Essays on Corporate Credit

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ABSTRACT

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This dissertation consists of three chapters related to issues in corporate credit. The first chapter studies whether credit rating agencies applied consistent rating standards to U.S. corporate bonds over the expansion and recession periods between 2002 and 2011. Based on estimates of issuing firms' credit quality from a structural model, I find that rating standards are in fact procyclical: ratings are stricter during an economic downturn than an expansion. As a result, firms receive overly pessimistic ratings in a recession, relative to during an expansion. I further show that a procyclical rating policy amplifies the variation in corporate credit spreads, accounting for, on average, 11 percent of the increase in spreads during a recession. In the cross section, firms with a higher rollover rate of debt, fewer alternative channels to convey their credit quality to the market, and firms that are more sensitive business to economic cycles are more affected by the procyclical rating policy.

The second chapter quantifies the causal effect of borrowing cost on firms' investment decisions. To overcome the empirical challenge due to a possible reverse causality where firms' investment prospects affect their borrowing costs, I apply an instrumental variable methodology where the identification comes from insurance companies' regulatory constraints regarding the credit rating of their bond holdings. Rating-based regulatory constraints are more binding for insurers with a weaker capital position. For this reason, bonds upon downgrades face different degrees of selling pressure depending on the different capital positions of their holders. Such differences are presumably not correlated with issuers' investment prospects. Using data from 2004-2010, I estimate that a one percentage-point increase in bond spread reduces investment during the same year by 12 percent. Moreover, a five percentage-point increase in bond spread halves the probability of new debt issuance.

Finally, in the third chapter, when the bankruptcy code protects the rights of lenders, I and my co-author Suresh Sundaresan show that there is no intrinsic reason to issue debt with safe harbor provisions. When the code violates APR or results in significant dead-weight losses, the optimal liability structure includes secured short-term debt, with safe harbor protection. The borrower is able to trade off between "run prone" safe harbored short-term debt and long-term debt depending on the inefficiencies in bankruptcy code, and the availability of eligible collateral to increase the overall value of the firm. The presence of a secured short-term debt will increase the spread of long term debt, and this reduces the long-term debt capacity of firms. Overall, the combined debt capacity increases for the firm. Using the onset of credit crisis in 2007 as

an exogenous adverse shock to the collateral value of assets and to the riskiness of collateral, we find that the leverage and short-term debt of financial firms fell much more rapidly than non-financial firms due to the greater exposure of financial firms to "run risk". The provision of short-term credit by the Fed is shown to significantly buffer the reduction in short-term debt and leverage of financial firms, supporting the presence of a supply (of credit) effect in the data. While the Fed's intervention resulted in credit spreads returning to the pre-crisis levels, there was still a net fall in the short-term debt and leverage of financial firms, suggesting a possible demand effect as well. These results are in broad conformity with the theory developed in our results.

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Chapter 1

Procyclical Credit Rating Policy

1.1 Introduction

Credit ratings convey pricing-relevant information to investors (Kliger and Sarig (2000); Dichev and Piotroski (2001)), and therefore, credit rating policy affects firms' cost of capital, their investment decisions and, ultimately, the real economy. For example, inflated ratings during booms may lead to over-investment, while overly pessimistic ratings during downturns may exacerbate recessions. Accordingly, policy makers, regulators, and academics have devoted significant attention to credit rating agencies (CRAs) to ensure the consistency of their rating procedures. [1] Rating agencies assert that their rating standards are consistent over the business cycle. One major rating agency states: "*We attempt to avoid assigning high ratings to a company at its peak of cyclical prosperity...Similarly, we may not lower ratings to reflect weakening performance because of cyclical factors*".[2] In spite of such assertions, recent theoretical research on the ratings process suggests that rating agencies are incentivized to implement "procyclical rating policies" such that rating standards become stricter in recessions than in expansions (Bar-Isaac and Shapiro (2012); Bolton et al. (2012); Fulghieri et al. (2012)). However, there is little empirical evidence on the cyclical bias of rating standards, and on the potential effect on firms' cost of capital. This paper fills the gap.

In this paper, I show that corporate bond credit ratings by the major rating agencies (Moody's, Standard & Poor's, Fitch, and Duff & Phelps) from 2002 to 2011 were indeed procyclical. Further, I quantify the effect of the procyclicality on firms' costs of capital through the business cycle. Rating agencies claim their

[1] Title IX, Subtitle C of the Dodd-Frank Act Wall Street Reform ("Improvements to the Regulation of Credit Rating Agencies") begins with the following acknowledgment *"...[C]redit rating agencies are central to capital formation, investor confidence, and the efficient performance of the United States economy."* The Dodd-Frank Act seeks to ensure rating quality by imposing provisions for internal controls, transparencies, and increased responsibility on rating agencies such that changes in incentive during the business cycle do not impair the consistency (or accuracy) of ratings. Also, the Act aims to lower potential vulnerability of the economy to credit ratings agencies by removing statutory references.

[2] Standard & Poor's (2008), p.28

ratings are exclusively determined by the credit quality of the issuing firm, and that the observation of more downgrades in a recession than in an expansion is not necessarily evidence of a procyclical rating policy since issuers' credit quality is likely to vary with the business cycle. [3] Yet if the rating standard is stable across economic regimes, then the credit quality of issuers *in a certain rating group* (say, firms with A-rated bonds) should not improve in a recession when credit quality generally deteriorates. Using U.S. corporate bond data from 2002 to 2011, I show that this is not the case: the median credit risk of firms within each rating class is *lower* during an economic downturn than during an expansion. I also find that bonds that are rated during a recession perform better ex-post in terms of lower default frequencies. These findings constitute strong evidence of procyclical rating policies.

Because the credit quality of a firm is not directly observable, I estimate a metric of credit quality: I use a structural model of default and the Markov-Chain Monte-Carlo (MCMC) method, employing market prices of equity as inputs. The structural estimation of credit quality yields several benefits. A structural model captures the non-linearity of credit risk with respect to observable covariates. Moreover, the MCMC procedure uncovers model parameters at the firm level, and allows for econometricians to quantitatively estimate the effects of rating standard changes within the context of the model by simulating a counterfactual economy.

After estimating firms' credit quality, I proceed to estimate rating agencies' rating policies. The rating policy is essentially a function that maps a firm's credit quality to a certain discrete rating. Changes in the function with respect to economic cycles reveal a regime-dependent rating policy. Since rating assignments are multiple-discrete choices, an ordered probit model is a natural specification to estimate the mapping function. Controlling for bond-specific features (e.g., seniority, covenant), the model estimates how issuers' credit worthiness transforms into ratings. The results show that there is a significant difference in rating standards across different phases of the business cycle, showing the procyclical nature of rating standards. As a result, a firm with a given credit quality is likely to receive a worse rating in a recession than in an expansion. For example, the probability of achieving an AAA rating is about 7 percentage points lower in a recession than in an expansion, when this rating is most likely to be received.

Using the estimated rating policy in an expansion period as a benchmark, I proceed to construct a counterfactual economy where the benchmark policy is applied to both upturns and downturns. Creation of counterfactuals distinguishes the economic impact of the procyclical rating policy. In a recession, I find that the bond spread significantly increases. The tightened rating policy delivers an overly pessimistic signal to the market, hence the cost of borrowing for a firm is amplified beyond the level implied by the economic downturn. For example, I show that procyclical rating policies account for 11.3 percent of the spread increase of investment grade bonds in a recession. The resulting rise in borrowing cost reduces equity values, thereby affecting firms' general cost of capital. Since issuers are endogenously prone to default sooner when their

[3] "*Credit ratings are expressions of opinion about credit risk*", Standard & Poor's (2012). Also see Manso et al. (2010) for related discussions.

debt servicing cost becomes higher (Leland (1994a,b)), the procyclical rating policy contributes to an even greater reduction in the value of equity during a recession. This phenomenon relates to the feedback effect caused by changes in credit rating: a credit downgrade decreases a firm's credit worthiness, while there is a corresponding increase in the cost of debt. This feedback channel may cause further downgrade and potentially trigger a downward spiral to default (Manso et al. (2010)).

In addition, I analyze the effect of procyclical rating policies in the cross-section of firms. I show that such a rating policy has more severe consequences for firms with a higher portion of debt to be rolled over. These firms are more likely to be exposed to the investors' reaction to rating changes when they roll over debts. Also, issuing firms are more affected by the change in the rating standard when they have a less liquid credit default swap (CDS) market on their bonds (or no CDS market at all), measured by the low number of CDS dealers. This finding is consistent with the hypothesis that rating agencies have less discretion for the rating policy for firms with deeper CDS markets. [4] I also find that firms that belong to a cyclical industry are more affected by procyclical changes in rating policies.

This paper contributes to the stream of literature on the stability of credit rating policies. While it does not offer any particular underlying cause of inconsistency in ratings standards, there are several theoretical papers that investigate the mechanisms. One prominent mechanism is the "issuer-pay system." It provides an incentive for an agency to offer issuers a more favorable rating in order to win their business especially in boom times (Bolton et al. (2012); Coffee (2010)).[5] On the other hand, rating agencies' concerns about reputation may cause them to adopt relatively stricter policies during recessions, when the likelihood of bankruptcy is greater (Bar-Isaac and Shapiro (2012); Fulghieri et al. (2012)). The dynamics of this tension leads to a procyclical rating policy.

Recent empirical research finds that the issuer-pay system induces inflated rating standards (He et al. (2012); Jiang et al. (2012); Cornaggia and Cornaggia (2013)). Given the issuer-pay system, several papers also investigate how competition among rating agencies has affected rating standards (Becker and Milbourn (2011); Xia (2013)). [6] Other studies have also found that structured finance markets were inflated during the expansion leading up to the 2008 financial crisis (Ashcraft et al. (2009); Griffin and Tang (2012)).

Using corporate bond data from 1978 to 1995, Blume et al. (1998) examines the instability of rating standards in the time-series. They discover a long-term trend of declining credit quality in the corporate bond market, and demonstrate that rating standards have become more stringent during this time. Alp (2012) shows that standards for issuer ratings before 2002 were more lenient than those after 2002. These results are consistent with my findings that rating standards vary in the time-series. However, on corporate

[4] Alternatively, the market may not react to the rating change as much when the firm has a good alternative instrument to signal their credit quality to the market. These two explanations are not mutually exclusive. More discussion can be found in Section 1.5.4.

[5] As David Jacob, a former head of rating division at S&P has remarked *"It's silly to say that the market share doesn't matter. This is not God's holy work. It's a business."* during an interview with the New York Times (7/31/2013).

[6] Fracassi et al. (2013) provide additional angle for inconsistent rating standards in relation to credit analysts' characteristics.

bond ratings, little empirical work has been done in documenting rating policy dynamics over the business cycle. Furthermore, the implications on the economy of these rating policy changes have not been explored.

This paper is the first to quantitatively document the change in corporate bond rating policies over the business cycle and to measure its implication, with the notable exception of Amato and Furfine (2004). They examine how S&P long-term issuer ratings correlate with four accounting ratios, and with proxy measures of the business cycle.[7] Their findings do not show consistently significant evidence that credit ratings are excessively sensitive to the business cycle. However, when they consider only newly assigned ratings, they find that ratings are overly sensitive to the business cycle. Beyond these mixed findings, they cannot conclusively determine whether S&P's rating standards are procyclical, given their reliance on only low-frequency, backward-looking accounting information to measure credit quality.[8]

In this paper, I address these concerns by directly estimating credit quality from current information embedded in equity values, using a structural model of default. Resulting estimates capture credit risk in a forward-looking way. By taking a structural estimation approach, I can also take the expected growth and volatility of the underlying firm asset into consideration in a non-linear way. Use of a structural model in the context of corporate bonds is also advantageous in measuring the economic consequences of changes in rating standards. The model provides a useful tool to distinguish equilibria with and without a procyclical rating policy, and to quantify the implications of such a policy in the cross section of firms as well as for the aggregate economy.

The findings of this paper bring attention to potential unintended effects of rating-based regulations imposed on bond investors.[9] This regulatory dependency on ratings has created a hard-wired mechanism through which changes in ratings affect firms' financing costs (Bongaerts et al. (2012); Ellul et al. (2011); Kisgen and Strahan (2010)).

Through this channel, the procyclical rating policy induces real consequences. Equity holders are more

[7]Those accounting ratios are interest coverage, operating margin, long-term debt, and total debt.

[8]They argue that this difference in their results could be due to the rating agency's sparse revision of individual issuer ratings. Given this non-consistent finding, there are two potential concerns for this paper. First, not only are the accounting ratios low frequency information, but they also fail to serve as a forward looking risk measure. Without controlling for important factors in credit risks such as dynamics of expected return and volatility of the firms' underlying asset, these ratios may not contain the consistent information in different economic regimes. Second, the long-term issuer ratings (at the end of each fiscal year) may not be the correct ratings to study rating sensitivity with respect to the business cycle. Issuer ratings are not directly sensitive to rating agencies' incentive to implement the procyclical rating policy. To illustrate this, I calculate the average discrepancies between issue and issuer ratings from S&P. I find that the issue ratings were more favorable than issuer ratings in an expansion, but in a recession, issue ratings were significantly harsher than issuer ratings. This pattern is consistent with their argument about the staleness of issuer ratings, and potentially reduces the statistical power of their study. I use the issue ratings from all major rating agencies to better address the staleness problem.

[9]For example, banks and insurance companies are required to have extra capital to hold securities with lower ratings. In the hearing before the committee on financial services on April 2010, FRB identified 46 similar statutory references to credit rating in its regulations.

likely to reduce investment when the cost of capital is higher. Auh (2013b) finds, using rating-based capital regulations of insurance companies, that 1 percentage point of the bond spread leads to a 12-percent reduction in investment. The procyclical rating policy, therefore, exacerbates reductions in investment during a recession.

This paper also contributes to the existing credit risk literature. Particularly, it has remained a puzzle why credit risk captured by a large class of structural models explains only a fraction of corporate bond spreads (Eom et al. (2004); Huang and Huang (2003); Korteweg and Polson (2010)). When rating standards tighten in a recession, such rating policy contributes to a further increase in spreads. While conventional structural models do not consider this factor, this paper suggests that a model that captures rating-policy-induced spread changes would better explain the observed spreads.

Empirically verifying the changes in rating standards is challenging because rating agencies' actual models (or processes) for assigning their ratings are kept confidential. I overcome this challenge with model-driven estimation. To ensure that results are robust to a particular specification of a model, I adopt the following empirical strategies: (1) I use different measures of credit worthiness from two different models, (2) I extend the baseline model to include borrowers' strategic behavior that might increase the default risk during a recession, and (3) I present *out-of-model* evidence that bonds rated during a recession show better ex-post credit performance. None of these approaches leads me to conclude that procyclicality is a reflection of a particular model specification.

The structure of the paper is as follows. Section 1.2 formalizes the motivation. Section 2.3 describes the data. Section 1.4 develops a base structural model and explains the procedure used to estimate credit quality. Sections 1.5 provides a quantitative measure of procyclical rating policy and its effect in the cross-section of firms. Section 1.6 considers several robustness checks. Section 1.7 studies the implication of the procyclical rating standard on the aggregate economy, and Section 2.7 concludes.

1.2 A Simple Illustration

This section features a thought experiment that illustrates how to empirically identify changes in rating policies. Consider a simplified economy in which there are only two ratings, investment grade (IG) and high yield (HY). These ratings are assigned according to a metric of the firm's credit risk. Suppose if the metric is below a certain threshold, a firm receives an IG rating; otherwise it receives a HY rating. Assume that, before a recession, firms are evenly divided into these two ratings. In a recession, as a result of a general decline in credit quality, more firms move to the HY category. If, at the same time, the rating standard becomes stricter, then receiving the IG rating becomes harder. As a result, only very safe firms retain the IG rating, and some relatively safe firms that otherwise would have retained the IG rating would join the HY group. In this case, the mean credit quality within each rating could be better in a recession. The following illustration formally demonstrates that observing better credit quality within rating is a sufficient condition for a procyclical rating policy.

Consider a scenario with three hypothetical ratings: H, M, L. Firms are distributed with respect to the physical measure of the default probability. The dashed curves in Figure 1 illustrate this hypothetical distribution during an expansion. The vertical lines are thresholds in the default probability that determine rating assignment. For example, if a firm's default probability is very low, then the firm belongs to the left end of the distribution and receives an H rating. The numbers in brackets on the top of the horizontal axis (left panel) display the average default probability for each rating category when the firms' distribution follows the dashed curve. For instance, firms with an H rating have, on average, a 12 percent default probability, while firms with an M rating have, on average, a 27 percent default probability.

Suppose the economy enters into a recession and the firm distribution changes. Since the macro economic situation worsens during a downturn, the firms' credit quality generally deteriorates, and the distribution "shifts to the right" as depicted in the solid curves of Figure 1. For now, assume that the rating thresholds (vertical dotted lines) are fixed with respect to economic regimes. The left panel demonstrates that the average probabilities with the shifted distribution (shown beneath the horizontal axis) are higher than the numbers before the distribution change (shown above the horizontal axis). This reflects a greater mass of firms is concentrated on the right end of each rating class.

[Insert Figure 1 here.]

