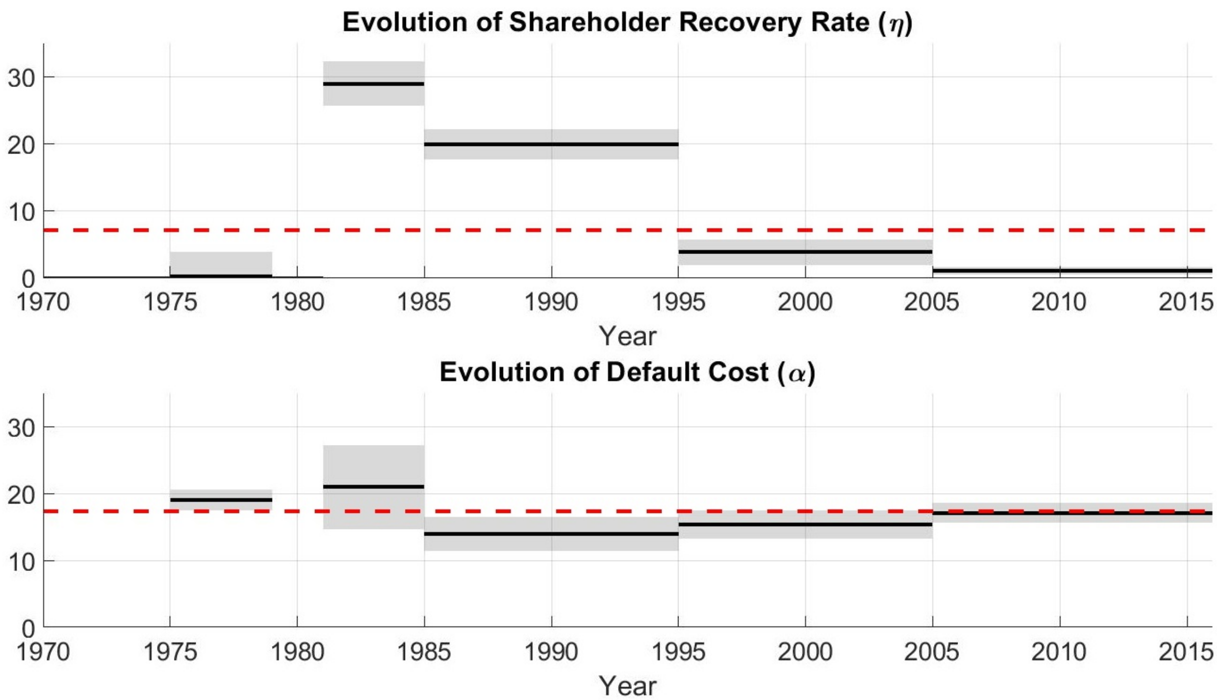

Figure 4: Evolution of Shareholder Recovery Rate and Default Cost in Percentages

This figure illustrates how structural estimates for shareholder recovery rate (upper panel) and default cost (lower panel) change over time. Red dashed line illustrates estimates for the entire sample: 1970Q1-2016Q4: $\hat{\eta} = 7.1\%(0.9\%)$ and $\hat{\alpha} = 17.3\%(1.0\%)$. Black solid line (estimates) along with gray region (95% confidence interval) illustrate estimates for each subperiod. $\hat{\eta} = 0.1\%(1.9\%)$ and $\hat{\alpha} = 19.0\%(0.8\%)$ for 1975Q1-1978Q3. $\hat{\eta} = 29.0\%(1.7\%)$ and $\hat{\alpha} = 21.0\%(3.2\%)$ for 1981Q2-1984Q4. $\hat{\eta} = 19.9\%(1.1\%)$ and $\hat{\alpha} = 14.0\%(1.3\%)$ for 1985Q1-1994Q4. $\hat{\eta} = 3.8\%(1.0\%)$ and $\hat{\alpha} = 15.3\%(1.1\%)$ for 1995Q1-2004Q4. Lastly, $\hat{\eta} = 0.97\%(0.3\%)$ and $\hat{\alpha} = 17.1\%(0.8\%)$ for 2005Q1-2016Q4.

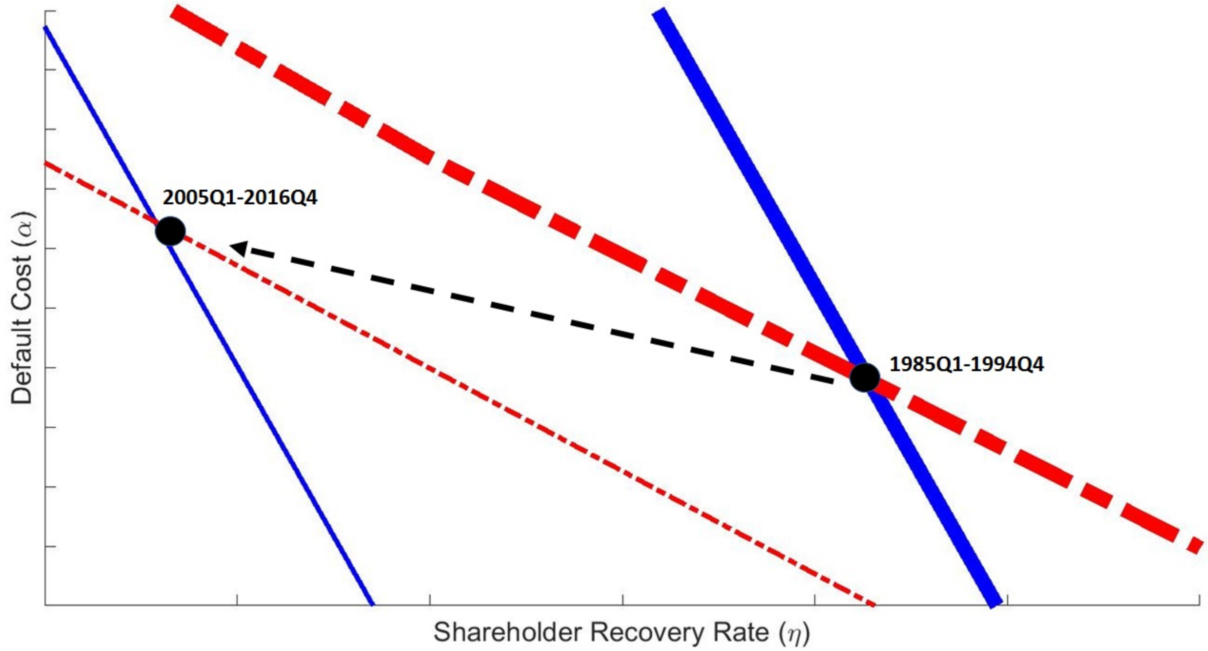

Figure 5: Identification of Time-Series Change in η and α

This figure illustrates how time-series change in leverage and default probabilities help to identify time-series change in η and α. As it moves from 1985Q1-1994Q4 to 2005Q1-2016Q4, solid line (locus of α and η that match a leverage) shifts downward and dashed line (locus of α and η that match a default probability) shifts downward. Intersection of thick solid line and thick dashed line is a structural estimate for 1985Q1-1994Q4. Intersection of thin solid line and think dashed line is a structural estimate for 2005Q1-2016Q4. As shown, as it moves from 1985Q1-1994Q4 to 2005Q1-2016Q4, η significantly decreases yet α slightly increases.

References

Alanis, Emmanuel, Sudheer Chava, and Praveen Kumar. 2015. "Shareholder Bargaining Power, Debt Overhang and Investment." *Working Paper, Georgia Institute of Technology.*

Almeida, Heitor, and Thomas Philippon. 2007. "The Risk-Adjusted Coste of Financial Distress." *Journal of Finance*, 62: 2557–2586.

Altinkilic, Oya, and Robert Hansen. 2000. "Are There Economies of Scale in Underwriting Fees? Evidence of Rising External Financing Costs." *Review of Financial Studies*, 13: 191–218.