Now, consider the possibility of a procyclical rating policy. The right panel of Figure 1 provides a graphical illustration. Without loss of generality, a procyclical rating policy can be defined as: *relatively* stricter rating standards in a recession than in an expansion. This definition implies that the rating thresholds shift to the left (to vertical solid lines in the right panel) when there is a general decline in credit quality (from dashed curves to solid curves). Thus a firm with a default probability that is at the left of the threshold of a certain rating (firms in the shaded area in the right panel) will be downgraded *even though* its default probability does not change. In this case, the average default probability of each rating group (shown beneath the horizontal axis in the right panel) actually becomes smaller than the original value during an expansion (shown above the horizontal axis in the left panel). Therefore, observing lower average default probabilities for each rating class in a recession than those in an expansion provides evidence of a procyclical rating policy. I present a formal statement of this claim in the following proposition. The proof is in the Appendix.

Proposition 1.1. *Suppose there are two continuous distributions of firms f, g defined over probability of default $\Theta = [0, 1]$. For each distribution $i = \{f, g\}$, take two arbitrary rating cut-off points p_i, $q_i \in \Theta$ such that $[p_i, q_i]$ has a positive measure ($q_i - p_i > \epsilon^+$). If the cut-off points are the same for each distribution ($p_f = p_g$) and g first-order stochastically dominates f in $[p_i, q_i]$, then $\mathbb{E}_g[\theta|p_g \leq \theta \leq q_g] > \mathbb{E}_f[\theta|p_f \leq \theta \leq q_f]$ for all $\theta \in \Theta$.*

The general deterioration of credit quality can be understood as a first order stochastic dominance shift of the firm distribution with respect to default probability (Figure 1). Proposition 1.1 states that if the firm distribution changes in this way during a recession, and the rating cut-offs do not move (with regime-independent rating standards), then the mean default probability, conditional on a certain rating, must be *higher*in a recession. This is consistent with the illustration presented in the left panel of Figure 1 (numbers on the top and bottom of the horizontal axis). Using Proposition 1.1, I obtain the following corollary.

Corollary 1.1. *Suppose there are two continuous distributions of firms f, g defined over the probability of default $\Theta = [0,1]$ such that g first-order stochastically dominates f, ($g \overset{FOSD}{\succ} f$). For each distribution $i \in \{f, g\}$, take two arbitrary rating cut-off points p_i, $q_i \in \Theta$ such that $[p_i, q_i]$ has a positive measure, i.e., $q_i - p_i > \epsilon^+$. If $\mathbb{E}_g[\theta|p \leq \theta \leq q] \leq \mathbb{E}_f[\theta|p \leq \theta \leq q]$ for some $\theta \in \Theta$, then the rating cut-off points in g are smaller than those in f ($p_g < p_f$).*

The proof of the Corollary is immediate from Proposition 1.1. The corollary states that if the average default probability in a given rating category is lower in a recession than in an expansion, it must be associated with the stricter rating policy in a recession. Hence the corollary specifies a sufficient condition for a procyclical rating policy.

Using U.S. corporate bond data from 2002 to 2011, Figure 2 shows that corporate bonds within the same categories (Investment Grade (IG) and High Yield (HY)) have a lower Expected Default Frequency (EDF), which measures the probability of default, in a recession than in an expansion.[10] By the corollary, this figure constitutes a sufficient basis for a procyclical rating policy. Quantifying the magnitude of procyclicality and its economic impact, however, requires a more systematic estimation of the rating policy change. In the following sections, I implement formal tests to provide further evidence of a procyclical rating policy, and I render quantitative estimates of its implications on the economy.

[Insert Figure 2 here.]

1.3 Data Description

The data used in this paper comprise corporate bonds of public U.S. non-financial firms, covered by the FISD Mergent database from 2002 to 2011. The FISD database includes comprehensive corporate bonds with issue and issuer characteristics, including credit ratings for bonds. The database has been used in research that studies related topics to this paper (e.g. Becker and Milbourn (2011)). Specifically, the FISD contains the history of bond rating changes from S&P, Moody's, Fitch and Duff & Phelps. Using the event of rating changes, I create a monthly panel of credit ratings of bonds in the sample. I fill up the time between events of rating changes with the preceding rating. Sometimes, there are multiple rating changes made by the same rating agency within a month; also, in a given month, the credit ratings assigned by different agencies are not necessarily the same. Given that the credit quality of the issuer of each bond is estimated at the end of each month, I use the latest rating information if there are multiple rating changes from the same rating agency

[10] TableA.1 in the Appendix shows the same pattern in finer rating categories.

within a month. Also, if there are cross-sectional differences in ratings across agencies at the same time, I use the worst rating among the ratings available. This approach captures the collective procyclical change of rating policies without specifying a particular agency. Moreover, lower ratings generally have greater direct impact on regulatory application (Bongaerts et al. (2012)). This method does not drive the results because there are few cross-sectional differences in coarse ratings. Also, the other rating agencies seem to follow the first downgrader quickly: by month's end, the cross section differences tend to be eliminated. For these reasons, all results hold with the best rating.

To quantify the economic impact of procyclical rating policy in pricing terms, I merge volume-weighted trading yield at monthly frequency to the resulting panel data, using corporate bond trading information in the TRACE database. Also, in order to analyze the ex-post credit performance of bonds, I merge the history of credit events, using Moody's Default and Recovery and Ultimate Recovery Database (URD/DRD). This database provides, for each failed issue, the date of the credit event and the recovery rate to the bond holders. The covered credit events include distressed exchanges, missed interest or principal payments, and Chapter 11 filings.

To test changes in rating standards, I consider two metrics of firms' credit quality. The detailed steps are explained in subsequent sections, but what follows is a brief description. First, I estimate distance-to-default of the issuer of each bond in the sample. The distance-to-default measures the credit quality of issuing firms. Second, I merge 5-year Expected Default Frequency (EDF) information from KMV Moody's, which is available at monthly frequency for each public firm. These two measures provide similar information about the credit risk of a firm. The resulting database includes a monthly panel data of bond issuance, with credit rating, bond specific information, monthly yield, distance-to-default and the EDF matched to each issuer. The database covers 486,918 issue-month observations with 878 unique issuers and 9,256 unique issues.

For each issuer, I add the following information in order to analyze whether any effect of procyclical rating policy varies cross-sectionally with firm characteristics. First, I match balance sheet information from Compustat and Capital IQ. Second, for each issuer, I match the number of Credit Default Swap (CDS) dealers using the Markit database. The Markit database provides a spread of CDS for a reference bond instrument as well as the number of quote providers. The number of dealers in the CDS market (if a firm has any traded CDS), provides a proxy for the depth of the CDS market (Qiu and Yu (2012)). I use the average of the number of dealers per bond issue to measure firm-wide liquidity in the CDS market.

[Insert Table 1 here.]

Table 1 provides summary statistics. While more detailed information can be found in the table, I summarize the characteristics of the sample bonds. Panel A of the table shows selected variables available at the issue level. For analytical convenience, I assign numbers to several categorical variables: coarse ratings, seniority of bonds, and types of coupon.[11] These variables indicate that (1) the monthly rating panel has the average

[11] For coarse ratings: AAA=1, AA=2, A=3, BBB=4, BB=5, B=6 and CCC=7. For seniority, higher numbers for more senior

bond rating close to BBB, (2) the majority of bonds are senior unsecured, and (3) most bonds have a fixed coupon. High yield bonds make up about 47 percent of the sample. About 16 percent of the sample bonds have credit enhancement features such as guarantees or letters of credit. Most of bonds have call features (78 percent) and 8 percent of bonds are puttable by the bond holder. About half (55 percent) of bonds are protected by covenants. Mean EDF and distance-to-default are 0.08 and 5.14, respectively. On average, a bond receives ratings from two rating agencies at the time of issuance. The mean and median yield are about 6 percent.[12] Bond age, time to maturity, and bond duration are about 5.5 years, 8.5 years and 6 years, respectively.

Panel B of Table 1 presents summary statistics of variables at the issuer level. Each data point at the issuer level is a firm-year observation. The distribution of the coarse ratings for issuers is similar to that of the issue rating. It is notable that non-financial firms use very little short-term debt (debt maturing in less than 1 year, excluding a current portion of long-term debt), indicating short-term debt makes up only 3 percent of total debt. The average par value-weighted maturity of bonds is about 11 years. The private debt ratio is the portion of bank debt over the total debt, indicating that, on average, 19 percent of the total debt of the sample firms is private debt. Finally, only 78 unique firms (460 firm-year observations) have traded CDS contracts on their debt, and there are, on average, 4 dealers for each firm in the CDS market.

1.4 Estimation Process

1.4.1 Estimation of Credit Quality

In this section, I provide a detailed procedure for estimating the credit quality of firms. I use a structural model of endogenous default to measure credit quality. In doing so, I capture its non-linearity with respect to observable covariates. Using a structural model also allows me to identify the effect of procyclical rating policies within the context of the model, through the creation of a counterfactual economy. Specifically, the base model of the estimation in this paper is Leland (1994b). The advantage of this model is a relaxation of the infinite maturity assumption in Leland (1994a). This extension is crucial to studying the implication of the procyclical rating policy. If all of a firm's debt is perpetual, the effect of such a procyclical rating standard should be limited, because its cost of debt is locked-in once the debt is issued. The issuing firm would then not be exposed to a change in market perception about their credit quality as the rating changes. Since their cost of borrowing is fixed for any existing perpetual bonds, they do not care about bonds' secondary market price, unless they want to increase their leverage by issuing more debt.

The causal relationship between credit rating and the cost of debt is a key channel for a procyclical rating policy to have economic implications. When a firm has to roll over a certain fraction of its debt by replacing

claims: Subordinated = 1, Junior Subordinated = 2, Junior = 3, Senior Subordinated = 4, Senior Unsecured = 5 and Senior Secured = 6. For coupon types: Zero coupon = 1, Variable = 2 and Fixed = 3.

[12]For the trading yield, I winsorize the yield at 1 percent level to remove extreme values.

maturing debt with new debt, the secondary market price of bonds becomes relevant to its borrowing cost. The current yield of existing debt in the secondary market will be the yield of newly issued debt, i.e., new bonds and old bonds are close substitutes. Therefore, a firm's cost of debt is affected by the credit rating, even though they want to keep the total debt amount constant. Section 1.7 explains in detail the implication of credit rating policy.

Let the firm asset value, V, follow Geometric Brownian Motion:

$$dV = (\mu - \delta)V dt + \sigma V dW \tag{1.1}$$

where, μ is a drift of the asset value, δ is the dividend ratio, and σ is the asset volatility. At each moment, the firm retires a fraction m of existing bonds and replaces them with new bonds featuring the same coupon and maturity. Therefore, m is the rollover rate of debt. In this set-up, the average maturity of debt, M, is the inverse of m.[13] Suppose that a credit event occurs when an asset value V declines and reaches the default boundary V_B. Credit events may include more general occurrences, such as debt renegotiation as well as typical default. In order to accurately reflect reality, I assume that, upon a credit event, the value of an asset will be divided among equity holders and creditors.

Specifically, I denote α_1 as the fraction of available asset value that the creditors recover, and α_2 as the share that the equity holders receive. These parameters have a restriction such that $\alpha_1 + \alpha_2 < 1$ due to dead-weight loss from bankruptcy. I define $\alpha \equiv 1 - (\alpha_1 + \alpha_2)$ as specifying bankruptcy loss. Conventional structural models typically assume that equity holders do not receive anything upon credit events. Therefore, setting $\alpha_2 = 0$ in the context of my model recovers the bankruptcy cost α in the conventional set-up, as in Leland (1994a) and Leland (1994b).

Structural models provide equity and debt valuations within the model. Particularly, security prices are determined by the likelihood of a credit event, captured by the firm's underlying asset value (V) and its distance from the endogenous boundary (V_B), as well as the recovery of claim holders at the time of default, specified by α_1 and α_2. For example, equity valuation is comprised of unlevered asset value, present value of tax shield, and payout upon the credit event. The following propositions summarize the debt and equity valuation under this set-up. All proofs are in the Appendix.

Proposition 1.2. *Consider that the asset process follows Equation (3.1). Suppose that, upon the credit event ($V \downarrow V_B$), the creditors recover the fraction α_1 and the equity holders receive the fraction α_2 of asset value. At that moment, the debt and equity valuations are:*

$$D(V|V_B) = \left(\frac{C + mP}{r + m}\right)\left(1 - (V/V_B)^{-y}\right) + \alpha_1 V_B (V/V_B)^{-y} \tag{1.2}$$

$$E(V|V_B) = V + \left(\frac{\tau C}{r}\right)\left(1 - (V/V_B)^{-x}\right) - (\alpha - \alpha_2) V_B (V/V_B)^{-x} - D(V|V_B) \tag{1.3}$$

where, C is a dollar coupon for total debt, P is a principal amount of total debt, τ is a corporate tax rate, r

[13] For detailed derivation, see Leland (1994b).

is a risk-free rate, $\alpha = 1 - (\alpha_1 + \alpha_2)$ *is the total bankruptcy loss and* x, y *are defined by model parameters and can be found in the proof.*

Note that $(V/V_B)^{-x}$ is the present value of the contingent asset that pays 1 when a credit event occurs. Since the default is an endogenous decision of equity holders, who are effectively decision makers, the optimal V_B is chosen to maximize their equity value E in Equation (1.3). The optimality condition $\frac{\partial E}{\partial V_B} = 0$ obtains the following optimal default boundary:

$$V_B = \frac{y\left(\frac{C+mP}{r+m}\right) - \frac{\tau C x}{r}}{1 + (1-2\alpha_2)x + \alpha_1(y-x)} \tag{1.4}$$

Note that V_B depends on α_2, how much the equity holders receive. When the equity holders receive a positive payoff upon a credit event, their default policy ,which triggers the credit event, also depends on this payoff. Specifically, as α_2 increases, V_B rises. That is, when the equity holders are in a position to receive more upon default, they will surrender the firm only at higher asset value levels. In the base line estimation, I set $\alpha_2 = 0$, following the conventional assumption of structural models that equity holders do not receive any payouts upon default. Different parameters for α_1 and α_2 across economic regimes may lead to additional implications for the determination of the default boundary over the business cycle. I explain this in the next subsection.

The estimation uses Markov-Chain Monte-Carlo (MCMC) methods. This procedure mostly follows Korteweg and Polson (2010). While a detailed procedure is explained in the Appendix, I describe conceptual steps here. The model depends on three key unobserved inputs: state variable V, asset volatility σ, and the drift term μ. The MCMC algorithm estimates joint posterior distributions of these unobserved model parameters, as well as the level of the latent state variable V. Estimation starts with observing equity prices. Equation (1.3) provides an inverse mapping from the equity value of a firm to the unlevered asset value V, for given priors of parameters. Once V is drawn from the conditional distribution, I sequentially draw each of the unknown parameters, using newly drawn parameters and the state vector. This set of conditional distributions uniquely determines the joint posterior distribution of parameters.[14]

In order to extract the asset value and unobserved parameters, I apply this procedure per firm at each sample month using daily equity prices, risk-free rates, and observed information from the most current year. The following observed parameters are time-varying: risk-free interest rates measured by a 1 year constant-maturity treasury rate, dollar coupon C, total principal of debt P, a fraction of retiring debt m, and dividend yield δ. The corporate tax rate τ and the bankruptcy cost α in the baseline estimation are assumed to be 35 percent and 51 percent, respectively, as in Korteweg and Polson (2010), and they are constant over time. With this information, at each sample month, the MCMC algorithm obtains the posterior distribution of estimated parameters. I use the mean of the posterior distribution as a point estimate of each parameter. The estimation is performed dynamically: at each month, I use the most recent information available to estimate

[14]This is guaranteed by the Clifford-Hammersley theorem. See Johannes and Polson (2003) for detailed explanations.

unknown parameters (σ, μ) and the latent state variable of the firm (V). Therefore, I allow the parameter estimates to change over time, reflecting the current economic situation. As a result, the estimated default boundary V_B also changes dynamically. Specifically, it tends to increase in an economic downturn, reflecting higher cost of borrowing during this period. This feature characterizes the countercyclical dynamics of the default barrier V_B.

The purpose of this exercise is to estimate the credit quality of the firm within a structural model of default. In order to do that, I define the distance-to-default measure, denoted by DD, as follows.

$$DD = \frac{log(V/V_B) + (\mu - \delta - \sigma^2/2)}{\sigma} \tag{1.5}$$

The first term in the numerator, $log(V/V_B)$, measures the relative distance between the asset value V and its default boundary V_B. This distance is divided by the volatility of asset σ, measuring how many standard deviations away the asset value V is from its default boundary. With the extracted asset value and parameter estimates, I calculate the distance-to-default for each firm at monthly frequency.

Note that, from the definition in Equation (1.5), distance-to-default is in the data-generating measure ($\mathbb{P}$-measure). This physical probability measure is different from the risk-neutral measure ($\mathbb{Q}$-measure). I explain the difference with the following illustration. Consider a simple two-period world ($t = 0, 1$) in which an investor receives \$1 if there is no default, otherwise 0 at $t = 1$. If the physical probability of default ($\mathbb{P}$ -measure) is 0.5, then a risk-neutral investor would price the security at \$0.5. However, if the investor is risk-averse, then she would pay less than \$0.5, say \$0.4, for this security. The difference between these two prices, \$0.1, is the risk premium, and the risk-neutral probability of default ($\mathbb{Q}$ -measure) in this case is 0.6. As seen in this example, when there is risk aversion, the risk-neutral probability of default is higher than the physical default probability. The difference between probabilities in these two measures captures the price of risk (or risk premium). The risk premium is determined by the risk aversion of bond investors. It must remain irrelevant to rating agencies in determining the credit rating. A rating agency's only concern in terms of default probability is the quantity of the risk (0.5 in the previous example). Therefore, any risk metrics relevant to this paper should be in the $\mathbb{P}$-measure. To check the robustness of results to the estimation procedure, I use Expected Default Probability (EDF) as an alternative measure of credit risk. While a more detailed explanation of this measure is to follow, note that it is also the $\mathbb{P}$-measure estimate of the default probability.[15]

1.4.2 Estimation of Rating Policy

Intuitively, the rating policy is a function that maps the credit worthiness to credit ratings. Suppose that distance-to-default fully captures all the factors necessary for rating agencies to determine ratings. The left panel of Figure 3 graphically demonstrates this intuition. A firm with higher distance-to-default is safer;

[15] For more discussion about EDF and its estimation methodology, see Berndt et al. (2005) and Bharath and Shumway (2004).

hence, it should receive a better rating (low rating number). Therefore, the slope of the mapping function should be negative in distance-to-default.