Altman, Edward. 1984. "A further empirical investigation of the bankruptcy cost question." *Journal of Finance*, 39: 1067–1089.

Andrade, Gregor, and Steven Kaplan. 1998. "How Costly is Financial (Not Economic) Distress? Evidence from Highly Leveraged Transactions that Became Distressed." *Journal of Finance*, 53: 1443–1493.

Bansal, Ravi, Dana Kiku, and Amir Yaron. 2012. "An Empirical Evaluation of the Long-Run Risks Model for Asset Prices." *Critical Finance Review*, 1: 183–221.

Betker, Brian. 1995. "Management's incentive, equity bargaining power, and deviation from absolute priority." *Journal of Business*, 68: 161–184.

Bhamra, Horjoat, Lars-Alexander Kuehn, and Ilya Strebulaev. 2010. "The Aggregate Dynamics of Capital Structure and Macroeconomic Risk." *Review of Financial Studies*, 23: 4187–4241.

Bharath, Sreedhar, and Tyler Shumway. 2008. "Forecasting Default with the Merton Distance to Default Model." *Journal of Financial Economics*, 21: 1339–1369.

Bharath, Sreedhar, Venky Panchapegesan, and Ingrid Werner. 2007. "The Changing Nature of Chapter 11." *Working Paper.*

Boualam, Yasser, Joao F Gomes, and Colin Ward. 2017. "Understanding the Behavior of Distressed Stocks." *Working Paper.*

Bris, Arturo, Ivo Welch, and Ning Zhu. 2006. "The Costs of Bankruptcy: Chapter 7 Liquidation versus Chapter 11 Reorganization." *Journal of Finance*, 61: 1253–1303.

Campbell, John, Jens Hilscher, and Jan Szilagyi. 2008. "In Search of Distress Risk." *Journal of Finance*, 63: 2899–2939.

Chava, Sudheer. 2014. "Environmental Externalities and Cost of Capital." *Management Science*, 60: 2223–2247.

Chava, Sudheer, and Robert Jarrow. 2004. "Bankruptcy Prediction with Industry Effects." *Review of Finance*, 8: 537–569.

Chen, Hui. 2010. "Macroeconomic Conditions and the Puzzles of Credit Spreads and Capital Structure." *Journal of Finance*, 65: 2171–2212.

Corbae, Dean, and Pablo D'Erasmo. 2017. "Reorganization or Liquidation: Bankruptcy Choice and Firm Dynamics." *Working Paper No. 17-14*.

Davydenko, Sergei, and Ilya Strebulaev. 2007. "Strategic Actions and Credit Spreads: An Empirical Investigation." *Journal of Finance*, 62: 2633–2671.

Davydenko, Sergei, and Jilian Franks. 2008. "Do Bankruptcy Codes Matter? A Study of Defaults in France, Germany, and the U.K." *Journal of Finance*, 63: 565–608.

Eberhart, Allan, William Moore, and Rodney Roenfeldt. 1990. "Security Pricing and Deviations from the Absolute Priority Rule in Bankruptcy Proceedings." *Journal of Finance*, 45: 1457–1469.

Elkamhi, Redouane, Jan Ericsson, and Christopher A Parsons. 2012. "The cost and timing of financial distress." *Journal of Fincial Economics*, 105: 62–81.

Fan, Hua, and Suresh Sundaresan. 2000. "Debt Valuation, Renegotiation, and Optimal Dividend Policy." *Review of Financial Studies*, 13: 1057–1099.

Franks, Julian, and Walter Torous. 1989. "An empirical investigation of U.S. firms in renegotiation." *Journal of Finance*, 44: 747–779.

Franks, Julian, and Walter Torous. 1994. "A comparison of financial recontracting in distressed exchanges and Chapter 11 reorganizations." *Journal of Financial Economics*, 35: 349–370.

Garlappi, Lorenzo, and Hong Yan. 2011. "Financial Distress and the Cross-Section of Equity Returns." *Journal of Finance*, 66: 789–822.

Garlappi, Lorenzo, Tao Shu, and Hong Yan. 2008. "Default Risk, Shareholder Advantage, and Stock Returns." *Review of Financial Studies*, 21: 2743–2778.

Gilson, S., K. John, and L. Lang. 1990. "Troubled debt restructurings: An empirical study of private reorganization of firms in default." *Journal of Financial Economics*, 27: 315–53.

Glover, Brent. 2016. "The Expected cost of Default." *Journal of Financial Economics*, 119: 284–299.

Goldstein, Robert, Nengjiu Ju, and Hayne Leland. 2001. "An EBIT-Based Model of Dynamic Capital Structure." *Journal of Business*, 74: 483–512.

Gomes, Joao, Marco Grotteria, and Jessica Wachter. 2018. "Cyclical dispersion in expected defaults." *Review of Financial Studies*, Forthcoming.

Graham, John. 1996*a*. "Debt and the marginal tax rate." *Journal of Financial Economics*, 41: 41–73.

Graham, John. 1996*b*. "Proxies for the corporate marginal tax rate." *Journal of Financial Economics*, 42: 187–221.

Graham, John. 1998. "Debt, Leases, Taxes, and the Endogeneity of Corporate Tax Status." *Journal of Finance*, 53: 131–162.

Graham, John. 2000. "How Big Are the Tax Benefits of Debt?" *Journal of Finance*, 55: 1901–1941.

Green, Daniel. 2018. "Corporate Refinancing, Covenants and the Agency Cost of Debt." *Working Paper.*

Hackbarth, Dirk, Rainer Haselmann, and David Schoenherr. 2015. "Financial Distress, Stock Returns, and the 1978 Bankruptcy Reform Acts." *Review of Financial Studies*, 28: 1810–1847.

Harrison, J. M. 1985. *Brownian Motion and Stochastic Flow Systems.* New York:John Wiley and Sons.

Hennessy, Christopher, and Toni Whited. 2005. "Debt Dynamics." *Journal of Finance*, 60: 1129–1165.

Hennessy, Christopher, and Toni Whited. 2007. "How Costly Is External Financing? Evidence from a Structural Estimation." *Journal of Finance*, 62: 1705–1745.

Ju, Nengjiu, Robert Parrino, Allen Poteshman, and Michael Weisbach. 2005. "Horses and Rabbits? Trade-Off Theory and Optimal Capital Structure." *Journal of Financial and Quantitative Analysis*, 40: 259–281.

King, Lawrence. 1979. "Chapter 11 of the 1978 bankruptcy code." *American Bankruptcy Law Journal*, 53: 107–132.

Leary, Mark, and Michael Roberts. 2005. "Do Firms Rebalance Their Capital Structures?" *Journal of Finance*, 60: 2575–2619.

Leland, Hayne. 1994. "Corporate debt value, bond covenants and optimal capital structure." *Journal of Finance*, 49: 1213–52.

LoPucki, Lynn, and William Whitford. 1990. "Bargaining over Equity's Share in the Bankruptcy Reorganization of Large, Publicly Held Companies." *University of Pennsylvania Law Review*, 139: 125–196.

Lyandres, Evgeny, and Alexei Zhdanov. 2013. "Investment opportunities and bankruptcy prediction." *Journal of Financial Markets*, 16: 439–476.

Merton, Robert. 1974. "On the pricing of corporate debt: The risk structure of interest rates." *Journal of Finance*, 29: 449–470.

Miller, Merton. 1977. "Debt and Taxes." *Journal of Finance*, 32: 261–275.

Morellec, Erwan, Boris Nikolov, and Norman Schurhoff. 2008. "Dynanmic Capital Structure under Managerial Entrenchment: Evidence from a Structural Estimation." *Swiss Finance Institute Research Paper Series.*

Morellec, Erwan, Boris Nikolov, and Norman Schurhoff. 2012. "Corporate Governance and Capital Structure Dynamics." *Journal of Finance*, 67: 803–848.

Newey, Whitney, and Daniel McFadden. 1994. "Chapter 36 Large sample estimation and hypothesis testing." *Handbook of Econometrics*, 4: 2111–2245.

Opler, Tim, and Sheridan Titman. 1994. "Financial distress and corporate performance." *Journal of Finance*, 49: 1015–1040.

Peters, Ryan, and Lucian Taylor. 2016. "Intangible Capital and the Investment-q Relation." *Journal of Financial Economics*, Forthcoming.

Posner, Eric. 1997. "The political economy of the bankruptcy reform act of 1978." *Michigan Law Review*, 96: 47–126.

Reindl, Johann, Neal Stoughton, and Josef Zechner. 2017. "Market Implied Costs of Bankruptcy." *Working Paper.*

Skeel, David. 2001. *Debt's Dominion: A History of Bankruptcy Law in America.* Princeton University Press.

Skeel, David. 2003. "Creditors' Ball: The 'New' New Corporate Governance in Chapter 11." *Faculty Scholarship. Paper 29.*

Vassalou, Maria, and Yuhang Xing. 2004. "Default risk in equity returns." *Journal of Finance*, 59: 831–868.

Weiss, Lawrence. 1990. "Bankruptcy resolution: Direct costs and violation of priority of claims." *Journal of Financial Economics*, 27: 285–314.

Weiss, Lawrence, and Karen Wruck. 1998. "Information problems, conflicts of interest and asset stripping: Chapter 11's failure in the case of Eastern Airlines." *Journal of Financial Economics*, 48: 55–97.

A. Estimation Procedure

The objective here is to estimate parameters: b, σ^F, η and α.

First of all, why do simulation at all? Don't I have everything in closed-forms? I do have closed-forms for firm value, equity value and debt value. But I do not have closed-forms for my moments because moments are path-dependent and a simulated sample is an unbalanced panel. Thus, I rely on simulations to generate model counterparts.

In order to address firm heterogeneity in the data, I account for firm fixed effects in calculating the higher-order moments. More specifically, let us assume that firm i's data at time t is d_{it}. I convert d_{it} to $\tilde{d}_{it}$ by accounting for firm fixed effects as follows:

$$\tilde{d}_{it} = d_{it} - \frac{1}{T_i}\sum_{t=1}^{T_i} d_{it} + \frac{1}{\sum_{i=1}^{N} T_i}\sum_{i=1}^{N}\sum_{t=1}^{T_i} d_{it}$$

Using the above, I construct 8×1 data moments vector M. Similarly, for parameter θ, for s-th simulated collection of earnings sample path, I calculate the model-implied moments $\mathcal{M}_s(\theta)$. Similar to the data counterpart, I account for firm fixed effects in the simulated data. Then, I estimate θ by minimizing SMM-weight weighted distance between data moments and model-implied moments:

$$\hat{\theta} = \arg\min_{\theta} \left(M - \frac{1}{S}\sum_{s=1}^{S}\mathcal{M}_s(\theta)\right)' W \left(M - \frac{1}{S}\sum_{s=1}^{S}\mathcal{M}_s(\theta)\right)$$

Here, W is covariance matrix of data-moments after accounting for time-series and intra-industry dependence:[17]

$$W = \left(\frac{1}{\sum_{i=1}^{N} P_i}\sum_{i=1}^{N}[u_i u_i']\right)^{-1}$$

where u_i is an $8 \times P_i$ matrix of influence functions. Here, N is the number of industries and P_i is the sample size for the industry i.

In calculating standard errors, I correct standard errors for the sampling variability in

[17]Here, I cluster by industries to account for apparent correlation between firms in the same industry. I use 17 industry definitions from Kenneth French's website. This clustering strategy also accounts for time-series autocorrelation within firms. This is more conservative than clustering by firms.

initially estimating μ. To that end, I update W as follows (Newey and McFadden, 1994):

$$\tilde{W} = \left(\frac{1}{\sum_{i=1}^{N} P_i} \sum_{i=1}^{N} \left[\left(u_i(\hat{\mu}) - \frac{\partial u_i(\mu)}{\partial \mu} u_i^{\mu} \right) \left(u_i(\hat{\mu}) - \frac{\partial u_i(\mu)}{\partial \mu} u_i^{\mu} \right)' \right] \right)^{-1}$$

where $u_i(\hat{\mu})$ is an influence function for 8 moments for given $\hat{\mu}$ and u_i^{μ} is an influence function for the earnings growth mean. Then, the standard errors for parameter estimates are given by:

$$\sqrt{\sum_{i=1}^{N} P_i} (\hat{\theta} - \theta_0) \rightarrow N \left(0, \left(1 + \frac{1}{S} \right) ((H_0)' \tilde{W} H_0)^{-1} \right)$$

where $H_0 = E \left[\frac{\partial \mathcal{M}_s(\theta_0)}{\partial \theta} \right]$.

I first simulate $S = 10$ time-series of the aggregate earnings growth. For each time series of the aggregate earnings growth, I simulate 4,435 firm-specific sample paths as there are 4,435 unique firms in my panel data set. In each simulation, I generate a sample path of $50+T_i$ quarters long earnings $X_{i,t}$. I discard the first 50 quarters of simulated earnings to reduce solutions' dependence on $X_{i,t}$ at time $t = 0$. I set T_i to actual time-series length of firm i in order to simulate the unbalanced panel as shown in Figure 6. This small time-series sample bias is important because default probability is significantly sensitive to how long T_i is. For example, for firms whose earnings growth was hit by negative shock, they would not have had enough time to recover under the shorter time, and thus their time-series sample average of default probability would have been larger compared to what would have been if they had been given a longer time.

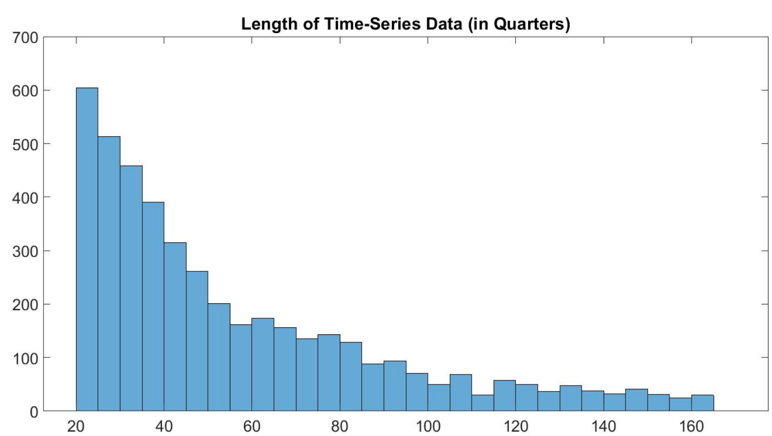

Figure 6: Distribution of Time-Series Length in Quarters

B. Simulated Panel Data

Using the models that are described in Section 3, I simulate panel data of leverage and default probability and moderately "taint" the simulated data with a model misspecification. I simulate panel data of leverage and default probability for 4,435 firms to mimic the true number of unique firms in the data. For a sequence of earnings level, $\{X_{i,t}\}$, firm i's observable leverage and observable default probabilities at time t are:

$$\begin{aligned} l(\alpha_i, \eta_i; X_{i,t}) + \epsilon_i^l \\ d(\alpha_i, \eta_i; X_{i,t}) \end{aligned}$$

where l and d are aforementioned functions of leverage and default probability, respectively, in terms of α_i and η_i. I randomly draw firm fixed effects ϵ_i^l from normal distribution $\epsilon_i^l \sim \mathcal{N}(0\%, 4\%^2)$ in order to simulate a model misspecification. I use two different cross-sectional distributions of α_i and η_i.