The changes in the shape of the mapping function reflect changes in the rating policy. The function corresponding to a strict rating policy should lie above the function associated with a lenient policy. In this case, the function corresponding to a strict policy always yields a more negative rating (higher rating number) even for the same credit quality. Changes in the rating standard do not necessarily mean inaccurate ratings. Suppose any rating standards correctly assign the worst rating to the riskiest group of firms. When the distance-to-default of a firm is very low, such that the firm is just about to default, the firm must receive the worst rating (highest rating number) under any policy. This restriction implies that the left-tails of both functions should converge. Imposing these conditions together, the strictness of rating policies must be associated with a slope of the function.

Consider a procyclical rating policy in which a rating standard tightens during a recession, relative to an expansion. As a result, a recession's rating policy corresponds to a function with a flatter slope. The difference in slopes thus reflects the procyclicality of rating policy. For example, the left panel of Figure 3 illustrates that, in order to acquire the fourth best rating, the firm has to cross the threshold of distance-to-default = 3 under the expansion rating policy (solid line). Suppose the economy enters into a recession and the slope of the line flattens, as depicted by the dashed line in Figure 3. Now the firm must reach a higher distance-to-default cut-off, 4, to acquire the same rating. Such shifts of thresholds characterize a procyclical rating policy. Moreover, the distance between two vertical dotted lines (or distance between points A and B) measures the degree of the procyclicality. In other words, a firm's credit quality has to be better by this distance to offset the effect of the procyclical rating standard. Note that the gap between these two points decreases for ratings associated with lower distance-to-default. However, this pattern does not mean that the effect of the rating change diminishes for firms with these ratings. The probability of default as a function of distance-to-default grows exponentially as the distance-to-default becomes lower. When a firm's asset level is very close to its default trigger point, a unit change of the distance-to-default makes a much larger difference to the default probability of this firm than it would with another firm whose asset value is significantly higher than its default boundary.

[Insert Figure 3 here.]

To formally test this intuition, I employ an ordered probit model. Let us suppose that there is a variable *Score*, which rating agencies reference to determine credit ratings. I assume that the *Score* is a linear function of distance-to-default and other variables that the estimated credit quality does not cover. They may include: a level of seniority, whether a bond has a credit enhancement feature, the industry of an issuer, and/or the number of rating agencies that covers a bond at the time of issuance.[16] Specifically, I impose the

[16]Bongaerts et al. (2012) document that ratings may depend on how many rating agencies cover that specific issue.

following relationship for the reference rating score of a firm i at time t:

$$Score_{it} = (\beta_1 + \beta_2 \cdot Regime_t) \cdot DD_{it} + \gamma' \cdot Z_i + u_{it} \equiv X \cdot B + u_{it} \tag{1.6}$$

where, $Regime_t$ is a dummy variable with a value of 1 during a recession and 0 otherwise, DD_{it} is the distance-to-default, Z_i is a vector of issue or issuer-specific variables that do not have a time-variation, and $u_{it}|X \sim N(0,1)$. Next, I map the $Score$ variable to the number-coded rating category $Rating$. Let θ_k ($\theta_1 > \theta_2 > \cdots > \theta_6$) be the cut-off points between a k and $k+1$ rating. For example, θ_3 represents the cut-off points between an A and BBB rating. Given the rating agency's policy and $Score$, suppose agencies assign their rating as follows:

$$Rating_{it} = \begin{cases} 1 & \text{if } \theta_1 \leq Score_{it} \\ j & \text{if } \theta_j \leq Score_{it} < \theta_{j-1} \\ 7 & \text{if } \theta_6 > Score_{it} \end{cases}$$

Then for $j = \{2, \ldots, 6\}$ [17],

$$\begin{aligned} Pr(Rating_{it} = j) &= Pr(\theta_{j+1} \leq Score_{it} < \theta_j) \\ &= Pr(\theta_{j+1} \leq X \cdot B + u_{it} < \theta_j) \\ &= F(\theta_{j+1} - X \cdot B) - F(\theta_j - X \cdot B) \end{aligned}$$

where $F(\cdot)$ is the standard normal CDF. The ordered probit model estimates the coefficient parameter, B, and cut-off points, θ, by maximizing the log-likelihood function given by $Pr(Rating_{it} = j)$.

The regression estimates the likelihood of acquiring a certain rating with a given reference score, that is specified in the Equation (1.6). Specifically, the reference score is an increasing function of the distance-to-default, such that higher distance-to-default is likely to yield lower numeric value assigned for the rating (better rating). Hence, β_1 should be negative in the distance-to-default. Moreover, a regime-dependent change of the slope is measured by the coefficient β_2 of the interaction term ($Regime_t \cdot DD_{it}$). Hence, β_2 teases out the rating policy variation over regimes. Specifically, the procyclicality of the rating standards predict that the β_2 in Equation (1.6) should be positive. This hypothesis is based on the following intuition: the positive β_2 corresponds to a flattening slope of the mapping function (as depicted by the dashed lines in the Figure 3) when the variable $Regime_t$ switches its value to 1, as the economy enters into a recession.

1.5 Empirical Results and Discussion

1.5.1 Results of MCMC

I present results of the distance-to-default estimation from the procedure described in Section 1.4.1 in Table 2. The table shows that both mean and median of distance-to-default monotonically decrease as ratings

[17] The cases of $j = 1$ and 7 are omitted but they are straight forward.

become worse. This pattern indicates that the distance-to-default captures credit risk similar to the way credit ratings do. Figure A.1 in the Appendix shows this pattern. In the figure, the better the credit rating, the darker the color (AAA is the darkest, CCC is the lightest). When each firm-month data point is sorted in the distance-to-default measure (from highest to lowest), I show that the data points with higher distance-to-default (at the left end of the curve) are darker, and that they lighten as the distance-to-default decreases (at the right end of the curve).

[Insert Table 2 here.]

1.5.2 Ordered Probit Regression

In this section, I the report results of the rating policy estimation from the procedure explained in Section 1.4.2. The left four columns of Table 3 show the results of the regression in Equation (1.6). They confirm that the rating policy is procyclical: the coefficient β_1 is negative and the coefficient β_2 is positive. Coefficients are consistently significant across all specifications. A typical ordered probit regression assumes that u_{it} is independently distributed. This assumption might not hold when corporate panel data is considered. There may be a potential serial correlation in time for some bond specific characteristics that could have an influence on the credit rating. To address this issue, one can use Newey-West standard errors, or standard errors clustered at the issue level. I report clustered standard errors per Petersen (2009), who shows that clustered standard error is robust to the lag assumption that Newey-West requires, and performs better than Newey-West.[18]

[Insert Table 3 here.]

Although Table 3 confirms that evidence of the procyclical rating policy is statistically significant, interpretation of the results is not straightforward. Toward a more intuitive interpretation, I show cumulative probabilities of gaining certain credit ratings in an expansion and in a recession. Specifically, the cumulative probability of achieving a rating R that is better or equal to $\underline{R}$ is defined as $Prob(R \leq \underline{R}) = \sum_{r=1}^{\underline{R}} Prob(R = r)$, where $Prob(R = r)$ is the probability of being in rating category r. From the ordered probit regression specified in Equation (1.6), I predict those probabilities, $Prob(R = r)$, using rating policies in a boom and a recession. Through this practice, I translate the difference in slopes of functions that map distance-to-default to ratings into differences in probability of achieving a certain rating.

Figure 4 illustrates these differences, which reflect the difference in the rating standard. In the figure, the lighter curve represents the probability of achieving a rating AA or above under the expansion rating policy, and the darker curve represents the same probability under the recession rating policy. When the credit quality is very low or the distance-to-default is very small, the probability approaches 0 under both rating policies. Both probabilities increase in distance-to-default as the issuing firm becomes safer and they

[18]The results are qualitatively similar when Newey-West with reasonable lag (24 month) is used.

approach 1. However, the probability under the expansion policy stays above the one under the recession policy for any given level of distance-to-default. The average difference in these cumulative probabilities understates the magnitude of the effect, because the difference converges at 0 at each extreme (where the distance-to-default is either very low or very high).[19]

[Insert Figure 4 here.]

These results confirm the procyclical rating policy by showing that receiving the same rating is harder in a recession than in an expansion *even with* the same credit quality. Table 4 presents the differences in cumulative probabilities for different reference ratings. The first and the third row of the table show these differences, measured at two regions of distance-to-default. The first row shows the probability differences, at the region of distance-to-default, where the reference rating is most likely attained. The difference of these probabilities is most crucial when the likelihood of achieving the rating is highest. For example, in order to receive a credit rating AA or above, a firm has to be relatively safe. Therefore, the difference in probability is more meaningful for firms that have large distance-to-default as they are likely to receive these high ratings. In this example, the probability of gaining a rating AA or higher is 5.9 percent lower in a recession than in an expansion, when the firm is most likely to receive an AA rating. The second row of the table shows this specific range of distance-to-default: the highest likelihood of achieving an AA rating occurs when the firm's distance-to-default is between 13 and 14. The third row represents the maximum difference of these probabilities. The range of distance-to-default in which the difference exhibits the maximum value is presented in the last row of the table. For example, the maximum difference in probability of gaining an rating AA or better is 6.4 percent, and this happens when a firm's distance-to-default is between 14 and 15.

It is worth noting that the difference in probability decreases as ratings become worse. However, this does not imply that the rating policy change is more severe only in the higher rating category. As explained earlier, this is a reflection of the fact that the rating policy should converge at the low end of credit quality (see left panel of Figure 3). One unit of distance-to-default corresponds to a much larger default probability as the distance-to-default becomes smaller. Through this analysis, I translate the magnitude of the rating standard change identified in Table 3 into the probability differences for attaining a rating, which can be more easily interpreted.

[Insert Table 4 here.]

1.5.3 Construction of Counterfactual

In this section, I create a counterfactual world, using the estimated rating policy during an expansion as a benchmark. Specifically, I calculate the counterfactual default boundary V_B' such that the *Score* in Equation (1.6) under the recession policy with V_B' yields the same level of *Score* as if it were under the benchmark

[19] Figure A.3 in the Appendix shows the same pattern between cumulative probabilities under two regimes for other reference ratings.

policy. In other words, I offset the difference in the estimated *Score* under two different regimes in Equation (1.6) by adjusting the default boundary V_B to the counterfactual level V_B'. The left panel of Figure 3 provides an insight for this exercise. In order to *undo* the effect of procyclical rating policy, I compensate a firm's distance-to-default (by the distance between point A and B), by lowering its default boundary to V_B', such that the firm would have achieved the same rating from the benchmark standard.

The difference between two default boundaries V_B (current) and V_B' (counterfactual) has several implications. If $V_B > V_B'$, for a given asset value V, the distance-to-default is smaller with V_B than with the counterfactual level of the default boundary V_B' because the distance-to-default essentially measures the distance between V and the default boundary, which is either V_B or V_B'. The consequence of having $V_B > V_B'$ becomes more severe during an economic downturn when an asset value V deteriorates. In this case, the distance between an asset value and the default boundary contracts even more when the default boundary increases.

In the counterfactual world where the bench rating policy is applied in both regimes, the market receives regime-consistent signals from rating agencies and reacts to risk changes due to the business cycle. In recessions, investors tend to observe downgrade events (pessimistic signals) and raise the bond spread. Equity holders reflect the change when determining their counterfactual default boundary (V_B'). When procyclical rating policies deliver overly pessimistic ratings in recessions, however, investors will require even higher risk compensation than they do at the counterfactual level. Equity holders further increase the default boundary (V_B) with amplified borrowing cost to creditors. I use these counter-factuals to study the cross-sectional effect and the economic impact of procyclical rating policy in the next subsection and in Section 1.7, respectively.

1.5.4 Cross-Sectional Analysis

In the cross section of firms, the consequence of a procyclical rating policy may be different. The effect of such a policy can be captured by two variables: (1) the rating difference between the actual rating and predicted rating under the benchmark policy, and (2) the difference between the default boundary and counterfactual default boundary. As discussed in the previous section, the effect of the procyclical rating policy is transmitted through the cost of debt, resulting in disparity between the current default boundary V_B and the counterfactual default boundary V_B'. Hence, the gap between default boundaries, $V_B - V_B'$, describes an equilibrium difference that the procyclical rating policy contributes to. Further, I normalize the difference by defining a percentage difference in default boundaries as $(V_B - V_B')/V_B'$.

The cross-sectional variation may come from two considerations. First, the procyclical bias may be unequal for different firms in the cross section. In this case, I allow for rating policy changes to vary cross-sectionally, where it is procyclical in the aggregate. Even if the sensitivity of a firm to a unit of procyclicality is identical for all firms, the effect of such a policy may have a cross-sectional variation because the procyclicality itself varies across firms. Second, there may be a variation in firms' sensitivity to the degree of procyclical rating policy. Suppose that the degree of procyclicality is constant for all firms in the cross section. Even so, one firm may be more affected by the procyclicality than another. While I collectively analyze differential consequences of the procyclical policy in the cross-section, I do not formally distinguish between these two sources of variation. However, the results with the variable of rating difference strongly suggest that the degree of procyclicality varies with firms.

I posit three hypotheses. First, in order for changes in rating standards to influence firms' borrowing costs and change firms' default boundaries, firms must roll over at least some portion of their long-term debt. In the extreme case where a firm initially finances itself with a consol bond of infinite maturity, the cash flow to the bond investor does not change as long as the firm keeps the amount of debt constant. In this case, the impact of a change in rating standards on the default boundary should be limited. However, if a significant portion of existing debt matures and a firm replaces the old debt with a new debt, then its cost of debt depends on the current market spread of its bonds. When the change in credit rating has a causal effect on the bond spread, these firms are more exposed to the rating policy change. Specifically, in recessions, these firms tend to pay a higher spread for the portion of debt they renew because their credit quality deteriorates during this period. If, at the same time, the rating policy becomes stricter, then the borrowing cost on the new debt will increase even more, additionally increasing the default boundary in the context of the model.[20]

Second, firms with a liquid CDS market are less exposed to the procyclical rating policy. CDS is a recently developed instrument which provides a market-implied proxy of credit quality for the reference firm. In this respect, a liquid CDS market may reveal a rating policy change if the change is significant enough. For these firms, rating agencies' ability to employ a procyclical rating policy can be limited. The effect of procyclical rating policy may, therefore, appear smaller for these firms. In this case, having a liquid CDS market limits the discretion of rating agencies when investors have other references readily available. Fong et al. (2012) show that stock analysts discipline rating agencies for a similar reason. This variation could also have an alternative explanation: the market does not react as much to a rating change if there is a good alternative source of information about credit quality. In this case, for a given magnitude of procyclicality, its effect would decrease in a proxy that measures the depth of the CDS market. While testing which aforementioned explanation is most prominent is beyond the scope of this paper, this scenario is plausible when the causal link of credit rating to bond spreads weakens as a result of a liquid CDS market. There are two possibilities for this case: (1) With a liquid CDS market, the market is less likely to believe that a credit rating contains private information that is not yet reflected in the price, and (2) Capital or holding regulations based on credit ratings can be relaxed due to the existence of the CDS market. Case (1) is plausible because a liquid market may make information more transparent, compared to a case without it. Case (2) refers to situations in which institutional investors with capital or holding regulations may be allowed to avoid a statutory penalty of holding downgraded securities by buying protection from the CDS market. Hence, the investors

[20] In the framework of the model, a firm's fraction of debt to be rolled over (m) is the inverse of the average maturity of existing debt (M). When all bonds are perpetual, then $M \to \infty$ and $m \to 0$.

would be less forced to sell the securities, circumventing the spread spike. [21] In 2011, insurance companies have adopted this concept, and called it Derivatives Risk Mitigation while calculating their risk-based capital requirements. [22] Because it was not implemented until 2011, it is not the specific channel for the effect in this analysis. However, other institutional investors might already have similar provisions in their rating-based regulation.

Third, belonging to a more cyclical industry may amplify the impact of the procyclical rating policy. Suppose the operation of a firm is very cyclical. In expansions, such a firm tends to issue more bonds to expand their operations. In this period, this type of firm may seem more important to rating agencies; from an agency's perspective, there is a greater incentive to assign more favorable ratings to win their business. This collective behavior engenders a more lenient standard during an expansion. This is consistent with He et al. (2012), where they document that ratings for mortgage-backed securities were more favorable for issuers with larger issuance size. In a recession, however, this type of firm is more likely to fail. Potentially, it makes rating agencies more conservative in order to protect their reputation. It is also possible that these firms' costs of borrowing are more sensitive to the rating. With the same magnitude of procyclicality in rating policy, a rating downgrade may create a larger shock to these firms' spreads than to firms with non-cyclical businesses.