First, I randomly draw η_i and α_i from truncated normal distributions: $\eta_i \sim \mathcal{TN}(7.1\%, 4.2\%^2)$ and $\alpha_i \sim \mathcal{TN}(17.4\%, 10.4\%^2)$, respectively. Here, a model misspecification accounts for 13.8% of the total cross-sectional variation for leverage. Second, I randomly draw η_i and α_i from truncated exponential PDF, $\lambda_\alpha \exp(-\lambda_\alpha \alpha_i)$ and $\lambda_\eta \exp(-\lambda_\eta \eta_i)$, respectively. λ_α and λ_η are chosen to set the cross-sectional mean of η_i and α_i equal to 17.0% and 7.0%. Here, a model misspecification accounts for 3.6% of the total cross-sectional variation for leverage.

Note that the above formulation captures different sources of firm heterogeneity: default cost, α_i, shareholder recovery rate, η_i, ϵ_i^l, or realized sequence of $X_{i,t}$.

C. Mathematical Appendix

C.1. Solution

For an arbitrary value for X_D, X_U and C, I first derive the debt value. Debt is a contingent claim to an after-tax interest payment. Thus, debt value $D(X)$ satisfies the following ODE:

$$\frac{1}{2}\sigma_X X^2 D^{''} + \hat{\mu} X D^{'} + (1-\tau_i)C = rD$$

Boundary conditions are

$$
\begin{aligned}
D(X_D) &= (1-\alpha-\eta)\frac{(1-\tau_{cd})X_D}{r-\hat{\mu}} \\
D(X_U) &= D(X_0)
\end{aligned}
$$

The first boundary condition captures that creditors recover only $1-\alpha-\eta$ fraction of the remaining unlevered firm value and the second boundary condition captures that creditors receive the par-value if the debt gets called at the refinancing point. Closed form solution for debt value is:

$$
D(X_t) = \frac{(1-\tau_i)C}{r} + A_1 X_t^{\lambda_+} + A_2 X_t^{\lambda_-}
$$

where[18]

$$
\lambda_\pm = \left(\frac{1}{2} - \frac{\hat{\mu}}{\sigma_X^2}\right) \pm \sqrt{\left(\frac{1}{2} - \frac{\hat{\mu}}{\sigma_X^2}\right)^2 + \frac{2r}{\sigma_X^2}}
$$

Similarly, for an arbitrary value for X_D, X_U and C, equity value is:

$$
E(X_t) = \sup_{\tau^D} \mathbb{E}^{\mathbb{Q}}\left[\int_0^{\tau^D} e^{-rs}(1-\tau_{cd})(X_t - C)ds + e^{-r\tau^D} \cdot E(X_D)\right]
$$

where $\tau^D \equiv \inf\{t : X_t \leq X_D\}$.

Here, it is important to note that the above tries to maximize equity value for given coupon amount C. This implies that "optimal" default decision X_D is made without internalizing the default decision's impact on cost of debt and leverage. For example, if the default decision was made after internalizing its decision's impact on cost of debt, the optimal default decision is not to default at all, i.e., $X_D = \infty$. As firms never choose to default, this effectively makes expected firm-value loss zero and thus firms choose to max out their leverage to enjoy the tax shield benefit. However, this is possible only when shareholders commit to constantly supplying cash by issuing equity even when firms' earnings are significantly low. This is economically unfeasible and unrealistic and thus I make an assumption that "optimal" default decision was made without regard to its impact on cost of debt and

[18]Here, $A_1 < 0$ and $A_2 < 0$ where

$$
\begin{bmatrix} A_1 \\ A_2 \end{bmatrix} = \begin{bmatrix} X_D^{\lambda_+} & X_D^{\lambda_-} \\ X_U^{\lambda_+} - X_0^{\lambda_+} & X_U^{\lambda_-} - X_0^{\lambda_-} \end{bmatrix}^{-1} \begin{bmatrix} (1-\alpha-\eta)\frac{(1-\tau_{cd})X_D}{r-\hat{\mu}} - \frac{(1-\tau_i)C}{r} \\ 0 \end{bmatrix}
$$

leverage.

Again, following the contingent claims approach, equity value $E(X)$ satisfies the following ODE:

$$\frac{1}{2}\sigma_X X^2 E^{''} + \hat{\mu} X E^{'} + (1-\tau_{cd})(X-C) = rE$$

Boundary conditions are:

$$E(X_D) = \frac{\eta(1-\tau_{cd})X_D}{r-\hat{\mu}}$$

$$E(X_U) = [(1-\phi_D)D(X_U) + E(X_U)] - D(X_0) = \frac{X_U}{X_0}[(1-\phi_D)D(X_0) + E(X_0)] - D(X_0)$$

The first boundary condition captures that shareholder recover η fraction of the remaining unlevered firm value and the second boundary condition captures that shareholders receive the firm value minus debt issuance cost and original debt's par value. The second equality in the second boundary arises due to homogeneity. Analytical solution for $E(X_t)$ is:

$$E(X_t) = \frac{1-\tau_{cd}}{r-\hat{\mu}}X_t - \frac{(1-\tau_{cd})C}{r} + B_1 X_t^{\lambda_+} + B_2 X_t^{\lambda_-}$$

where B_1 represents additional benefit for being allowed to upward refinance and B_2 represents additional benefit for being allowed to default.[19]

The last remaining step is to solve for an optimal coupon C, upward refinancing point X_U and default threshold X_D. C and X_U are determined at time 0 (initial point or refinancing point) by solving the following maximization problem:

$$[C, X_U] = \arg\max_{C^*, X_U^*} \left(E(X_0; C^*, X_U^*) + (1-\phi_D)D(X_0; C^*, X_U^*)\right)$$

The equity value at the time of debt issuance is equal to the total firm value. Thus, shareholders' incentives are aligned with the maximization of the total firm value. Here, X_D is determined based on the following smooth pasting conditions (see the heuristic derivation of

[19] Here, $B_1 > 0$ and $B_2 > 0$ where

$$\begin{bmatrix} B_1 \\ B_2 \end{bmatrix} = \begin{bmatrix} X_D^{\lambda_+} & X_D^{\lambda_-} \\ X_U^{\lambda_+} - \frac{X_U}{X_0}X_0^{\lambda_+} & X_U^{\lambda_-} - \frac{X_U}{X_0}X_0^{\lambda_-} \end{bmatrix}^{-1}$$
$$\begin{bmatrix} \frac{(1-\tau_{cd})C}{r} + (\eta-1)\frac{(1-\tau_{cd})X_D}{r-\hat{\mu}} \\ \left(\frac{X_U}{X_0}(1-\phi)-1\right)\left(A_1 X_0^{\lambda_+} + A_2 X_0^{\lambda_-} + \frac{(1-\tau_i)C}{r}\right) + \frac{X_U}{X_0}\left(\frac{(1-\tau_{cd})}{r-\hat{\mu}}X_0 - \frac{(1-\tau_{cd})C}{r}\right) - \left(\frac{(1-\tau_{cd})}{r-\hat{\mu}}X_U - \frac{(1-\tau_{cd})C}{r}\right) \end{bmatrix}$$

smooth pasting condition in Appendix C.2)

$$\lim_{X_t \downarrow X_D} E^{'}(X_t) = \frac{\eta(1-\tau_{cd})}{r-\hat{\mu}}$$

A few points are worth noting here. First, X_D can be smaller than C, i.e., firms are allowed to costlessly issue equity. Second, as emphasized by Bhamra, Kuehn and Strebulaev (2010), due to fluctuations in the earnings and the assumed cost of refinancing, the firm's actual leverage drifts away from its optimal target. In the model, the firm is at its optimally chosen leverage ratio only at time 0 and subsequent refinancing dates.

Now, I solve for government tax revenue. Following the contingent claims approach, I solve:

$$\frac{1}{2}\sigma_X X^2 G^{''} + \hat{\mu} X G^{'} + (\tau_{cd} X - \tau_{cdi} C) = rG$$

I impose the following boundary conditions:

$$\lim_{X_t \to X_D} G(X_t) = 0$$
$$\lim_{X_t \to X_U} G(X_t) = \frac{X_U}{X_0} G(X_0)$$

The first boundary condition specifies that the government does not collect any future tax if firms declare bankruptcy. The second boundary condition captures the homogeneity of the problem. Then, the analytical solution for $G(X_t)$ is:[20]

C.2. Smooth Pasting Condition

As a reminder, a function for equity value is

$$E(X_t) = \frac{1-\tau_{cd}}{r-\hat{\mu}} X_t - \frac{(1-\tau_{cd})C}{r} + B_1 X_t^{\lambda_+} + B_2 X_t^{\lambda_-}$$

First, because X_D is chosen to maximize $E(X)$, we need to have:

$$B_1'(X_D) = 0 \text{ and } B_2'(X_D) = 0$$

[20]Here, G_1 and G_2 satisfy:

$$\begin{bmatrix} G_1 \\ G_2 \end{bmatrix} = \begin{bmatrix} X_D^{\lambda_+} & X_D^{\lambda_-} \\ \frac{X_U}{X_0} X_0^{\lambda_+} - X_U^{\lambda_+} & \frac{X_U}{X_0} X_0^{\lambda_-} - X_U^{\lambda_-} \end{bmatrix}^{-1} \begin{bmatrix} -\frac{\tau_{cd}}{r-\hat{\mu}} X_D + \frac{\tau_{cdi} C}{r} \\ \left(\frac{X_U}{X_0} - 1\right) \frac{\tau_{cdi} C}{r} \end{bmatrix}$$

Second, the value-matching condition specifies that

$$\frac{1-\tau_{cd}}{r-\hat{\mu}}X_D - \frac{(1-\tau_{cd})C}{r} + B_1(X_D)X_D^{\lambda_+} + B_2(X_D)X_D^{\lambda_-} = \frac{\eta(1-\tau_{cd})X_D}{r-\hat{\mu}}$$

where B_1 and B_2 are functions of X_D. Let us take a derivative of both sides with respect to X_D

$$\frac{1-\tau_{cd}}{r-\hat{\mu}} + B_1'(X_D)X_D^{\lambda_+} + B_1(X_D)\lambda_+X_D^{\lambda_+-1} + B_2'(X_D)X_D^{\lambda_-} + B_2(X_D)\lambda_-X_D^{\lambda_--1} = \frac{\eta(1-\tau_{cd})}{r-\hat{\mu}}$$

Substituting $B_1'(X_D)=0$ and $B_2'(X_D)=0$, we have:

$$\frac{1-\tau_{cd}}{r-\hat{\mu}} + B_1(X_D)\lambda_+X_D^{\lambda_+-1} + B_2(X_D)\lambda_-X_D^{\lambda_--1} = \frac{\eta(1-\tau_{cd})}{r-\hat{\mu}}$$

Thus, we have:

$$\lim_{X_t\downarrow X_D} E^{'}(X_t) = \frac{\eta(1-\tau_{cd})}{r-\hat{\mu}}$$

and this is exactly the smooth pasting condition.

C.3. Firm Characteristics

This section summarizes formulas for each firm characteristic. I define the leverage as follows:

$$\frac{D(X_t)}{D(X_t)+E(X_t)}$$

Based on Harrison (1985), I define default probability under physical measure as:

$$DP(X_t) = \begin{cases} \Phi\left(\frac{\log\left(\frac{X_D}{X_t}\right)-(\mu-\sigma_X^2/2)T}{\sigma_X\sqrt{T}}\right) + \left(\frac{X_t}{X_D}\right)^{1-2(\mu)/\sigma_X^2}\Phi\left(\frac{\log\left(\frac{X_D}{X_t}\right)+(\mu-\sigma_X^2/2)T}{\sigma_X\sqrt{T}}\right) & \text{if } X_t \geq X_D \\ 1 \quad \text{Otherwise} \end{cases}$$

where I set $T=1$.

Next, I discuss the formula for the market beta. The equity return is:

$$
\begin{aligned}
dR_t &= \frac{dE(X_t) + (1-\tau_{cd})(X_t - C)dt}{E(X_t)} \\
&= \left(\frac{(1-\tau_{cd})(X_t - C)}{E(X_t)} + \frac{E'(X_t)X_t}{E(X_t)}\mu + \frac{1}{2}\frac{E''(X_t)X_t^2}{E(X_t)}\sigma_X^2 \right) dt \\
&+ \frac{E'(X_t)X_t}{E(X_t)}(b\sigma_A dW_t^A + \sigma_F dW_t^F)
\end{aligned}
$$

Let x_t^A be a log of aggregate earnings X_t^A. Then,

$$
dx_t^A = \sigma_A dW_t^A
$$

Using this, a term for market beta is:

$$
\text{Market beta} = \frac{1}{dt}\mathbb{E}_t[dx_t^A dR_t] / \frac{1}{dt} var_t[dx_t^A] = \frac{E^{'}(X_t)X_t}{E(X_t)}b
$$

Lastly, I define credit spread as:

$$
\frac{C}{D(X_t)}
$$

C.4. Proof

This subsection lists all of the proofs for all of the propositions when upward refinancing is suppressed. I allow upward refinancing in the simulation and numerically show that the same intuition still carries through.

$$
D(X_t) = \frac{(1-\tau_i)C}{r} + \tilde{A}_2 \left(\frac{X_t}{C \cdot X_{DC}} \right)^{\lambda_-}
$$

where

$$
\tilde{A}_2 / C = -\frac{1-\tau_i}{r} + (1-\alpha-\eta)\frac{(1-\tau_{cd})X_{DC}}{r-\hat{\mu}} < 0
$$

On the contrary, as η increases, $E(X_t)$ increases because shareholders gain η and X_{DC} is determined to maximize $E(X_t)$. Similarly, this increase gets magnified by larger $\left(\frac{X_t}{C\cdot X_{DC}}\right)^{\lambda_-}$.

$$\begin{aligned}E(X_t) =& \frac{1-\tau_{cd}}{r-\hat{\mu}}X_t - \frac{(1-\tau_{cd})C}{r} + \tilde{B}_2\left(\frac{X_t}{C\cdot X_{DC}}\right)^{\lambda_-}\\ \tilde{B}_2/C =& \frac{1-\tau_{cd}}{r} + (\eta-1)\frac{(1-\tau_{cd})X_{DC}}{r-\hat{\mu}} > 0\end{aligned}$$

Proof of **Proposition** 2: I can approximately write the leverage as:

$$lev = \frac{D(X_t)}{E(X_t)+D(X_t)} \approx \frac{\frac{(1-\tau_i)C}{r}}{\frac{(1-\tau_{cd})}{r-\hat{\mu}}X_t + \frac{\tau_{cdi}C}{r}}$$

where the second approximate equality exists because default probability is typically very small. Then, I can write partial derivative terms as:

$$\begin{aligned}\frac{\partial lev}{\partial \eta} &= \frac{\partial lev}{\partial C}\frac{\partial C}{\partial \eta}\\ \frac{\partial lev}{\partial \alpha} &= \frac{\partial lev}{\partial C}\frac{\partial C}{\partial \alpha}\end{aligned}$$