The regression specification to test these hypotheses, for a firm i and time t, is as follows:

$$Effect_{it} = \beta_1 \cdot m_{it} + \beta_2 \cdot N_i^{CDS} + \beta_3 \cdot Corr_i + \lambda' \cdot X + e_{it} \tag{1.7}$$

where, m is the fraction of debt to be rolled over, N^{CDS} is the number of CDS dealers which proxy the depth of the CDS market, $Corr$ measures the cyclicality of the firm, and X is a vector of control variables. The left-hand-side variable $Effect$ measures the outcome of procyclical rating policy, which is either the Rating Difference or Pct. Difference in Default Boundary. Their definitions are as follows:

$$\begin{aligned} \text{Rating Difference} &= \text{actual rating} - \text{counter factual rating} \\ \text{Pct. Difference in Default Boundary} &= (V_B - V_B')/V_B' \end{aligned}$$

A higher number for Rating Difference means that the actual rating is worse than the counterfactual rating under the benchmark policy. It indicates the firm receives overly harsh ratings due to the procyclical rating policy.[23] Using these two variables has an implication for determining sources of cross-sectional variation. If

[21] The seller of the protection (normally dealers of the CDS) would hedge it potentially by taking a short position on the bond, creating a similar price pressure. But since they usually net out the risk from different positions, the impact of the hedging activity on the bond spread tends to be smaller than a shock from the fire-sale. Also, the amount of bonds that dealers have to take a short position on is typically smaller than the full notional of a CDS contract. It is analogous to a situation in which put-option sellers hedge themselves by taking short-positions on the underlying stock but the delta is typically less than 1.

[22] See Capital Markets Special Report from NAIC (http://www.naic.org/capital_markets_archive/110624.htm).

[23] Rating Difference is an issuer-level variable which is calculated by taking an average of rating differences in bonds of the issuer. Therefore, it is not a categorical variable anymore.

the effect of a procyclical rating policy varies across firms solely due to different price reactions to each firm when its rating changes, the Rating Difference variable should not vary in the cross section.

The exposure to the roll over is captured by m, which is an inverse of the average maturity of existing debt. To check the second hypothesis, I proxy the depth of the CDS market with the number of CDS quote providers (N^{CDS}), as in Qiu and Yu (2012). Not all firms have a CDS market. For firms that do not have one, I assign zero for this measure. The industry-wide correlation with GDP ($Corr$) measures how cyclical a certain industry is to business cycle. To obtain the proxy, I first calculate profitability of a firm by computing a ratio of net income over total revenue. Then I calculate the raw correlation between these ratios and the 4-quarter average of GDP growth rate. I take an average of these correlations of individual firms within their industries, according to the Fama and French 49 industry classifications. This calculation yields an industry-wide cyclicality. Also, I put several commonly used control variables in firm panel regression variables, including book-to-market, logarithm of market value of equity, leverage ratio, and industry fixed effect. When the industry fixed effect is used, I omit the industry-wide correlation to avoid multicollinearity.

Table 5 presents the result of the regression. It confirms the three aforementioned hypotheses: the impact of procyclical rating policy is (1) larger when a firm has to roll over more of its debt, (2) smaller when there is a liquid CDS market, and (3) stronger when a firm belongs to a more cyclical industry. According to the specification (1), if a firm has 10 percent higher m, the firm's actual rating is 0.13 notch lower than a counterfactual rating under the benchmark policy. Also, if the depth of CDS market improves by adding 1 CDS dealer, a firm might suffer less from the procyclical bias by 0.04 notch. If the industry has 10 percent greater correlation, a firm tends to receive larger consequences of the procyclical rating policy by 0.075 notch. Note that I use notch points of coarse ratings in this analysis. In this case, the difference between BBB and BB rating, for example, constitutes a 1 notch point difference. However, there are actually 5-notch points (from BBB+ to BB-) of difference. Interpretation of this result should therefore be adjusted to this simplification. Also, results of the regression when Rating Difference is used for the left-hand-side variable (column (1) to (4) of the left side of Table 5) suggest that procyclicality is not consistent across firms and that cross-sectional variation is not entirely due to the differential reaction to price.

[Insert Table 5 here.]

1.6 Robustness Checks

The previous sections provide evidence of procyclical rating policy and how the economic consequence of having such a rating policy varies in the cross section of firms. The results rely on a model specification of the estimation of credit quality. One could raise a concern that previous results are biased due to potential model incompleteness. In this section, I address this concern through the use of several empirical strategies.

Suppose that rating agencies have a model (or a procedure) that measures firms' credit risk. With this measure, they assign ratings according to certain criteria (rating policies). Unfortunately, outsiders have no access to the actual model that rating agencies use. To overcome this challenge, I have implemented the following strategy in the previous section: I estimate the credit quality using a structural model of default and verify the changes in rating standard by showing that within-rating credit quality is better in a recession. Even with a regime-stable rating policy, rating agencies may make their model (or inputs that go through the model) more conservative in a recession. This possibility yields an alternative explanation: any other models (not theirs) which are consistently applied to measure the credit quality would generate better within-rating estimates of credit worthiness than what rating agencies arrive at. This explanation would attenuate, at least partly, the argument that the improved credit quality within ratings is sufficient evidence for the procyclical rating policy.

There are two possibilities for this alternative explanation: (a) the change of model is due to non-risk-related factors such as concern for reputation or business-oriented motivation, or (b) the model becomes more conservative so as to capture potential unobservable risks that may increase in a recession. If there is no good risk-related reason for the model change, as in (a), then it is conceptually identical to the rating standard change. For example, in a recession, rating agencies assign ratings according to a stricter standard with outputs from a time-consistent model; or they assign ratings using outputs from an *unnecessarily* conservative model with a time-consistent rating standard. In either case, what they implement is compatible with the definition of the procyclical rating policy: a firm must have a better fundamental credit quality to acquire the same rating in a recession than in an expansion. The more relevant concern of the two scenarios presents itself when the model change is because of (b). In this case, within-rating credit quality may merely appear different across regimes since my model fails to capture the valid risk.

To address this issue, I propose the following empirical strategies to check the robustness of the finding: (1) I use an alternative measure of credit worthiness from a different model, (2) I consider a possibility of strategic borrower behavior (a risk that may increase during a recession, but cannot be easily seen in the data), and finally (3) I show *out-of-model* evidence that bonds rated during a recession show better ex-post credit performance. None of these approaches suggests that my findings on procyclicality are a reflection of model misspecification.

1.6.1 Using an Alternative Measure of Credit Quality

If the model used in this paper to estimate credit quality has regime-dependent biases, identified variations of the rating standard may be partly due to the discrepancy between a model of rating agencies and a model used here. To alleviate this concern, I repeat the analysis in Subsection 1.4.2 with the Expected Default Frequency (EDF) of KMV Moody's (which is an estimated probability of default), as an alternative measure. In principle, EDF and distance-to-default measure the same thing: firms' credit worthiness. The right three columns of Table 2 in Section 1.5 show that EDF is monotonically increasing as credit ratings become worse. The table indicates that distance-to-default and EDF generally reflect credit quality in a similar way. The difference between these two measures are summarized in two aspects. (1) They come from different models.

EDF uses a Merton model, whereas I use a Leland (1994a) model to estimate the distance-to-default and (2) EDF is a probability based on the historical default and bankruptcy frequencies.[24]

A risky firm that has a low distance-to-default would have high EDF. [25] Since the distance-to-default and EDF have an inverse relationship, the shape of the function that maps credit quality to ratings is also reversed. The right panel in Figure 3 exhibits the opposite in this case, showing a positively-sloped mapping function. The positive slope implies that a firm with higher EDF is riskier and therefore it should receive a worse rating (higher rating number). Moreover, a stricter rating policy requires the mapping function to stay above a function associated with a lenient rating policy. When a firm is very safe, any rating policy must yield the best rating, requiring the left-tail of both functions to converge. Similarly, it is predicted that a more stringent rating policy corresponds to a steeper slope.

In the case of EDF, it is a bit trickier to make this argument, because theoretically EDF is bounded by 0 and 1 and there should be no difference among different mapping functions at both extremes. With the convergence restriction at both-ends, mapping functions must show concavity in order for a function of stricter policy to stay above the function corresponding to a lenient policy. However, the empirical distribution of a 5 year EDF used in the analysis is very right-skewed; the 75th percentile of EDF is only about 7 percent. In other words, a significant mass of EDF is concentrated at the left end of its range (domain with low default probability); hence, a linear line fitted to these data points is likely to impose a steeper slope for the function of a stricter rating policy. The right four columns of Table 3 in Section 1.5 report results of the regression in Equation (1.6), using EDF instead of distance-to-default. They are also consistent with the prediction and eventually verify the result with distance-to-default: the coefficient β_1 and β_2 are positive and significant.[26]

1.6.2 Borrowers' Strategic Behavior

This sections discusses potential risk that rating agencies may consider, but may not be properly captured when credit quality is estimated: the possibility of borrower's strategic behavior. If a rating agencies' model (or a process) correctly factors this risk into its rating assignment, then other models that do not consider

[24] Since distance-to-default does not rely on assumptions about default distribution, it is more normally dispersed from its mean, relative to EDF which has a long right-tail in its distribution. To see this, consider the following example. Suppose the credit events are normally distributed in terms of distance-to-default. Then for a given distance-to-default, I make a probabilistic interpretation ("x distance-to-default corresponds to y percent of default probability"). In this case, even though the distance-to-default is normally distributed, the resulting default probability is right-skewed.

[25] Figure A.2 in the Appendix displays the relationship between these two measures of credit quality.

[26] For EDF, the measure is bounded by 0 and 1 and, at either ends, it should assign the highest rating (AAA) and the lowest rating (CCC). So both mapping functions under the two regimes should be concave in EDF, and the one under a recession should envelope the one under an expansion. The ordered probit assumes that $Score$ is linear in EDF, so it is still the case that the linear fit has higher slope under the recession. For this reason, the difference in slope is expected to be smaller in magnitude when EDF is used instead of distance-to-default.

it may overestimate the credit quality. If the omitted risk is an economically valid one, it should attenuate my findings about procyclicality in the rating policy. To address this concern, I propose a simple extension of the model to capture this risk that the existing model may miss. Borrower's strategic behavior refers the following: in a recession, the equity holders may want to default sooner for reasons other than what a canonical model may suggest.[27]

In the context of the model, this has implications for setting the default boundary V_B shown in Equation (1.4) in Section 1.4. With higher V_B, a firm is more likely to experience a credit event, holding other parameters fixed. Although the estimation procedure permits the default barrier V_B to reflect current economic situations, I allow V_B to have further fluctuation across the business cycle by considering the strategic behavior of the borrower. As defined in Section 1.4, recall that α_1 denotes creditors' recovery rate, and α_2 denotes equity holders' payoff in the form of a percentage of available assets upon a credit event. In the baseline estimation, I use $\alpha_2 = 0$ while setting $\alpha = 51\%$ across two regimes. Now suppose that α_1 and α_2 take two different values with respect to the regime. I denote a payoff to creditors by α_1^j and a payoff to equity holders by α_2^j in an expansion ($j = E$) and a recession ($i = R$). Chen (2010) provides evidence that the recovery rate (α_2) is cyclical, i.e, the recovery rates for creditors in a recession is lower than in an expansion. These empirical findings imply that $\alpha_1^E > \alpha_1^R$. The equity holders' rents, α_2, may have a similar variation. During a recession, creditors may have worse outside options. They may face higher losses in liquidating firms' assets due to less favorable economic conditions. Therefore, creditors do not particularly want to experience the default event in this period. It gives an equity holder larger negotiation power during a recession. This argument implies that $\alpha_2^R > \alpha_2^E$ in the model framework. With the variation of α_1 and α_2 across regimes, the V_B becomes regime-dependent. Equation (1.4) makes it clear that V_B increases in α_2 and decreases in α_1 . Therefore, with $\alpha_1^E > \alpha_1^R$ and $\alpha_2^R > \alpha_2^E$, it is easy to show that $V_B^R > V_B^E$, where $V_B^{j=\{E,R\}}$ denotes V_B in Equation (1.4) with $\alpha_{i=\{1,2\}}^{j=\{E,R\}}$, holding other inputs the same. The regime-relevant dynamics of the default boundary are similar to those of Hackbarth et al. (2006), where they show a similar prediction that the default boundary increases in a recession rather than in an expansion, although their mechanism relies on the regime-dependent cash flow shock.

I use Moody's DRD/URD database to proxy the recovery rates for creditor $\alpha_1^{j=\{E,R\}}$. In the sample, the mean recovery rate during an expansion (α_1^E) is 0.44 and during a recession (α_1^R) is 0.41. This loss given default is almost identical to that of Altman and Kishore (1996). The ability of equity holders to extract rent from credit event, $\alpha_2^{j=\{E,R\}}$, requires separate attention because it is not directly observed in the data. To measure this, I calculate the fraction of equity value at the date of the credit event over the most recent

[27]As an analogy in consumer finance, individual borrowers who end in delinquency in a recession tend to have a higher FICO score. According to a report from FICO, the delinquency propensity rises as the economy enters into a recession across all levels of FICO score. For example, a person with a 700 FICO score tends to show a higher rate of delinquency in recessions than in expansions. The borrower's strategic behavior may contribute to this trend: borrowers are more prone to declare default in a recession when they can extract higher rent from the creditor. (The FICO report can be found at http://www.fico.com/en/firesourceslibrary/insights_fico_score_trends_2575wp.pdf)

reported asset value.[28] If equity holders are expected to receive nothing, theoretically equity price should be close to zero. Therefore, a departure of the equity price from zero proxies positive payoffs to equity holders upon credit events. Using the history of credit events in Moody's DRD/URD database, I find that the mean of α_2^E is 0.045 and α_2^R is 0.064. The variation in α_1 and α_2 gives an additional rise in the default boundary beyond what time-varying market and firm-specific parameters deliver. I repeat the analyses in Section 1.4.2 with these changes, altering the model to factor in the borrower's strategic behavior during a recession. The results are qualitatively same as the baseline case.[29] From this analysis, I confirm that this unobserved risk is not a factor that merely makes the rating policy *look* procyclical.

1.6.3 Ex-Post Analysis

While estimates of credit quality from several models consistently provide evidence of procyclical rating policy, the results still depend on model specifications. One can always argue that *any* particular model may fail to capture all factors that influence agencies' rating assignments. Addressing this issue is challenging because the actual rating agencies' models or procedures are kept confidential and cannot be directly observable.

To further ensure that the identified policy change is not merely a reflection of model incompleteness, I present *model-independent* evidence of procyclical policy change. If a certain credit rating reliably corresponds to the same level of credit quality over time, the ex-post default frequency in this rating category should also be similar over time. However, if bonds which are issued at a BBB rating, for instance, fail more in an expansion than those issued in a recession with the same BBB rating, this is evidence that the rating standard for this particular credit rating is more relaxed in expansion periods and stricter in recessions.

To test this hypothesis, I compute the fraction of bonds that have any credit events per regimes, conditioning on a rating assignment. The rating assignment event includes subsequent rating changes as well as initial assignment at the time of issuance. For example, for a BBB rating, I start with identifying bonds that are issued with BBB ratings or whose ratings are subsequently changed to BBB ratings, both in the expansion and the recession, creating two groups of the BBB rating: "expansion-BBB" and "recession-BBB", respectively. Among bonds in these two groups, I count how many of them defaulted within 3 years of the rating assignment event, and calculate the ratio of the number of failed bonds over the total number of bonds in each group. The 3-year window is chosen because the sample data has a maximum 3-year history after the end of the recession period (Jan 2009) until the end of sampling period (Dec 2011).

Table 6 presents the ex-post performance of bonds in each rating category. This result shows a stark contrast in the ex-post default frequency between the expansion group (left column) and the recession group (right column). First, bonds that are issued with, or subsequently changed to, a rating A and above do not

[28] There are several definitions of default dates such as a Chapter 11 filing date or a date that a firm misses an interest payment. The most relevant date is the earliest date among these default dates, determined by different trigger events.

[29] The results are reported in Table A.2 in the Appendix.

show any credit events in a 3-year window, for both groups. Bonds in the expansion group start showing credit events once the assigned rating falls to a rating of BBB and below. Bonds in the recession group, however, suffer credit events only in the CCC rating category. This means none of the bonds that were issued with ratings from AAA to B (or bonds that experienced subsequent rating changes to any ratings between AAA and B) in a recession failed within 3 years of the rating assignment event. Moreover, the failure frequency of CCC is also lower in a recession than in an expansion. I find that 5.6 percent of bonds issued at a CCC rating, or downgraded to a CCC rating in an expansion, eventually default. However, only 3.9 percent of those bonds that are assigned a CCC rating in the recession fail.

The effect of the business cycle may contribute to this difference in ex-post performance. Even without rating policy changes, it would be natural to see more credit events with bonds that experienced recession periods. If bonds are issued with a certain rating before a recession, they are likely to show a higher frequency of default than bonds issued with the same rating during the recession, because pre-recession rated bonds may be exposed to some or all of a recession period. To rule out this possibility, I exclude bonds that are issued or assigned with new ratings within 3 years preceding the beginning of a recession. Because the 3-year window is used to measure the ex-post performance, the resulting sub-sample includes none of credit events which occurred in a recession period. The middle column of Table 6 shows the result with the sub-sample. I find that bonds in this sub-sample show slightly worse ex-post performance than bonds that include credit events during the recession. This result bolsters the argument that the difference in ex-post performances must be explained by changes in rating standards. The consistent patterns of ex-post performance imply that bonds in each rating class generally have better credit quality in a recession, rather than an expansion, and provide additional evidence that the the rating standard becomes noticeably more stringent during a recession. Furthermore, the findings of this section address concerns with model incompleteness because they do not depend on any model.