Because $\frac{\partial lev}{\partial C} > 0$, proving $\frac{\partial lev}{\partial \eta} < 0$ and $\frac{\partial lev}{\partial \alpha} < 0$ is equivalent to proving that $\frac{\partial C}{\partial \eta} < 0$ and $\frac{\partial C}{\partial \alpha} < 0$. So, let us focus on terms for C. The optimization problem to solve for C is as follows:

$$C = \arg\max_{C^*}\left\{\frac{1-\tau_{cd}}{r-\hat{\mu}}X_0 + \underbrace{\frac{\tau_{cdi}-\phi_D(1-\tau_i)}{r}C^*}_{\text{Benefit}} + \underbrace{\left(\frac{X_0}{X_{DC}}\right)^{\lambda_-}((1-\phi_D)A_{2c}+B_{2c})C^{*(1-\lambda_-)}}_{\text{Cost}}\right\}$$

where $A_{2c} = A_2/C$ and $B_{2c} = B_2/C$. The closed form solution for optimal coupon C is

$$C = \underbrace{\left[\frac{\tau_{cdi}-\phi_D(1-\tau_i)}{r}\right]^{-1/\lambda_-}}_{\text{Tax Shield Benefit}^{-1/\lambda_-}}\cdot \underbrace{\frac{X_0}{X_{DC}}}_{\text{1/Default Threshold}} \cdot \underbrace{[-(1-\lambda_-)((1-\phi_D)A_{2c}+B_{2c})]^{1/\lambda_-}}_{\text{Loss}^{1/\lambda_-}} \tag{8}$$

Because $\frac{\partial C}{\partial \alpha} < 0$ and $\frac{\partial C}{\partial \eta} < 0$, I can say that C decreases over α and η. Intuitively, the denominator of the second term shows that C decreases as shareholders strategically determine high threshold X_{DC}. High X_{DC} implies a high default probability thus a high expected firm-value loss and low optimal C. The third term represents the loss of firm value upon bankruptcy adjusted for debt issuance cost. High loss of firm value $((1-\phi_D)A_{2c}+B_{2c})$

implies low C. ■

Proof of **Proposition** 3 As shown in Section C.3, for given μ, b and σ^F, there is monotonic relation between default probability and X_D (default threshold). Thus, comparative statistics between default probability and η and α is equivalent to that between X_D and α and η. Using closed forms for C and X_{DC}, I derive closed-form terms for X_D:

$$\frac{X_D}{X_0} = \left[\frac{\tau_{cdi} - \phi_D(1-\tau_i)}{r}\right]^{-1/\lambda_-} \cdot [-(1-\lambda_-)((1-\phi_D)A_{2c} + B_{2c})]^{1/\lambda_-}$$

Here, X_D decreases over α and η because $\frac{\partial X_D}{\partial \alpha} < 0$ and $\frac{\partial X_D}{\partial \eta} < 0$. Intuitively, for given C, the rise in η increases both default probability and value loss. Thus, C has to decrease sufficiently enough to offset high expected firm-value loss driven by an increase in both default probability and value loss. Thus, the decrease in C more than offsets the increase in X_{DC}. As a result, X_D decreases over η and so does default probability. ■

Proof of **Proposition** 5: Now, I prove for market beta:

$$\text{Market beta} = b\frac{E'X}{E}$$

$$E'X = \frac{1-\tau_{cd}}{r-\hat{\mu}}X + B_2\lambda_-\left(\frac{X}{C \cdot X_{DC}}\right)^{\lambda_-}$$
$$E = \frac{1-\tau_{cd}}{r-\hat{\mu}}X - \frac{(1-\tau_{cd})C}{r} + B_2\left(\frac{X}{C \cdot X_{DC}}\right)^{\lambda_-}$$

Thus, I have:

$$\text{Market beta} = \frac{E'(X_t)X_t}{E(X_t)}b = \left(1 + \frac{(1-\tau_{cd})C}{r \cdot E} + (\lambda_- - 1)\frac{B_2}{E}\left(\frac{X_t}{C \cdot X_{DC}}\right)^{\lambda_-}\right)b$$

Because $\frac{\partial \text{Market beta}}{\eta} < 0$, this proves the proposition. Intuitively, conditional on leverage, shareholders' strategic action first decreases market beta. After allowing firms to de-lever in response, its distress risk decreases and market beta further decreases. One interesting point to note is that as X gets very close to X_D, the market beta becomes less sensitive to η because equity gets converted to a fixed fraction of unlevered asset value in default. ■

Proof of **Proposition** 6: I set $\phi_D = 0$ and show closed-form expression for the credit spread.

$$\begin{aligned}\frac{C}{D(X_0)} =& \frac{1}{\frac{1-\tau_i}{r} + A_2/C\left(\frac{X_0}{X_D}\right)^{\lambda_-}} \\ =& \frac{1}{\frac{1-\tau_i}{r} + \frac{-\tau_{cdi}}{r(1-\lambda_-)}\left(1 + \frac{\frac{1}{1-\lambda_-}\frac{1-\tau_{cd}}{\tau_{cdi}}}{1+\frac{-\lambda_-}{1-\lambda_-}\frac{1-\tau_{cd}}{\tau_{cdi}}\frac{\alpha}{1-\eta}}\right)}\end{aligned}$$

It is immediately clear that the credit spread decreases over η. Intuitively, lower default probability caused by the commitment problem more than offsets creditors' higher value loss (normalized by C) and results in a lower credit spread. Again, this commitment problem exists because α is non-zero and thus the credit spread decreases over η. If α is 0, then the above formula clearly tells you that the credit spread does not change over η. ■

Proof of **Proposition** 7: Let me prove the proposition by illustrating my points in Figure 1. I need to prove that point A always corresponds to higher firm value than point C does. To that end, I prove this by contradiction. Let us assume otherwise: point C's firm value is greater than point A's. Now, pick a point D on the solid curve that has the same coupon rate as point C. Because the solid curve always sits above the dotted curve ($\because$ $(1-\phi_D)D(X_t)+E(X_t)$ always decreases as η increases), point D's firm value is greater than point C's. This implies that point D's firm value is greater than point A's. This contradicts that point A is the optimal point on the solid curve. This completes the proof. ■

Proof of **Proposition** 8: Government tax revenue $G(X_t)$ is:

$$G(X_t) = \frac{\tau_{cd}}{r-\hat{\mu}}X_t - \frac{\tau_{cdi}C}{r} + \tilde{G}_2\left(\frac{X_t}{C\cdot X_{DC}}\right)^{\lambda_-}$$

where

$$\tilde{G}_2/C = \frac{\tau_{cdi}}{r} - \frac{\tau_{cd}}{r-\hat{\mu}}X_{DC}$$

As η increases, C decreases and thus government tax revenue $G(X_t)$ increases and this completes the proof. On the related note, $\tilde{G}_2$ illustrates an interesting intuition. Upon firms' default, even though the government loses potential tax revenue on the firm's future income stream, the government is no longer exploited by corporations. ■

Proof of **Proposition** 4: Here, I prove that leverage and DP (default probability) have different sensitivities with respect to η and α.

$$\frac{\partial DP/\partial\eta}{\partial DP/\partial\alpha} = \frac{(\partial DP/\partial X_D)\partial X_D/\partial\eta}{(\partial DP/\partial X_D)\partial X_D/\partial\alpha} = \frac{\partial X_D/\partial\eta}{\partial X_D/\partial\alpha}$$

where $\frac{\partial X_D}{\partial\eta}$ and $\frac{\partial X_D}{\partial\alpha}$ are:

$$\begin{aligned}\frac{\partial X_D}{\partial\eta} &= \frac{\partial(C\cdot X_{DC})}{\partial\eta} = C\cdot\frac{\partial X_{DC}}{\partial\eta} + X_{DC}\cdot\frac{\partial C}{\partial\eta}\\ \frac{\partial X_D}{\partial\alpha} &= \frac{\partial(C\cdot X_{DC})}{\partial\alpha} = C\cdot\frac{\partial X_{DC}}{\partial\alpha} + X_{DC}\cdot\frac{\partial C}{\partial\alpha} = X_{DC}\cdot\frac{\partial C}{\partial\alpha}\end{aligned}$$

where the last equality holds because $\frac{\partial X_{DC}}{\partial\alpha} = 0$.

Now, let us think of a leverage.

$$\begin{aligned} lev &= \frac{D(X_0)}{E(X_0)+D(X_0)} \approx \frac{\frac{(1-\tau_i)C}{r}}{\frac{(1-\tau_{cd})}{r-\hat{\mu}}X_0 + \frac{\tau_{cdi}C}{r}}\\ \Rightarrow \frac{\partial lev/\partial\eta}{\partial lev/\partial\alpha} &= \frac{(\partial lev/\partial C)\partial C/\partial\eta}{(\partial lev/\partial C)\partial C/\partial\alpha} = \frac{\partial C/\partial\eta}{\partial C/\partial\alpha}\end{aligned}$$

Thus,

$$\frac{\partial DP/\partial\eta}{\partial DP/\partial\alpha} \neq \frac{\partial lev/\partial\eta}{\partial lev/\partial\alpha}$$

Two points are worth making. First, we point out that $\frac{\partial DP/\partial\eta}{\partial DP/\partial\alpha} < \frac{\partial lev/\partial\eta}{\partial lev/\partial\alpha}$ because $X_{DC}\frac{\partial C}{\partial\eta} < \frac{\partial X_D}{\partial\eta} < 0$. Second, when $\frac{\partial X_{DC}}{\eta} = 0$, the above becomes equality and implies that leverage and default probability cannot separately identify α and η. ■

C.5. Upward Refinancing

Even when upward refinancing is allowed, the economic channels, discussed in Section 3.2, still hold. As debt becomes more costly, firms internalize higher costs and optimally choose to de-lever *and* refinance less frequently.

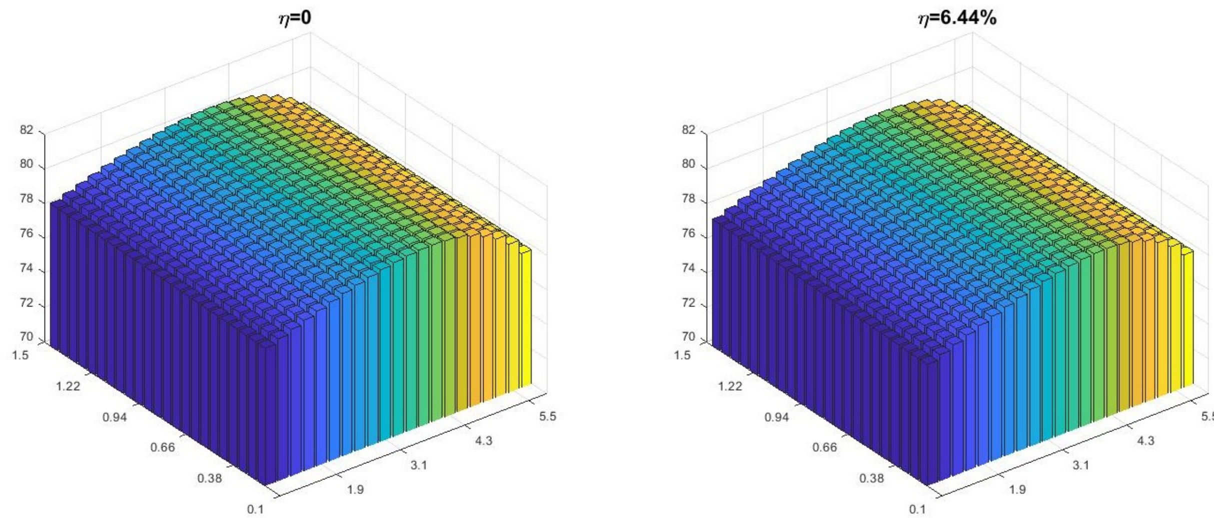

Figure 7: Illustration of trade-off theory when upward refinancing is allowed

When $\eta = 0$ (left panel), firm value is maximum at 80.23 when optimal coupon C is 0.66 and X_U is 3.7. However, $\eta \neq 0$ (right panel), firm value is maximum at 79.75 when coupon C is 0.59 and $X_U = 3.75$. This clearly illustrates that high η implies lower firm value, lower leverage and less frequent upward refinancing.

C.6. The Whole Economy

Here, I examine the case when upward refinancing is suppressed. I show that the value of the entire economy, $D(X) + E(X) + G(X)$, increases over η as lower default frequencies lead to smaller loss of default cost. This can be easily seen below:

$$D(X) + E(X) + G(X) = \frac{X}{r - \hat{\mu}} + (A_2 + B_2 + G_2)\left(\frac{X}{C \cdot X_{DC}}\right)^{\lambda_-}$$

where

$$(A_2 + B_2 + G_2)/C = -[\alpha(1 - \tau_{cd}) + \tau_{cd}] \cdot \frac{X_{DC}}{r - \hat{\mu}}$$

Here, $\alpha(1 - \tau_{cd})\frac{X_{DC}}{r-\hat{\mu}}$ is the deadweight loss from the firms as a whole whereas $\tau_{cd}\frac{X_{DC}}{r-\hat{\mu}}$ is the government's loss of future tax revenue.

D. Data Variables

D.1. Firm-level Variable Definitions

D.1.1. Variables Excluding Default Probabilities

- Earnings growth: $\tilde{e}_{i,t+1} = \log\left(\frac{\sum_{j=0}^{K} OIADPQ_{i,t+1-j}}{\sum_{j=0}^{K} OIADPQ_{i,t-j}} - 1\right)$ where K is set to 8 and $OIADPQ$ is operating income after depreciation.
- Market beta: calculated based on rolling window of 24 months of monthly returns.
- Leverage: $\frac{DLTTQ+DLCQ}{DLTTQ+DLCQ+ME}$ where $DLTTQ$, $DLCQ$ and ME are long-term debt, short-term debt and market equity, respectively.

D.1.2. Default Probabilities

Because level of default probability is an important matching moment, it warrants a separate discussion. At large, there are two ways to derive default probability. The first is the Merton distance-to-default model, which is based on Merton (1974). The second is based on the hazard model and is used by several papers including Campbell, Hilscher and Szilagyi (2008). I use the former approach, which is more compatible with the model-implied moments that use Merton-style default probability. Specifically, I follow Bharath and Shumway (2008) to construct default probability, which is found to closely match various corporate default probability measures. Its definition is

$$\pi = \Phi\left(\frac{-\log\frac{V}{B} - (\mu_v - \frac{\sigma_v^2}{2})}{\sigma_v}\right)$$

where Φ is a cumulative normal distribution function, V is the market value of assets, B is the amount of debt that's due for that quarter, μ_v is the expected asset return and σ_v is the asset return volatility. Because V, B, μ_v and σ_v are all unobservable, each of these warrant a separate discussion.

First, let us discuss how I derive B and V. In order to derive distance-to-default over the next one year, Campbell, Hilscher and Szilagyi (2008) and Vassalou and Xing (2004) assume that short-term debt plus one half long-term debt come due in a year. As Campbell et al. noted, "This convention is a simple way to take account for the fact that long-term debt may not mature until after the horizon of the distance to default calculation." Extending upon this convention, in order to derive distance-to-default in the next quarter as opposed to next year, Gomes, Grotteria and Wachter (2018) assume that one quarter of Campbell et al.'s comes due within the next quarter. Accordingly, I set B to $DLCQ/4 + DLTTQ/8$. Due to the lack of data on market value of debt, I use B to proxy market value of debt and set V to market value of equity plus B. Second, following Bharath and Shumway (2008), I use monthly equity returns to calculate average equity returns and set it to μ_v. Third, following Bharath and Shumway (2008), I set σ_v to

$$\sigma_v = \frac{E}{E+F}\sigma_E + \frac{F}{E+F}(0.05/\sqrt{3} + 0.25 \cdot \sigma_E)$$

where σ_E is the quarterly volatility of the equity returns and $0.05/\sqrt{3} + 0.25 \cdot \sigma_E$ is the quarterly volatility of the bond that is due in a quarter. I estimated σ_E using the daily returns of trailing 3 months.