[Insert Table 6 here.]

1.7 Economic Implications

The identified procyclical rating policy has implications for the economy. When investors' perception about a firm's creditworthiness naively relies on the credit rating, the impact on the economy can be especially significant. Suppose that bond investors cannot directly observe corporate bond issuers' credit quality. They rely on rating agencies' technology to extract credit quality and receive signals about it via ratings. In this framework, a change of ratings is a major determinant of bond prices in the secondary market as well as the primary issuance market. Therefore, the rating will have a significant effect on firms' borrowing costs. Obviously, this example is exaggerated. Bond investors may have other information to help them measure credit quality, such as financial statements or price of credit derivatives.

Even in real-world situations where credit ratings are not investors' only source of information, there are several mechanisms by which credit ratings can still affect the market price of a bond. First, a credit rating is the mostly widely used metric for measuring only the credit quality of a firm. Even if rating agencies use only public information to extract credit worthiness, investors might not have the capacity to translate this information into a variable that measures credit risk only.

Second, the market may believe that rating agencies have private information. In fact, until the end of 2011, by Rule 100(b)(2)(iii) in Section 12 of the Securities Exchange Act of 1934, credit rating agencies had been exempted from Regulation FD. This provision exempts firms from disclosing private information that they share with agencies in the course of a rating determination. After the financial crisis, Section 939B of the Dodd-Frank Act removed this exemption.[30] Therefore, at least until the end of 2011, the market must have reacted to rating changes based on the assumption that ratings may reflect the use of private information.

Finally, a large fraction of corporate bond investors are subject to capital and holding regulations based on credit ratings. Property & casualty and life insurance companies are the largest investor in the U.S. corporate bond market. As of then end of 2011, they hold about one third of all corporate bonds.[31] They are required to keep the risk-based capital (RBC) ratio higher than the regulatory level. The RBC ratio depends on the ratings of bonds in their portfolio. Whenever a bond is downgraded, the RBC ratio falls, and the equity holders of these companies have to inject more capital or sell the downgraded security to push the ratio back up. Broker-dealers are also subject to a similar provision which prescribes capital charges for debt securities.[32] Likewise, enhancements to credit rating have a significant influence on institutional investors' demands for rated securities. For example, according to SEC rule 2a-7, the eligible securities that money market mutual funds can hold depends on the credit rating. They are allowed to hold long-term debt securities only if the security has one of the three highest long-term ratings.[33] The effect of these hard-wired mechanisms of credit rating on the borrowing cost and secondary market yield is well documented in Ellul et al. (2011) and Kisgen and Strahan (2010).

I show that the credit rating and eventually changes in the credit rating policy have economic implications through the associated changes in borrowing cost due to aforementioned mechanisms. The counterfactual constructed in Section 1.5.3 provide useful instruments for analyzing this problem. As explained, the counterfactual default boundary V_B' is identified such that the disparity between current (V_B) and counterfactual

[30]In spite of the enactment of this regulation change, it seems that there is no practical impact on the issuing firms' ability to keep the information between them and CRAs private. For more legal discussion, see a publication from Weil , Gotshal & Manges LLP (Finance Digest, Jul 2010).

[31]FRB, Financial Accounts of the United States 2013

[32]See Exchange Act Rule 15c3-1.

[33]These CRAs must be within the Nationally Recognized Statistical Rating Organization (NRSRO) system to satisfy the SEC regulation. Also, there is a recent amendment for Rule 2a-7. The main purpose of the amendment is to reduce over-reliance on the CRA when the board of money market funds decides if the security is eligible. For more discussion, see the SEC documentation (http://www.sec.gov/rules/final/2010/rule2a-7amendments.pdf).

default boundary (V_B') *undoes* the effect of the procyclical rating policy. Specifically, for a given default boundary V_B, I calculated the model-implied spread as follows:

$$Spread(V|V_B) = \frac{C}{D(V|V_B)} - r \tag{1.8}$$

where C is a dollar coupon of total debt, debt valuation $D(\cdot)$ is defined in Equation (1.2), default boundary V_B can be found in Equation (1.4), and r is a risk-free rate from yields of U.S. treasury securities.[34] The difference between $Spread(V|V_B)$ and $Spread(V|V_B')$ during the recession is the portion of the spread difference due to the rating policy change. If a firm were evaluated under the benchmark rating policy during a recession, its borrowing cost would have been more favorable (lower) than a spread under the recession policy. To measure the magnitude of this effect, I compare the median of spread differences due to the tightened rating policy with the median of actual spread changes per rating class. The actual spreads of bonds are obtained through a union of FISD (for the initial yield) and TRACE databases (for the secondary yield) for each sample firm, covering bonds at issuance as well as in the secondary market. To aggregate bond yields to issuer-level, I calculate the volume-weighted average of yields per issuer in each month. Then, I subtract a 1-year constant maturity US treasury rate, to make it comparable to the model-implied spread in Equation (1.8).

[Insert Figure 5 here.]

The lighter bars in Figure 5 indicate median changes in actual spreads between the recession and the expansion for each rating class. During the recession, the credit quality is likely to decline, and the spread of bonds increases to compensate investors for the larger risk. For example, the spread of investment grade bonds, on average, has risen by 101 basis points during the recession.[35] The darker bars in the figure display the difference between $Spread(V|V_B)$ and $Spread(V|V_B')$, the spread change that otherwise would have been zero if the benchmark rating policy had been applied. This result suggests that a certain fraction of actual increase in spreads during the recession can be explained by the procyclical rating policy. On average, such a policy accounts for 11 basis points change or an 11.3 percent of the spread increase of investment grade bonds. In other words, if the benchmark policy were applied in the recession, the spread of investment grade bonds would have increased less by 11.3 percent than it did.

The portion corresponding to the procyclical rating policy differs across credit ratings. The result suggests that the fraction that is attributable to a procyclical rating policy is particularly larger for high yield bonds, making up 21 basis points of the actual increase. This pattern can be attributed to a typical practice of holding regulations that have statutory references to ratings. The cost of holding a security by such

[34] The individual bond is not perpetual debt, therefore their yield to maturity is time dependent. However, when aggregated to the firm level, total debt of a firm preserves the time homogeneity for yield calculation. The result holds for alternative proxies of the risk-free rate such as OIS or Fed fund rate.

[35] These spread changes might not be purely due to the increase in credit risk. They may also reflect changes in market liquidity that tend to dry up upon a negative shock to the economy.

regulations tends to increase exponentially as the rating is downgraded to a lower category. For example, the additional capital the equity holder has to inject in order to hold a unit of bond when a bond is downgraded from B to CCC is much larger than when a bond is downgraded from AAA to AA.[36] Therefore, the selling pressure may also increase exponentially as the bond's rating becomes worse. This channel makes the market yield more sensitive to the rating change when the credit rating of a bond is low.

This result has an implication for the credit spread puzzle. Eom et al. (2004) and Huang and Huang (2003) document that a wide range of structural models produces credit spreads below the historical average. Chen (2010) addresses this problem by linking the business cycle to risk premia that the bond investor requires. Typically, the risk premium increases in recessions, amplifying the rise in actual spreads. Therefore, the change of risk aversion through the business cycle explains the dynamics of the credit spread. I provide an additional explanation to this anomaly: when there is a pricing-relevant impact of the credit rating, the procyclical rating policy also contributes to the spread spike in recessions. For example, Huang and Huang (2003) argue that 56.54 basis points of historical spread in AA rating cannot be explained by the model in Leland and Toft (1996). I find that the actual spreads of investment grade bonds were amplified by 11 basis points in the recession due to the tightened rating standards. This result suggests that spread changes not related to credit risk may contribute to the poor performance of structural models (Schaefer and Strebulaev (2008)), and a model that captures rating-policy-induced spread changes would better explain the observed spreads.

Also, in the context of the model, an equity security can be interpreted as a call option with a knock-out barrier of a default event. When the barrier is hit and a credit event is triggered, the call option value is "knocked out". This security loses value whenever the knock-out barrier increases, holding other things equal. Therefore, comparing the equity value with two default boundaries V_B and V_B' identifies the loss of equity value due to the procyclical rating policy. Specifically, I define the loss as follows:

$$Loss = \frac{E(V|V_B') - E(V|V_B)}{E(V|V_B')} \tag{1.9}$$

where, the equity valuation $E(\cdot)$ is defined as Equation (1.3) in Section 1.4. This comparison shows how much the equity value could have been different if V_B were same as the counterfactual level V_B', i.e., if the benchmark rating policy were applied during a recession. The dashed line of Figure 6 represents the time series of the equity loss for overall firms. It shows that, on average, about 1.65 percent was lost due to stricter rating standards at the peak of the financial crisis. The average loss across firms may not look large. However, the *Loss* can be significantly higher for generally lower-quality firms because the effect of the knock-out barrier is not linear to the equity value. In other words, for firms whose asset level is close to the default boundary, a unit change of V_B makes a larger difference in their equity value than for firms far from default. The comparison of two other solid lines in Figure 6 confirms this argument. The thick solid

[36] For example, property & casualty insurance companies are required to add a 0.7 percent of the bond notional to their capital when the bond is downgraded from AAA to AA. However the required additional capital is a 20 percent of the bond notional when the bond is downgraded from B to C.

line indicates the equity loss of firms with CCC ratings, whereas the thin solid line displays that of firms with AAA ratings. There is almost no loss for equity value of AAA firms due to the procyclical rating policy. However, the equity loss is noticeably larger for CCC firms, reaching close to 5 percent in the recession.

[Insert Figure 6 here.]

This analysis suggests that the procyclical rating policy may have implications for the real economy. Although formally providing quantitative estimates of the real effect of the procyclical rating policy is beyond the scope of this paper, firms make real investment or employment decisions based on their cost of capital, which depends on the rating policy.

Gilchrist and Zakrajsek (2007) provide evidence that the secondary yield of bonds has a causal effect on firm's capital stock and investment. According to their result, a 1 percentage point increase in the bond spread reduces the rate of investment by 50 to 75 basis points and capital stock by 1 percent in the long run. Auh (2013b) explore a mechanism directly related to credit ratings to identify the causal effect. Due to the rating-based capital regulation, constrained insurance companies are forced to sell bonds upon downgrades. The fire-sale transaction depresses the price of the bonds and increases issuers' borrowing costs. Cross-sectional variation of bond investors' regulatory constraints imposes differential shocks to issuing firms. Using the investors' constraints as an instrument, Auh (2013b) finds that a 1 percentage point of the bond spread corresponds to a 12 percent reduction in investment. Using his finding, I approximate the real effect of the procyclical rating standard. The 15 basis point increase due to such policies can be roughly translated to a 1.8 percent reduction in firms' capital flow.

The impact of procyclical rating standards, measured in price terms, is underestimated. In fact, the price elasticity of demand may become significantly lower for high yield bonds: when a new bond is issued with a high yield rating, many investors may not want to (or simply cannot) buy the bond at any price. This tendency is more prominent during an economic downturn. As a result, in some cases, firms with certain ratings cannot borrow money at all. Furthermore, these firms may not even try to issue new bonds, expecting that the financing will not succeed. If a firm falls into this situation due to the procyclical rating policy, the effect would exceed the extra rise in borrowing cost. In the sample, the issuance of high yield bonds is significantly lower in a recession: only about 29 percent of the total amount of debt issuance lies within the high yield category, while it reaches about 49 percent in an expansion. Auh (2013b) examines this extensive margin, and finds that the likelihood of issuing new debt reduces by half when there is a 5 percentage point increase in bond spreads. The drop in both quantity and price of high yield bonds suggests a contraction in the demand of these bonds (or credit supply to firms with high yield ratings). This prediction is consistent with Chernenko and Sunderam (2011). They investigate firms right above and below the investment grade cut-off in terms of observable covariates, and find that belonging to the speculative grade group reduces the issuance and investment.

1.8 Conclusion

In this paper, I show that credit policy is procyclical in the U.S. corporate bond market: rating standards become more generous in an expansion and stricter in a recession. In the wake of the recent financial crisis, there has been an active policy debate about supervision of credit rating agencies as well as investors' rating-based regulations. The analysis of this paper has an implication on those reforms. The existing regulations impose identical treatments on each rating, independent of economic regimes. When the same rating means different things over the business cycle, such regulations may create unintended effects for the economy: a procyclical credit rating policy may amplify the fluctuations of the business cycle. The findings of this paper raise a general question about whether it is efficient to keep the dependency of the financial system on these private entities that potentially implement different rating standards in different times.

Chapter 2

Real Effect of Cost of Financing

2.1 Introduction

The cost of financing is one of the most important factors in a corporation's behavior.[1] The net present value of new project depends on cost of financing, therefore, firms make decisions on capital investment based this information. However, measuring the effect of financing cost on investment decisions is challenging because cost of financing is also endogenously determined by corporate actions. If a firm lacks good investment opportunity or engages in inefficient projects, a bond investor would internalize these facts and raise the required risk compensation, thereby increasing the cost of financing. Therefore, directly running a regression of corporate actions on financing cost potentially yields biased coefficients. Ideally, one would run a random experiment, in which firms receive a random shock to their cost of borrowing. In this experiment, the change in cost of borrowing is not related to any of corporate action or underlying risk. Examining the firm's behavior and decision upon such shocks would, therefore, enable econometricians to measure the causal effect of the cost of financing.

In this paper, I propose an approach with an instrumental variable to address the endogeneity concern and to quantitatively measure the causal effect of borrowing cost. A valid instrument variable should not be related to corporate decisions or firm's fundamental risk while it should have economic reasons to be correlated with the firm's cost of borrowing. The cross-sectional variation of bond investor's characteristics provides a basis for the instrumentation. One of the biggest corporate bond investors are insurance companies. They collectively hold about 30% to 40% of U.S. corporate bonds. This group of investors is highly regulated in terms of capital adequacy. These regulations eventually affect their portfolio choices. In particular, insurers are required to keep their risk-based capital (RBC) ratio above a certain regulatory

[1] The terms of cost of financing, cost of debt or cost of borrowing are interchangeably used in this paper because I focus on the debt financing only.

level. The RBC ratio is calculated as:

$$\text{RBC ratio} = \frac{\text{Equity}}{\text{Risk Charges}}$$

Credit rating of bonds in a insurer's portfolio is one of the factors *among other factors* that define the "Risk Charges". Bonds with low credit ratings have high risk charges, resulting in a lower RBC ratio. If the ratio falls below a certain threshold, the regulator of the state in which the company is registered will take over. Suppose that the RBC ratio of a certain insurance company is near the regulatory level. If a bond in the insurer's balance sheet is downgraded, the RBC ratio of the company would become even closer to the regulatory level. There are two ways to raise the RBC ratio: (1) raising more equity or (2) selling the downgraded bonds. Since raising equity or injection of additional capital would take a long time than selling the downgraded bonds, the insurance company is more likely to sell the troubled bond. This fire-sale transaction would depress the bond's price and increases the issuer's spread. Once downgraded, the pressure due to fire-sales is particularly larger for bonds that are held by insurance companies whose RBC ratio is low.

The risk profile of the insurance companies holding a firm's bonds is exogenous to the firm's policy. The allocation of corporate bonds across investors is not a firm's decision. In the primary market, corporate bonds are typically allocated through underwriting process. Several investment banks form a syndicate that buys the entire issue and eventually distributes it to its clients (in this case, insurance companies). Hence, a firm cannot chose to be held by a particular group of investors. Hence, the cross-sectional variation of regulatory constraint across bond investors provides a valid instrument by imposing differential shocks to firms' borrowing cost upon downgrades.

The fire-sale mechanism due to the regulatory constraint investors is documented by Ellul et al. (2011). They find that bonds held by insurance companies with low RBC ratio experience much more severe price decline after the downgrade event relative to otherwise similar bonds held by insurance companies with high RBC ratio. While they document the price-relevant effect of fire-sales by insurance companies, I analyze the effect of the bond price departure due to the fire-sale to the issuing firms' policy.

Using the RBC ratio and bond position information of both life and property&casualty insurance companies from 2004 to 2010, I create a firm-specific variable that summarizes its bond investors' RBC ratio. Also, in order to measure the cost of borrowing, I create a firm-wide bond spread by aggregating the spread of each bond. Using the bond investor's RBC ratio as the instrument, the result of this paper suggests that 1 percent increase of the cost of borrowing has a causal effect on 12% reduction in capital flow. In order to measure the bias from aforementioned endogeneity problem, I compare results from OLS regression which is not adjusted for the endogeneity. The comparison finds that such endogeneity understates the effect of cost of borrowing on the investment. I find results from the instrumental variable approach is 3,4 time bigger than results of Gilchrist and Zakrajsek (2007) that are consistent with OLS results.

This paper contributes to the strand of literature that document the real effect of security mispricing. Gilchrist et al. (2005) and Lou and Wang (2012) analyze how firm's investment sensitivity changes with respect to equity mispricing. The instrumentation of this paper for the security mispricing is similar to Edmans et al. (2012), who use mutual funds' fire-sale events to measure the causal effect of stock price on the likelihood of take-over. Those papers focus on equity securities, while corporate bonds are the main focus of this paper. Gilchrist and Zakrajsek (2007) ask a similar question and measure the causal effect of bond spread on the capital stock. Unlike their approach, I rely on a specific economic mechanism to address a potential concern related to the reverse causality.

Since the identifying mechanism of this paper relies on the statutory references to credit ratings, this paper also contributes to general discussion about real effects of credit rating and rating agencies' behavior. Kisgen and Strahan (2010) study the effects of rating-based regulations on the cost of debt. They find that one-notch difference in credit rating corresponds to 39 basis points in the cost of capital. Together with their results, the findings of this paper help quantify the real effect of rating changes, through such statutory references to ratings. Moreover, Auh (2013a) documents that rating standards become stricter in recessions relative to expansions, implying that firms receive overly harsh ratings in an economic downturn. As a result, the market spread of bonds tends to increase beyond a level reflecting the declined economic conditions. Findings of this paper and Auh (2013a), taken together, suggest such procyclicality of rating standards may amplify the economic downturn, by imposing a further contraction of investment during recessions.

The analysis is based on two underlying assumptions. First, from the bond investor's perspective, new bonds and old bonds are close substitutes. That is, a bond investor should be indifferent between, say, buying a 5-year-old, 10-year bond and buying a fresh 5-year bond, by the same issuer. Then the secondary market yield affects the yield of new issues, and, the firm must bear the higher cost of debt. If the existing bond has higher yield than the new bond, there is no reason for an investor to prefer the new bond over the old bond, because both are exposed to the same credit risk. For this reason, an issuing firm cannot issue new debt at a yield that is very different from that of existing debt. Indeed, I show that 1 percentage points increase of secondary yield in the previous quarter predicts about 50 basis points of increase in the cost of borrowing of the current quarter. Economic impacts of secondary yield through the observed prices of new bonds are understated. When financing conditions are adverse, a firm may even revoke a financing plan. Therefore, the firm is less likely to issue a new bond. I find that 5 percentage points increase of secondary yield cuts the probability of issuing a new bond by half.

Second, the price effect of such fire-sale event has to prevail long enough to affect firm's decision. If the spread increase is transient and disappears in very short period of time, it is not like to have any impact on firms' investments. Ellul et al. (2011) present evidence that the price reversal is slow. According to their finding, on average, the price dislocation on bond under fire-sale pressure lasts more than 30 weeks. One might think that the deviation of bond price due to the fire-sale should be immediately arrested by arbitrageurs in the market. Therefore, the argument is related to the notion of limits to the arbitrage or slow-moving capital. The effect of fire-sale on the asset price through mechanism of limits to arbitrage are well established both theoretically and empirically. Shleifer and Vishny (1997) propose a model where the fire-sale activity and further price departure from the fundamental value reinforces each other, creating limits to arbitrage. Kiyotaki and Moore (1997) show that this feedback channel can be exacerbated if the arbitrageurs are financed by debt, linking the declining value of a collateral asset and the downward spiral of the asset price. Brunnermeier and Pedersen (2008) develop a model where the price departure is caused by an interaction between market liquidity of the asset and borrowing constraints. The fire-sale effects on price are documented for general class of assets. Coval and Stafford (2007) shows that mutual funds that go through large outflows generate significant downward price pressures on equity securities they hold. Mitchell and Pulvino (2012) provide evidence that the relative price divergence across similar assets, including convertible bonds and credit default swaps, were very high at the peak of the financial crisis of 2008.

The structure of the paper is as follows. Section 2.2 considers a simple illustration to motivate the insight for identification. Sections 2.3 provides data description and summary statistics. Section 2.4 describes the empirical methodology with discussion of its validity. Section 2.5 presents the results regarding the causal effect of cost of borrowing on firms' investment decisions. Section 2.6 provides supporting evidence on assumptions. Section 2.7 concludes.

2.2 Motivation for Identification Strategy

The key identification strategy is that it is not a decision of an issuing firm whether its bonds to be held by good insurance companies (with a high RBC ratio) or bad insurance companies (with a low RBC ratio). Consider two identical issuing firms, A and B. Since they have equivalent underlying risk, the price of their bonds should be also identical. The bond of firm A happens to be bought by a good insurance company and that of firm B is held by a bad insurance company. Now suppose that they receive some negative economic shocks, hence both bonds are downgraded (they are identical firms). As a result, the RBC ratios for both bond investors decline. However, the RBC ratio of the insurance company that holds firm B's bond becomes even closer to the regulatory level. Therefore, the RBC constraint for the bad insurance company is more likely to bind and this insurer is forced to sell the bond. This fire-sale transaction increases the bond spread of firm B relative to that of firm A.

During the period that the price dislocation prevails, firm B has to pay a relatively higher cost of financing. Also, compared to firm A, B is more likely to even retract the plan to issue a new bond as it expects high funding cost. Hence, this change in cost of borrowing would affect the corporate decision to start a new projects. The net present value of the project, which would have been otherwise positive, may become negative with the elevated cost of funding. These decisions will be expressed as the change in capital expenditures. Note that, in this hypothetical illustration, the only difference between these two firms is the variation in investors' characteristics that are out of the issuer's control. Therefore, the difference of investment policies between firm A and firm B arises from the relative difference in the cost of borrowing, and this makes it possible to measure its causal relationship.

2.3 Data Description

I start from non-financial public firms in U.S. stock exchanges, covered by Compustat from 2004 to 2010. To these firms, I merged Capital IQ data to add more variables. Further, I match two different sources of information to construct the sample data. The first source is the TRACE database that contains the secondary trading marks of corporate bond for the sample period. To this database, I merge the detailed bond information such as maturity dates, coupon rates or call features from the FISD database. The spread of a bond is defined as the difference between yield of the bond and yield of a benchmark risk-free security. Therefore, the bond spread captures a risk compensation to the investors for the firm-specific credit risk that they bear, for a given time. The bond spread is the normalized cost of borrowing because subtraction of the benchmark yield eliminates the time variation of common risk in the macro economy. For the risk-free benchmark yield, I use yield of U.S. treasury bond. U.S. treasury issues series of bonds with different durations. However, it does not always issue the whole spectrum of bonds in terms of the maturity. Hence, yields of certain maturities are not available in some quarters. In this case, I interpolate or extrapolate the missing points using cubic-spline fitting methodology.[2] Using this information, I create duration-yield pair of benchmark securities in quarterly basis. To construct a corporate bond spread, I classify the bond yield in the duration bucket and subtract the benchmark yield from the same bucket. For some corporate bonds, their duration is significant longer (as long as 40 year) than the maximum duration from 30 year treasury bond (about 15 year). In this case, I assign a benchmark yield from the maximum duration for these long-maturity bonds.

The resulting bond-level data contains 408691 bond-quarter observations or 42832 unique number of bonds. Panel (I) of Table 7 provides the summary statistics of selected variables. I use this set of data for analyzing how the secondary yield influences the yield at issuance or the probability of issuing a new debt in Section 2.6. To examine the effect of borrowing cost to firms' behavior, I further create quarterly firm-wide borrowing cost by aggregating these bond spreads, using a weight of trading volume of each bond. Finally, to match with the balance sheet data at annual frequency, I create the average spread of a firm of the last 4 quarters, denoted by *Spread*.

The second source is the quarterly holding information of life insurance and property&casualty insurance companies from the National Association of Insurance Commissioners (NAIC) from 2004 to 2010. NAIC is the regulatory support body created by insurance regulators of each state in U.S. territory. The regulated insurers are required to report their holding and transaction information of their asset to NAIC in quarterly basis. The holding data provide detail information about the asset position of reporting insurers (information about bond-investor pair) as well as bond specific information such as bond ratings and market yields.

[2]Cubic-spline fits a curve to the data points by minimizing the curvature of the fitted curve.

Further, I match the RBC ratio information to the insurance companies' bond holdings at each quarter. As fully explained in the Appendix B.1, the RBC ratio is determined by surplus capital and various risk factors including bonds' credit ratings. The RBC ratio considers generally three aspects of risk: asset risk, insurance risk, and business risk. The asset risk captures risks that come from insurance companies' asset composition such as fixed income securities, equity and other derivatives. Through the asset risk calculation, credit ratings of bonds in the balance sheet affect the RBC ratio. The insurance risk is related to the insurer's liability. For example, a variation of insured individuals in terms of mortality (or a fluctuation of the mortality) is one of risk factors for life insurance companies. The business risk generally captures operation risk such as a growth of the litigation cost.

Using this data, I create an issuing firm-specific variable that summarizes the RBC ratio of the firm's investors (insurance companies) at each quarter, denoted by RBC_I. To construct this variable, for each borrowing firm, I aggregate the RBC ratios of firms' investors weighted by bond size in the balance sheet of each bond holder. Therefore, the RBC_I would depend more on the RBC ratio of major bond holders of the firm than other holders whose positions are not substantial. There are firms whose bonds are not held by any of reporting insurance companies. These firms do not experience the forced fire-sale due to the regulation constraint of insurance companies. For the purpose of the analysis, I assume that these firms are held by a hypothetical insurance company with very high level of the RBC ratio (at 90th percentile of the distribution of the RBC ratio) so that the insurer has little motivation to sell the bonds to boost the RBC ratio. The resulting database constitutes a panel data of firms with the collective RBC ratio of their bond investors (RBC_I) and their firm-wide bond spread (*Spread*) as well as other information from the financial statements. The data includes 3958 firm-year observation or 914 unique firms. Panel (II) of Table 7 presents summary statistics of selected variables.

[Insert Figure 7 here.]

2.4 Research Methodology

2.4.1 2SLS IV

The key scope of this study is to measure the causal effect of cost of debt to a firm's investment decision. Specifically, I estimate the following form:

$$\Delta Investment = \beta \cdot Spread + \lambda \cdot X + e \tag{2.1}$$

where $\Delta Investment$ is the change in capital flow measured by percentage change of capital expenditures, *Spread* is a 4 quarter average of firm-wide borrowing cost, and X is a vector of control variables. The coefficient of the interest would be β. However, it is difficult to make a causal statement from the coefficient. In the efficient market, a firm's investment prospects or any future likelihood of investment policy are typically priced in, changing the bond spread. The coefficient may be biased due to this potential reverse causality because, in this case, the residual term e is correlated with $Spread$.

To avoid this possibility, I employ 2-stage least-square regression with instrument variable (2SLS-IV) . The first stage regression for the endogenous variable $Spread$ in Equation (2.1) is

$$Spread = \alpha \cdot RBC_I + \gamma \cdot \tilde{X} + \tilde{e} \tag{2.2}$$

where RBC_I is a firm-wide collective RBC ratio of its bond investors, and $\tilde{X}$ is a vector of control variables. When there is a rating downgrade, bond spread generally increase. However, for a given rating downgrade, the spread is likely to increase even further if the bond is held by an investor that is more forced to sell it, i.e., $corr(Spread, RBC_I) \neq 0$. On the other hand, allocation of the bond across different insurance companies is not a firm's choice. Therefore, the RBC ratio of its investor is exogenous to firm's policy, i.e., $corr(\Delta Policy, RBC_I) \approxeq 0$.

2.4.2 Exclusion Restriction of IV

In order to use the RBC ratio as an instrument, it is necessary to satisfy an exogeneity between the firm's policies and allocation of their bonds across insurance companies. Firms are not likely to consider their investor's RBC ratio when they decide the investment policy, nor are firms likely to choose investors by their RBC ratios. However, this does not assure that there is no economic correlation between the RBC ratio and firms' investment policy. I can think of two possibilities for such a correlation. First, insurance companies with a certain risk profile may intentionally pick bonds of firms that have common characteristics. If these characteristics are likely to affect firms' future investment, then it is possible to have a correlation between RBC ratio and the investment decision. Any such a correlation may vitiate the result from IV approach. However, it is not certain that a bond investor would necessarily prefer firms that are expected to increase their investment. New and potentially risky investment may shift risk from equity holders to bond holders (Jensen and Meckling (1976)). Therefore, there is no obvious reason that an insurance company with a certain range of RBC ration would prefer holding bonds, according to their prediction about the issuer firms' investment policy.

To further show that insurance companies' RBC ratio are not correlated with firms' future investment policy, I examine several characteristics of issuing firms across RBC ratio of their investors. Specifically, I classify insurers into two groups by their RBC ratio: high RBC ratio group and low RBC ratio group. In Table 8, I show that, at the time of purchasing bonds, there are no significant differences in several variables of firms that can be relevant to future investment between the two groups of investors. The table presents that 4 quarter average of investment trend (Inv. Ratio), profitability (NI Ratio), and estimated investment opportunity (Tobin's q) of issuing firms are not statistically different, at the time of purchasing bonds, between each group by RBC ratio. Also, 4 quarter average rating changes (Notches Chg.) and yield (Yield) of purchased bonds are not significantly different. There are also no significant difference in firm size (Mkt. Val.), firm characteristic (Book/Mkt.), and industry (Industry) of issuing firms between two investor groups. While these variables may allow for investors to predict firms' future investment, similarity of these variables supports the exclusion restriction that that RBC ratios of investors are not correlated with investment decision.

[Insert Figure 8 here.]

2.5 Result and Discussion

For each firm-year observation in the sample, I create a variable that indicates a firm has any downgrade on any of its obligations in the past 4 quarter period.[3] If a bond is downgraded, then its spread and eventually cost of borrowing increase accordingly. The higher cost of borrowing causes a reduction in the investment. In Table 9, I present regression results from the OLS regression and the 2SLS-IV specified in Equation (2.1) and (2.2), respectively. Comparison of results from these two models uncovers the potential bias due to the endogeneity. For both regressions, the coefficients β are consistently negative and significant in all specifications. This means that when the spread increases, there is a reduction in investment. However, coefficients from OLS regression are much smaller than those from 2SLS-IV, confirming that the endogeneity creates the upward bias on the coefficient.

The results from 2SLS-IV allow me to make a causal interpretation: 1% change of the spread corresponds to about 12% contraction of capital flow which is measure by $Capex_t/Capex_{t-1} - 1$, where $Capex$ is the capital expenditure from firms' income statements. More intuitively, I find that, when the borrowing cost increases by 1 percent, an average firm reduces the capital expenditure to 88 cents from 1 dollar. Also, the results suggest that the price dislocation from the investors' regulatory constraint prevails in the market long enough to have an impact on firms' investment decision. In fact, Ellul et al. (2011) reports that the abnormal return between bonds in two constrained groups (bonds held by insurance companies with high and low RBC ratio) lasts about 35 weeks after a downgrade event.

In the similar context, Gilchrist and Zakrajsek (2007) document that the 1 percent change of the bond spread reduces 50 to 70 basis point of investment rate. Their definition of investment rate is I_t/K_{t-1} ,where I_t is the nominal investment during period t and K_t is book value of net property, plant, and equipment at the end of period t. The investment I can be backed out from the innovation of the capital $K_{t+1} = K_t + I_t - \delta_t$, where δ_t is a depreciation during period t. To compare my results with theirs, I replicate their measure of investment rate and repeat the analysis. I find that the magnitude of effect in Table 9 is much larger than theirs: my results correspond to 1.8% to 2.1% reduction on the rate of investment, which is 3 or 4 times

[3]For the purpose of this analysis, the downgrade is defined by the NAIC. The NAIC takes the bond ratings from Nationally Recognized Statistical Rating Organization (NRSRO) designated by SEC, such as S&P, Moody's or Fitch. When all of the rating agencies in the NRSRO system downgrades then NAIC also downgrades and the insurance companies' RBC ratio will be affected.

bigger than their results. Their result is consistent with my findings from OLS approach that does not correct biases from the endogeneity. I contemplate several explanations for this difference. First, their strategy to tease out the causal effect of borrowing cost on investment decision depends on a model specification and it may not fully address potential bias. Second, a reduction on the investment due to increase in the borrowing cost may be particularly stronger through the channel of statutory references to ratings.

[Insert Figure 9 here.]

2.6 Additional Analysis

2.6.1 Close Substitutability between Existing Debt and New Debt

Forced sale due to the regulation constraint of the insurance companies creates yield spike in the secondary market. The secondary yield of bonds is not the direct cost of borrowing from a firm's perspective. The issuing firm's cost of debt is determined by a contractual interest rate that the firm promises to pay creditors, when the bond is newly issued. Once the bonds are issued, it can be freely traded in the secondary market and the transaction price among bond investors determines the secondary yield. Even if the a bond is traded at a yield which is significantly different from the initial yield, that risk compensation is not borne by the issuing firm.

However, the secondary price of bonds affects the initial price of the bond which is directly related to the firm's borrowing cost. This is because, for an investor's perspective, old bonds on the secondary market are arguably close substitutes of a newly issued bond of a certain firm. In other word, for a given secondary market yield, the firm is not able to issue a new debt at very different (obviously, lower) yield. If a firm sets the price high for a new bond when the secondary price of bonds from same issuer is much lower, then investors have no incentive to pay more to buy the new bond because both bonds' payout depends on the same underlying credit worthiness of the firm. The substitutability of different bonds from same issuer is documented in previous literature such as Crabbe and Turner (1995) in which they show that bonds with different size from the same issuer are also close substitutes.

Figure 7 shows the time series of median yield of bonds in secondary market and initial yield at the issuance of firms that have at least one issuance in each quarter. The figure shows that they are almost identical over time. Since old bonds and a new bond have the same issuer, an investor is exposed to same credit risk of underlying firm. While same exposure to the credit risk generally makes secondary yield and initial yield similar, they can be a disparity if there are differences in liquidity of old bonds and a new bond. Generally, bonds become less liquid after they are issued. The scarcity of old bonds can make their trading price higher. [4] The liquidity premium may contribute to the small difference between the two curves in the figure. This explanation is consistent with Collin-dufresne et al. (2001) who show that the credit spread is

[4] It is analogous to the price difference between "on-the-run" treasury bond and "off-the-run" treasury bond.

locally affected by liquidity as well as the supply and demand shocks. Nevertheless, the figure shows that the secondary bonds yield and initial yield cannot be far apart.