D.1.3. Tax Rates

First, I augment the sample with panel data of corporate marginal tax rates,[21] which were constructed according to Graham (1996*a*,*b*). They provide both *before-financing* marginal tax rates (MTR) and *after-financing* MTR. Both measure firms' MTR by incorporating many features present in the tax code, such as tax-loss carryforwards and carrybacks, the investment tax credit, and the alternative minimum tax. *Before-financing* MTR are based on taxable income *before* financing expenses are deducted, whereas after-financing MTR are based on taxable income *after* financing expenses are deducted. As Graham (1998) argues, by construction, *after-financing* MTR are endogenously affected by the choice of financing. Because the model treats τ_c exogenous of firms' financing decision, this paper uses *before-financing* MTR to set corporate earnings tax rates τ_c

Second, I closely follow Graham (2000) to construct τ_i and τ_d. As documented in Graham (2000), I set $\tau_i = 47.4\%$ for 1981 or prior, 40.7% between 1982 and 1986, 33.1% for 1987, 28.7% between 1988 and 1992, and 29.6% afterwards. Based on these estimates for τ_i, I estimate τ_d as $[d + (1-d)g\alpha]\tau_i$. The dividend-payout ratio d is the firm-quarter-specific dividend distribution divided by trailing twelve-quarters moving average of earnings. Since

[21] I would like to thank John Graham for sharing panel data of corporate marginal tax rates. `https://faculty.fuqua.duke.edu/~jgraham/taxform.html`. I impute missing marginal tax rates with the time-series average for each firm if the firm is covered in Graham's database or panel-wide-average if the firm is not covered at all.

d needs to be less than or equal to 1, if d is greater than 1, I set it to 1. If dividend is missing, I set $d = 0$. The proportion of long-term capital gains that is taxable (g) is 0.4 before 1987 and 1.0 afterwards. I assume that the variable measuring the benefits of deferring capital gains, α, equals 0.25. The long-term capital gains rate, $g\tau_i$ has a maximum value of 0.28 between 1987 and 1997, 0.2 between 1998 and 2003 (Taxpayer Relief Act of 1997) and 0.15 afterwards (Jobs and Growth Tax Relief Reconciliation Act of 2003).

It is worth noting that τ_c is different across firms because firms face different tax-loss carryforwards/carrybacks, the investment tax credit and the alternative minimum tax. τ_d is different across firms because dividend-payout ratios are different. However, for given year, τ_i is the same across firms because I assume that marginal investors face the same τ_i. Also, I assume that τ_c and τ_i stay constant for all four quarters for any given year (due to data limitation) whereas τ_d can potentially change every quarter due to varying dividend-payout ratios.

D.2. Aggregate Variables

D.2.1. Variable Definitions

- Aggregate earning: Source: NIPA, Section 1, Table 1.14, Series: Line 8 Net Operating Surplus, Quarterly series from 1947Q1 to 2016Q4
- Consumer price index: Source: FRED, Series: CPIAUCNS (Consumer Price Index for All Urban Consumers: All Items), Monthly series from 1913Jan through 2016Dec
- Nominal risk free rate: Source: FRED, Series: TB3MS (3-Month Treasury Bill: Secondary Market Rate), Monthly series from 1934Jan through 2016Dec

D.2.2. Variable Construction

- Realized Inflation=$[CPI(t) - CPI(t-1)]/CPI(t-1)$ where $CPI(t)$ is the consumer price index in year-quarter t computed as the average monthly CPI for that year-quarter.

E. Magnitude of Credit Spread

Using the estimates reported in Table 5, as noted in Table 6's column (5), quarterly credit spreads are 191 bp. These credit spreads are much larger than what is empirically observed and contrast with Morellec, Nikolov and Schurhoff (2012)'s success in matching quarterly credit spreads at 53bp. The main reason for this discrepancy is the value used for earnings growth volatility, σ^F. Using $\sigma^F = 0.1380$[22] that is reported in Morellec et al. and keeping everything else equal, my model-implied quarterly credit spreads are 56bp, which is very close to Morellec's. The large sensitivity of credit spreads with respect to σ^F is noted in Morellec et al.'s Table 1.

However, lowering σ^F decreases quarterly default probabilities from 0.36% to 0.003%, which is counterfactually small. More importantly, $\hat{\sigma}^F = 0.2444$ is a relatively conservative measure, as implied earnings growth variance is under-matched relative to its data counterpart (see Table 4). More specifically, if σ^F is chosen just to match earnings growth moments, then $\hat{\sigma}^F = 0.2786$, which is apparently greater than $\hat{\sigma}^F = 0.2444$. Lastly, the current model features bonds with infinite maturity and thus is not suitable to match data counterparts that have finite maturity. Noting this limitation, it is still interesting to study how much credit spreads change over η and thus I continue reporting such results.

F. Bankruptcy Reform Act 1978 (BRA)

First, let us review the literature's stance on how BRA changed shareholder recovery rate. Hackbarth, Haselmann and Schoenherr (2015) argues that BRA increased shareholder recovery rate due to four specific clauses. First, relative to the old code, BRA added equity as one additional class to confirm a reorganization plan. Second, managers were given a 120-day exclusivity period to propose the plan. Third, if no plan could be agreed upon, a new procedure, called cramdown, allowed firms to continue operating while a buyer was sought. This was considered a costly and time-consuming process and thus acted as a disciplinary tool in negotiations in favor of shareholders. Lastly, firms could now declare bankruptcy even when firms were solvent, thus shareholders can use the threat of bankruptcy as a strategic tool against creditors. Thus, BRA increased shareholder recovery rate.

Now, let us discuss how BRA could have changed default cost. Prior to 1978, as discussed in Section 2, an increasing number of firms sought to file under shareholder-friendly Chapter 11 rather than Chapter 10. However, applying for Chapter 11 required an expensive hearing (LoPucki and Whitford, 1990). Moreover, as discussed in Section 2, the prior bankruptcy laws were considerably ambiguous (Posner, 1997; King, 1979). BRA addressed both of these

[22]Morellec et al. report annual volatility of earnings growth at 28.86%. Thus, $\sigma^F = \sqrt{0.1443^2 - (\hat{b}\hat{\sigma^A})^2} = 0.1380$.

issues. BRA permitted creditors to take less than full payment, in order to expedite or insure the success of the reorganization.[23] This effectively made it easy to deviate from APR. BRA reduced the ambiguity present in the bankruptcy law by spelling out a number of provisions important in enabling the shareholders to reorganize (Skeel, 2001)[24] and this could have reduced friction in the bankruptcy process. Taken together, this could decrease time spent in bankruptcy and thus reduce lawyers' fees, which are typically charged by the hour, and opportunity cost caused by delayed investment due to uncertain future and loss of business relationships with customers and suppliers. In other words, BRA could have effectively decreased default cost.[25] However, the above argument goes against one of the notorious bankruptcy cases in the post-BRA era, specifically that of Eastern Airlines, which lost 50% of its value during bankruptcy (Weiss and Wruck, 1998). Again, it is not clear how BRA changed default cost. Obvious way to test my hypothesis is to check how BRA changed time spent in bankruptcy. However, data on bankruptcy cases during pre-BRA are limited and thus makes it hard to compare. This warrants a need for a structural estimation that can identify changes in unobservable firm characteristics.

[23]H.R. Rep No. 595, 95th Cong., 1st Sess. 224 (1978))

[24]The list includes an automatic stay, an exclusive period, the ability to use cash collateral and/or obtain post-petition financing, the ability to assume or reject leases and other executory contracts, the ability to sell assets free and clear of liens, the ability to retain and compensate key employees and the ability to reject or renegotiate labor contracts and pension benefits.

[25]This explanation is consistent with the literature's use of time spent in bankruptcy as a proxy for default cost (Bris, Welch and Zhu, 2006).