[Insert Figure 7 here.]

I further perform a predictive regression of firms' initial yield at the issuance on their secondary yield. If the yield of exiting bonds traded in the secondary market changes in the current period, then the initial yield of new bonds to be issued in the following period will be affected. In other words, the current secondary market price of bonds has a prediction power to the price of new bonds in the future. This is because, once an investor observes the secondary market yield, they will demand similar risk compensation for the newly issuing bond. To test this hypothesis, I perform the regression specification as follows:

$$Cost_{i,t} = \beta_0 + \beta_1 \cdot Secondary_{i,t-1} + \beta_2 \cdot Secondary_{i,t-2} + \lambda \cdot FE + e_{i,t} \tag{2.3}$$

where $Cost_{i,t}$ is the issue-size-weighted initial yield or spread that firm i pays at quarter t, $Secondary_{i,t}$ is the trading-volume-weighted secondary yield or spread of firm i's existing bonds at quarter t. When the bond yield is used for $Cost$, a part of its variation may be due to the common factor from the macro economic condition. The changes of borrowing cost due to the time-varying macro factor should be eliminated, in order to measure its dependency on the secondary yield. To address this, I include the time fixed effect, FE, when yield is used for the left hand side variable for Equation (2.3).

2.6.2 Effects of Spread on Decisions to Issue New Bonds

The analysis in Equation (2.3) is from the observation of an equilibrium outcome. It might not capture the full effect of the secondary yield on the economy because a firm may forgo the plan of the issuance when their secondary yield is high enough, with an expectation of worsen financing condition. In this case, the effect through the decision change would not even show in the data of spreads. I also find that the decision to issue new bond is affected by the secondary yield. The following logit regression specification is used to test this:

$$Pr(I_{i,t} = 1) = \pi(\beta_0 + \beta_1 \cdot Secondary_{i,t-1} + \beta_2 \cdot Secondary_{i,t-2} + \lambda \cdot FE + e_{i,t}) \tag{2.4}$$

where $I_{i,t}$ takes value of 1 if there is at lease one new issuance of bonds, and $\pi(\cdot)$ is the logistic distribution function. The other variables have same definition as in Equation (2.3).

The columns from (1) to (3) in Table 10 reports the regression results of Equation (2.4). They consistently show that lagged values of the secondary yield or spread positively affect the contemporaneous cost of borrowing in the primary market. Columns (1) and (2) indicate that 1 percentage point increase of the last quarter's secondary yield has a positive effect on this quarter's initial yield as much as about 50 basis points. Similarly, column (3) shows that, on average, initial spread increases by 32 basis points when last quarter's secondary spread rises by 1 percentage point. Columns from (4) to (6) of the table present the result of regression specified in Equation (2.4). They confirm that increase in the secondary yield or spread makes the issuance of new debt less likely by showing negative and significant coefficients. The marginal probability of the first lagged variable is about 25 basis points. If there is a 1 percentage point change in the yield or spread, then the probability of issuance drops by 25 basis points. It may not look a big effect but given that the unconditional probability of issuance is only about 2.7%, hence 5% changes of the secondary yield would cut the issuance event by half.

[Insert Figure 10 here.]

The Figure 7 and Table 10 provide evidence that the secondary market price of bond has an important implication on the cost of borrowing and firms' financing decision. The results further confirm the mechanism that when a firm receives differential price shock in the secondary market due to a cross-sectional variation of regulatory constraints of its bond holder, the firm also faces differential shocks on the borrowing cost and financing decision.

2.6.3 Implication of Credit Rating Standard

In this paper, causal effects of the cost of borrowing on the real economy is identified through a channel of the regulation based on credit ratings. Therefore, my findings have an implication to general discussions about importance of information quality in credit ratings. In fact, insurance companies are not the only institutional investor that is subject to holding/capital regulations based on credit ratings. Broker-Dealers, banks, money market mutual funds, and pension funds have similar provisions.[5] In the presence of the statutory references to ratings, there is a hard-wired selling pressure of bonds upon rating downgrade. Hence, rating changes for *any* reason may result economic consequences via changes of borrowing cost. Suppose that a bond has a rating downgrade for some reason that is not relevant to credit risk of the issuer. Even in this case, the issuer of the bond may face higher borrowing cost because investors are forced to sell this bond due to such a regulation.

In particular, Auh (2013a) shows that credit rating agencies implement tougher rating standard in recessions and more lenient one in expansions for their own incentive. He finds that this "procyclical rating standards" explains 15 basis points of spread increase in recessions. Using the findings in Section 2.5, the price effect due to the procyclical rating policy corresponds to about 1.8% of capital flow. Intuitively, without the changes of rating standards, 1.8% of reduction in investment could have been avoid during recessions. Putting together, these results suggest that the business cycle may be amplified due to regime-inconsistent rating standard.

[5]See Auh (2013a) for detailed discussions.

2.7 Conclusion

In this paper, I quantify the causal effect of cost of debt to firms' investment decisions through insurance companies' capital regulation based on credit ratings. The bonds are exogenously allocated over investors with different levels of RBC ratio. When a downgrade event occurs, firms held by insurance company with lower RBC ratio face stronger downward pressure on prices, resulting in higher bond spread. This price dislocation due to the fire sale of constrained insurance companies affects borrowing cost of these issuers and tends to last long enough to influence firms' investment decision, creating a real consequence. This paper implies that when investors are subject to holding/capital regulation strictly based on credit rating, changes of credit ratings for *any* reason, may have a significant effect in the economy. In this respect, findings of this paper also suggest that the economy may be vulnerable to any time-inconsistent or inaccurate rating standard.

Chapter 3

Liability Structure and Creditor's Right

3.1 Introduction

We develop a structural model of default in which the optimal capital structure and the optimal mix of short-term debt and long-term debt, known as the liability structure are determined endogenously. Specifically, the paper links the optimal liability structure and the emergence of secured short-term debt protected by "safe harbor" structures to the underlying bankruptcy code, and its lack of effectiveness in protecting the rights of creditors, or entailing dead-weight losses[1].

It is well known that very short-term loans/debt provided by lenders as in repurchase agreements (repo), and asset-backed commercial paper are protected by safe harbor provisions and bankruptcy remote structures respectively. The provision of safe harbor protection to lenders (such as money market mutual funds, for example) who supply short-term financing can be traced back to the Securities Exchange Act of 1934, which was amended in 2005 by the Bankruptcy Abuse Prevention and Consumer Protection Act of 2005 (BAPCPA) to give similar protection to repo loans based on mortgage collateral. The original purpose for giving safe harbor protection was to prevent systemic risk that may arise when a major repo borrower fails, and enmesh a number of repo lenders and other significant counterparties in lengthy and costly bankruptcy proceedings that can precipitate a domino effect. Duffie and Skeel (2012) provide a backdrop to this and other arguments that have been presented in favor of safe harbor provisions.

The BAPCPA of 2005 extended the safe harbor protection to mortgages and mortgage-backed securities in the Bankruptcy Code. This implies that when a repo borrower, who has pledged Treasury, Agency or mortgage-related collateral to borrow cash, files for bankruptcy, the repo lender does not have to join the

[1] There can be other reasons for creating bankruptcy-remote SPV structures, relating to capital relief, and accounting disclosures. These are not treated in our analysis

other creditors and can walk free with the repo collateral. These features make it clear that an important feature of the safe harbor provisions is that it provides super-senior rights to lenders in seizing the collateral which is held *outside the bankruptcy code*.

Our paper's focus is to develop a theory of liability structure in which short-term secured debt and long-term unsecured debt arise optimally. Our theory applies to any secured short-term debt. But of particular interest is "safe harbored" short-term debt, which we model as a special case. To our knowledge, there has been no explicit treatment of how a firm decides on its optimal liability structure when it has the ability to issue such super senior short-term debt, that subjects the firm to "run" risk. In addressing this problem, our paper falls right in the middle of two strands of literature. The first strand is the literature that focuses on how short-term debt such as repo financing can exacerbate aggregate risk by precipitating fire-sale of assets, when there is an aggregate macro shock. The second strand is the literature that attempts to explore how a firm selects its optimal capital/liability structure. Our empirical work fits into the growing body of literature, which examines the empirical determinants of liability and capital structure. We briefly review the literature to place our work in a perspective.

3.1.1 Literature survey and an Overview of Main Results

A number of authors have weighed in on the super-senior rights of repo lenders and the holders of collateral in derivatives transactions. Several authors, notably Gorton and Metrick (2012) have identified the "repo run" due to declining value of collateral and increased "hair cuts" as an important triggering event in pushing the financial sector to the brink of insolvency. Krishnamurthy et al. (2011) argue that the "run" was more severe in repos backed by private sector securities, and that the crisis looked less like a traditional bank run of depositors and more like a credit crunch among dealer banks.

There is a series of papers that discuss about special treatment of bankruptcy code on derivatives [2]. Roe (2011) concludes that "the Bankruptcy Code's safe-harbor, super-priorities for derivatives and repurchase agreements are ill conceived". He observes that "Not only do the provisions facilitate runs on financial institutions during financial crises, they also seriously weaken counter-parties' ex ante incentives for financial stability". Roe (2011) suggests the following counter-factual: in the absence of safe harbor provisions, we should ordinarily expect players to substitute into other financing channels. Bolton and Oehmke (2011) also conclude that safe harbor provisions in derivative markets may lead to undesirable outcomes. They suggest that such provisions for derivatives can lead to inefficiencies by shifting credit risk to the firm's creditors. They further note that as a result of safe harbor provisions, firms may take on derivative positions that are too large from a social perspective. Acharya, Anshuman and Vishwanthan (2012) argue that the automatic stay provisions may be ex-post optimal for loans made under repo agreements, due to the "fire sale" of collateral of firms that were highly levered. They are not concerned with the issue of firm's optimal liability/capital structure, ex-ante. Antinolfi et al. (2012) argue that the exemption from bankruptcy may

[2] This discussion can be traced back to Edwards and Morrison (2005).

result in increased repo lending, and lead to damaging fire sales in the secondary markets. Duffie and Skeel (2012) and Skeel and Jackson (2012) have argued that repo loans should not be insulated from bankruptcy provisions such as automatic stay, although they have concluded that repo loans based on cash-like securities need not be subjected to automatic stay. They suggest that repo loans based on illiquid collateral should be covered by automatic stay.

In the context of this strand of literature, we make the following contributions[3]: first, we examine what should be the optimal response of the borrower when faced with the choice of issuing short-term, secured debt (which subjects the borrower to run risk) *and* long-term unsecured debt. We show that the borrower will internalize the run risk and choose in general a finite amount of secured, short-term debt. In our framework, when the illiquidity of the pledged collateral reaches a certain threshold low value, borrowers will optimally choose not to issue short-term debt protected by safe harbor. This result in consistent with the one of the policies advocated by Duffie and Skeel (2012).

The optimal capital literature in a structural setting has tended to work with a single, homogeneous debt setting, following the insights of Merton (1974), Black and Scholes (1973), Black and Cox (1976) and Leland (1994b).[4] More recently, some papers have attempted to determine the optimal liability structure. Hackbarth and Mauer (2011) emphasize the importance of priority structure of debt in the context of growth options, but they do not address the problem run risk posed by short-term creditors nor do they model super senior rights. Hackbarth et al. (2007) consider bank debt and public debt, and model a situation where the bank debt can be negotiated outside the bankruptcy code. But they treat both debt as perpetual: in their setting, there is no short-term debt, which can expose the borrower to run risk.

He and Xiong (2011) provide a dynamic model of debt runs. They derive an equilibrium and interpret it in a model where each creditor, in deciding whether or not to roll-over his debt, must reflect on other creditors' roll-over actions. Chen et al. (2012) also build a dynamic model of debt structure and make a distinction between idiosycratic risk and systematic risk of firms, and note that this distinction plays an important role in the choice of maturity structure and roll over decisions. Brunnermeier and Oehmke (2013) develop a model that endogenously determines maturity structure of financial institutions in the presence of multiple creditors. The model has a prediction that, during the economic turmoil, each creditor has an incentive to shorten their loan to the bank which would result excessive short-term financing and unnecessary roll-over risk. These papers, by and large, are not concerned with the question of the link between the bankruptcy code and the emergence of safe harbor protected debt as an optimal outcome. Nor are they concerned explicitly about the optimal liability structure of the firms when there is a possibility of a "run" by short-term lenders protected by super-senior provisions. These issues form the basis of our paper. Our paper thus focuses on the question of the level of short-term debt that a firm should optimally select, and abstracts

[3]The policy implications of systemic risk arising from the fire sale of repo collateral is examined by Acharya and Oncu (2012) and Oehmke (2014). We abstract from this question.

[4]Black and Cox (1976) consider both senior and subordinated debt of finite maturity.

from the question of the implications of such debt in the aggregate when there is a macro-economic shock. We believe that this is the first necessary step in tackling that more ambitious policy question.

First, we derive the optimal liability structure of the firm, and show the conditions under which short-term debt with or without safe harbor protection emerges as a component of the optimal liability structure. Second, we show that the borrowers recognize that the short-term lenders (such as money market lenders) have an incentive to "run" and make their loans risk-free. This opportunistic behavior of short-term lenders, who run with their safe harbored collateral is fully internalized by the borrowers when they choose their optimal capital and liability structure. Third, we explore how the extent of dead-weight losses, and the extent to which absolute priority rights are respected influences the optimal liability structure and the use of short-term debt with super-senior provisions. By virtue of the fact that we have a structural framework, we can compute the credit spreads of long-term debt, which internalizes the run risk of safe harbored short-term debt, and effectively reduces the long-term debt capacity of the firm issuing short-term debt protected by safe harbor. The overall debt capacity of the borrower is shown to be higher. Our paper shows that safe harbored short-term debt may increase the value of the firm by lowering the expected dead-weight costs of bankruptcy and escaping potential APR violations.

On the empirical front, Rauh and Sufi (2010) document that lower rated firms tend to have a multi-tiered debt structure consisting of both secured bank debt with tight covenants and subordinated non-bank debt with relatively loose covenants, in comparison with more highly rated firms. Colla et al. (2013) find that unrated firms are much more specialized in their use of debt than rated firms. Within rated firms, degree of debt specialization is hump-shaped. Specifically, the middle group (A and BBB) relies on senior bond and notes and the lower group (BB and B) have multi-tier debt such as term loans, senior bonds and subordinate bonds. Highly rated groups (AAA and AA) use senior bond and commercial paper. This evidence is consistent with our model, which predicts that, in cross-section, only high quality firms will use short-term debt. Billett et al. (2007) deliver an insight that the debt structure and leverage decision are made jointly, rather than independently. Supply-side and financial contracting views suggest debt structure and leverage are tightly linked. Lemmon et al. (2008) document two stylized facts: (1) leverage ratios exhibit a significant amount of convergence over time; firms with relatively high (low) leverage tend to move toward more moderate levels of leverage and (2) despite this convergence, leverage ratios are remarkably stable over time; firms with relatively high (low) leverage tend to maintain relatively high (low) leverage for over 20 years. Thus, they argue that leverage ratios are characterized by both a transitory and a permanent component that is not identified yet. Benmelech and Dvir (2013) use Asian crisis in 1997 as a natural experiment and show that the average maturity within the long-term debt category of banks shortened during the crisis. Their study is about the potential causal relationship between debt maturity and crisis. In order to avoid endogeneity, they focus on long-term debt that was issued well before the crisis but has a maturity date during the crisis period. They conjectured that if short-term debt is the primary cause of the bank failure, then we should expect the probability of failure to be increasing when there is any debt maturing. They do not find any evidence of this and conclude that a decrease in the duration of long-term debt is an equilibrium result of the crisis which is consistent with a prediction of Diamond and Rajan (2001). Almeida et al. (2009) show that the heterogeneity of the debt structure has an effect on the real economy (investment). They focus on firms with a large fraction of their long-term debt maturing right at the time of the crisis and observe that they reduce investment by 2.5% more than matching firms that do not have such debt.

On the empirical front, we examine the following implications of our model: when there is an unanticipated adverse shock to the collateral values and an increase in the riskiness of the collateral, in our model, financial firms face the risk of a run by short-term creditors, which is by far greater than the run risk faced by non-financial firms. It is then optimal for the financial firms to reduce their level of short-term debt and de-lever more than non-financial firms. Using the onset of the credit crisis of 2007 as an exogenous shock to the collateral value and riskiness of collateral, we find support for the model's predictions. We use the ABX prices as a proxy for collateral value, and show that the financial firms, post-crisis, significantly reduced their leverage and short-term debt, when they are exposed to ABX risk. By mapping the Fed's provision of credit to the cross section of firms in our sample, we also demonstrate a supply effect: the Fed's provision of short-term credit buffered the financial firms' decline in leverage and the use of short-term debt. Even after accounting for the Fed's interventions. which brought the credit spreads in the money markets to the pre-crisis levels, there was still a fall in short-term debt and leverage for financial firms, post-crisis. This evidence suggests the presence of a demand effect as well.

The road map of the paper is as follows. Section 2 outlines the pay off functions to creditors and borrowers when the borrowers optimally decide to restructure under the shadow of a bankruptcy code. Section 3 contains the main results of the paper on restructuring, optimal leverage, liability structure, and how they relate to the underlying bankruptcy code. Section 4 contains results about the relationship between the secondary market liquidity of the assets pledged and the incentives of the borrower to use safe harbor debt. This section also contains results about long-term and short-term debt capacities with and without safe harbor provisions. Section 5 contains a detailed empirical analysis of the theory developed in the paper and its related implications for leverage, liability structure and the incentives to use safe harbor debt. We treat the emergence of credit crisis in 2007 as an exogenous event causing a negative shock to the value of collateral that is eligible for pledging and for increasing the riskiness of that collateral. These interpretations allow us to test the empirical implications of our model. Section 6 concludes. Appendix to the paper contains all the derivations, and some supporting evidence.

3.2 Bankruptcy code & the incentives to issue safe harbor debt

The bankruptcy code and its implications for the design of debt contracts has been stressed in the work of Hart (1999), in which he identifies the following desirable goals for an "optimal" bankruptcy code: first, the code must deliver efficient ex-post outcome in terms of maximizing the value available to all claimants.

Second, the code must deliver ex-ante efficiency inducing borrowers to commit themselves to service debt obligations. Such a commitment should be enforced by penalizing borrowers in bankruptcy states. Finally, Hart suggests that a good bankruptcy procedure must respect absolute priority (APR), with the exception that some portion of value should possibly be reserved for shareholders[5].

We explore, in the context of a structural model of default, how these desired properties of the bankruptcy code influences, ex-ante, the choice of firm's optimal liability structure and optimal capital structure. Specifically, we assume that the unlevered asset value of the borrowing firm follows a Geometric Brownian Motion (GBM) process:

$$\frac{dV}{V} = (r - \delta)dt + \sigma dW^{\mathbb{Q}} \tag{3.1}$$

where, r is risk-free rate, δ is the dividend yield, σ is the volatility of asset return and $W^{\mathbb{Q}}$ is standard Wiener process under risk neutral measure $\mathbb{Q}$.

The specification above implies that the investment policy is fixed. This assumption, while restrictive, allows us to focus on the optimal liability structure and optimal leverage decisions of the borrower. In our stylized setting, the borrower can issue two types of debt: one type is instantaneously maturing debt, which serves as a metaphor for short-term secured debt. The debt can be simply secured within the bankruptcy code. Or, lenders of this type may either require the super seniority provisions of safe harbor or a bankruptcy remote structure. We assume that they will be able to monitor the firm closely and "run" at the right moment to make their debt risk-free. The other type of debt is the long-term, unsecured debt, which in our setting is simply a perpetual debt with a specified coupon. The setting is very similar to the classic structural models of default such as Merton (1974), and Leland (1994b). What distinguishes our setting from these papers is the fact that we consider two types of liabilities, and that the short-term lenders make their debt risk-free. Key to our model is the nature of the bankruptcy code, and the implied restructuring possibilities that the code presents to lenders and borrowers. We turn to this next.

3.2.1 Bankruptcy, "run risk" and restructuring

The presence of a bankruptcy code can lead to endogenous restructuring as noted in papers such as Anderson and Sundaresan (1996), Mella-Barral and Perraudin (1997), François et al. (2004), and in Broadie et al. (2007). In these papers, a well defined bankruptcy code, with an automatic stay provision and an associated exclusivity period allows the borrowers to file for bankruptcy and suspend their contractual debt payments as they decide whether to restructure or liquidate. These papers show, under the shadow of such a bankruptcy code, lenders and borrowers will endogenously restructure their claims, without formally entering the bankruptcy process. They provide micro-foundations for the restructuring triggers and relate them

[5]The proviso that "some portion of value should possibly be reserved for shareholders" arises because the borrowers can take excessive amount risk near bankruptcy in the absence of such provisions. In our model, this possibility is ruled out as the investment policy is assumed to be fixed. See Milbradt and Oehmke (2012) and Cheng and Milbradt (2011) who study the link between investment decisions and optimal maturity structure

to the provisions of the bankruptcy code. In this context, the default event can be generally interpreted as a restructuring event between debt holder and equity holder where liquidation of the firm is the special case of the restructuring event. Fan and Sundaresan (2000) present a model of endogenous restructuring under the shadow of Chapter 7 liquidation. Consistent with the approach taken by these papers, we focus our attention on the endogenously determined restructuring boundary V_B, which is the threshold level of the value of the firm at which the borrower decides to restructure. The restructuring boundary is assumed to be optimally chosen by the borrower.

When the borrower has raised capital by issuing both short-term and long-term debt, the question of restructuring becomes more complicated. The short-term lender can "run" precipitating a restructuring of the firm between the long-term lenders and equity holders. Alternatively, the borrower can decide to restructure before the short-term lenders can run.

The firm's short-term debt is assumed to mature at each instant. This nature of the maturity gives the short-term creditor a priority over the long-term creditor. The advantage of short-term debt in our context is that it is essentially risk-free: with the GBM process in Equation (3.1) for the underlying value of the firm's assets, and continuous monitoring, the short-term creditors (who have full information) can promptly act and be repaid the amount lent. This process may come from either channels: (a) run of the short-term creditors culminates in the restructuring of the firm resulting in pay outs to all claim holders, or (b) short-term lender seizes the assets via security or super-senior rights optimally to make their claims risk-free.

The motive for issuing debt can be either due to the tax code or due to agency theoretic considerations. Following the structural models of default, we will assume that the interest expenses associated with servicing debt contracts are tax-deductible. Thus, value is created by short-term debt (and long-term debt) in this model. We assume that the tax rate is τ [6].

3.2.2 Short-term Secured Debt

We denote the value of short-term debt as S. A fraction $\theta \in [0, 1]$ of the assets of the firm is pledged to the short-term creditors. If these pledged assets are held outside the bankruptcy code (as in safe harbor), the short-term lenders can liquidate them at a proportionate liquidation cost of β.[7] The short-term creditors

[6] One may question whether repo debt, an important short-term financing channel for financial firms, would yield any tax benefits, since the transaction is technically selling the asset to the lender with an agreement to buy it back. However, according to GAAP, the difference between original sales proceeds and repurchase amount is considered as interest expenses (see FASB ASC paragraph 860-10-40-24(c)). Also court decisions have ruled that, for tax purposes, repo transactions constitute money borrowings from secured loan. (see Nebraska v. Lowenstein, 513 U.S. 123 (1994); American National Bank of Austin v. United States, 421 F. 2nd 442 (5th Cir. 1970); First American National Bank of Nashville v. United States, 467 F.2nd 1098 (6th Cir. 1972); Rev. Rul. 77-59, 1977-1 C.B. 196.)

[7] He and Milbradt (2012) model how corporate default decisions interact with the endogenous secondary market liquidity through the roll over channel, and identify the potential for a feedback loop between default and secondary market liquidity.

get the assets that have been pledged outside the bankruptcy code. The parameter θ reflects the fraction of assets of the borrower that are eligible to be pledged to secure short-term financing. Not all borrowers will have the same level of eligible collateral. We denote by $\bar{\theta} \leq 1$ as the upper limit on this fraction. This can vary from one borrower to another. Formally, at the "run" boundary, V_R, the payoffs to the short-term lender will be given by the expression below.

$$S(V_R) = \theta(1-\beta)V_R \equiv S \tag{3.2}$$

From the short-term creditor's perspective, they will stop lending when restructuring event occurs. This is the instant when $V_R = \frac{S}{\theta(1-\beta)}$. While our theory will focus on safe harbored short-term debt, the model is general enough to treat secured debt inside the bankruptcy code as we will explain below. Consider a firm that operates in a bankruptcy code in which upon filing for chapter 11, the firm will either emerge with restructured debt and equity claims or liquidate under chapter 7. We assume that the underlying bankruptcy code will lead to a restructuring boundary V_B at which the borrowers (equity holders) get a payout as shown next.

$$E(V_B) = (1-\theta)\alpha_2 V_B \tag{3.3}$$

The parameter α_2 captures the extent to which the borrowers (equity holders) are able to extract some surplus in the restructuring process, and hence reflects the degree to which the underlying bankruptcy code allows borrowers to violate absolute priority rule (APR). If we set $\alpha_2 = 0$ then the equity holders get nothing and the absolute priority rule is fully respected. The possibility that $\alpha_2 > 0$ implies that the bankruptcy code may result in the violation of creditor's rights to the entire residual value of the firm. In the context of Hart (2000), the parameter α_2 captures the extent to which some value is reserved for the equity holders in the bankruptcy procedure, and addresses Hart's goal 3 for a desirable bankruptcy code. Note, however, in our model, there is no scope for the borrower to increase the riskiness of investments as the firm approaches financial distress. Hence the APR violations are pure rents that the borrowers are extracting from the long-term lenders due to some deficiency in the bankruptcy code. This presents another reason as to why safe harbor can add value to the firm, by diminishing this avenue of rent extraction by equity holders.

Long-term debt holders will receive at the restructuring boundary the following payout.

$$D(V_B) = (1-\theta)\alpha_1 V_B \tag{3.4}$$

α_1 indicates the fraction of the firm that the long-term creditor get at default. Therefore $1-(\alpha_1+\alpha_2) \equiv \alpha$ is the total loss in the bankruptcy process. We assume that $\alpha_1 + \alpha_2 \leq 1$ with the understanding that when $\alpha_1+\alpha_2 = 1$, the restructuring process (under the shadow of the bankruptcy code) is fully efficient in the sense that there are no deadweight losses, and the entire residual value is split between equity holders and long-term debt holders. Thus, we distinguish two things: the dead-weight losses associated with restructuring,

We abstract from such issues in our paper.

and the violation of creditor's rights to the full residual value of the firm. The magnitude of $1-(\alpha_1+\alpha_2) \geq 0$ addresses the question of "ex post efficient outcomes" that is delivered by the bankruptcy code.

We formally distinguish between secured debt within the rubric of bankruptcy code, and secured safe harbored debt as follows. If $\beta = \alpha$ and $\alpha_2 > 0$, then we can think of the short-term debt as secured and inside the bankruptcy code. The reasoning is as follows: the short-term lender is subject to the APR violations attributable to the code, but can seize the secured assets at a cost of α. If $\beta < \alpha$, then the safe harbor provision provides an advantage to the lender in seizing the collateral at a lower cost β. We will formally show that the relationship between β and α as well as the presence or absence of APR violations will determine whether or not it is optimal to issue short-term secured debt, and conditional on issuing such short-term, secured debt, whether it should be safe harbored or not.

3.3 Optimal Restructuring and Liability Structure

Let C be the dollar coupon rate promised by the borrower to long-term creditors. Let S be the par value of short-term debt issued by the borrower, which matures at each instant. We begin by asking the following question: given a liability structure $\{C, S\}$ how would the borrower select the optimal restructuring boundary? As in any structural model of default, we assume that the borrower commits to maintain this level and composition of debt until default. Typically, negative pledges are placed to prohibit further issuance of debt and sale of assets. Such provisions can serve to limit significant changes in the capital and liability structure. Based on data gathered from Capital IQ, out of 6315 issuances of financial debt from Jan 1967- April 2012, 88.9% have negative pledge covenants or restriction of asset sales. In addition, 69.7% have negative pledge covenants or cross acceleration provisions.

Let us first suppose that the borrower ignores the "run risk" presented by the short-term lenders in selecting the equity-value maximizing restructuring boundary, V_B. Alternatively, let us suppose that the short-term creditors do not run until the firm chooses to default. We will later explicitly incorporate the run risk imposed by the short-term lenders in the determination of the optimal liability structure and the restructuring boundary by the borrower. This problem is no different from the one studied in the literature before except that we replace the debt cash flows C in the single debt case to $C + Sr$ in the context of our model. This leads to the restructuring boundary, which is stated below.

Proposition 3.1. *Optimal restructuring boundary for equity holders is:*

$$V_B = (1-\tau)\left(\frac{C+Sr}{r}\right)\left(\frac{x}{1+x}\right)\frac{1}{1-(1-\theta)\alpha_2}$$

where $x > 1$ is the root of the equation below:

$$0 = \frac{1}{2}x^2\sigma^2 - x\left(r - \delta - \frac{\sigma^2}{2}\right) - r$$

□

Note that as the APR violations admitted by the code increases, i.e., as α_2 increases, the borrower would like to restructure early to get his share of the residual value of the firm earlier. Finally, note that when $\theta = 1$, APR violations do not influence the choice of restructuring boundary: this is due to the fact that the debt is secured by all assets that the borrower is able to pledge.

Now we relax the assumption that there is no run risk. In the presence of a run risk, the borrower will rationally anticipate that the short-term lenders will run precisely when the market value of the collateral held by them reaches the value S. In other words, when $V \downarrow V_R \equiv \frac{S}{\theta(1-\beta)}$, the lenders will run and refuse to lend any further. Lenders behave this way in our model as they are very risk averse and are content to earn risk-free rate on their loans. Borrowers will reflect the actions of the lenders and choose S^* such that $S^* = V_B\theta(1-\beta)$. This is stated next.

Proposition 3.2. *Borrowers pick S^* such that a) it is equity value-maximizing, and b) the short-term debt is risk-free. In other words, S^* is chosen so that V_B, is set to be equal to the "run" boundary of short-term creditors, V_R, i.e., $S^* = V_B\theta(1-\beta)$.*

□

The economic intuition for the proposition is the following: the run boundary must be such that the short-term debt is risk-free. This is due to the fact that the lenders can continuously monitor the firm and run and make their debt risk-free, and will effectively insulate themselves from default. Hence V_R cannot be less than V_B. On the other hand, if $V_R > V_B$, the borrower will have to retire the short-term debt much sooner, and operate only with long-term debt. The borrower loses the tax-shield, and incurs costs of liquidating collateral, as well as the opportunity costs of losing collateral. So, at the equity-maximizing default boundary V_B the pair $\{C, S\}$ will satisfy the following locus as shown in Figure 8 next.

Figure 8 provides the economic intuition behind Proposition 3.1 and 3.2. Let us set $S = 0$ and note that $\alpha_2 = 0$. In this case, there is only long-term debt and the default boundary coincides with the one found by Leland (1994) as can be seen from Proposition 3.1. This is the Y-intercept of the line V_B in Figure 1. As we increase S, it is intuitive that V_B should increase, but so does V_R. In fact, V_R increases much more rapidly, as the short-term lender will exit sooner to make his loans risk-free. The point where V_R and V_B intersect pins down the level of S that the borrower will choose to pick the restructuring boundary, which maximizes his equity value. It must be emphasized that the level S found will depend on C, and later we will determine the value-maximizing level of C and the associated level of S.

[Insert Table 8 here.]

Combining the two results above, we can express the optimal restructuring boundary solely as a function of the promised coupon rate C on long-term debt. This is presented below.

$$V_B(\theta) = \left(\frac{C}{r}\right) \cdot f(\theta) \tag{3.5}$$

where, we have defined $f(\theta)$ below:

$$f(\theta) = \left(\frac{(1-\tau)(\frac{x}{1+x})(\frac{1}{1-(1-\theta)\alpha_2})}{1-(1-\beta)\theta(1-\tau)(\frac{x}{1+x})(\frac{1}{1-(1-\theta)\alpha_2})} \right)$$

We now turn to the value-maximizing choice of optimal liability structure. The optimal liability structure which maximizes the total value of the firm is given next.

Proposition 3.3. *Optimal liability structure is:*

$$\begin{aligned} C^\star(\theta) &= \frac{rV}{f(\theta)} \left[\frac{1+f(\theta)\cdot(1-\beta)\theta}{(1+x)(1-f(\theta)\cdot g(\theta)/\tau)} \right]^{\frac{1}{x}} \\ S^\star(\theta) &= V \left[\frac{1+f(\theta)\cdot(1-\beta)\theta}{(1+x)(1-f(\theta)\cdot g(\theta)/\tau)} \right]^{\frac{1}{x}} \cdot (1-\beta)\theta \end{aligned}$$

where $g(\theta)$ is:

$$g(\theta) = ((1-\tau)(1-\beta)\theta + (1-\theta)(\alpha_1+\alpha_2) - 1) \tag{3.6}$$

□

Proposition 3.3 is one of the main implications of our model. It shows how the firm chooses the optimal mix of short-term and long-term debt levels, fully internalizing the run risk posed by the short-term lenders. In addition, it links the optimal liability structure to the deep parameters of the model such as a) the fraction of assets that are eligible for pledging, b) deviations from APR admitted by the bankruptcy code, c) the extent to which the financial distress and the resulting restructuring is costly, and d) the volatility of the underlying assets of the borrower.

We discuss below in detail these implications of Proposition 3.3. In the left panel of Figure 9, we plot along the X-axis, α_2, which measures the extent to which the bankruptcy code admits deviations from absolute priority, and along the Y-axis, the value-maximizing ratio of short-term debt to long-term debt implied by our model. These are plotted for three levels of θ: the lowest line refers to the lowest θ and the topmost line refers to the highest θ. We note that when the bankruptcy code admits no violations of APR, generally the firm is able to support a much higher level of long-term debt in all the three cases, with the observation that the firm with greater fraction of eligible collateral for pledging tends to use more short-term debt. As the code begins to admit greater deviations from APR, all the firms (irrespective of their θ) tend to increase their use of short-term debt, although the incentives are much greater for the firms with lowest θ as they have the lowest level of short-term debt to begin with.

The right panel of Figure 9 plots along the X-axis, $\bar{\theta}$, which measures the fraction of eligible collateral that may be used for pledging, and along the Y-axis, the value-maximizing ratio of short-term debt to long-term debt implied by our model. These are plotted for three levels of α_1: the lowest line refers to the lowest α_1 and the topmost line refers to the highest α_1. We note that when the bankruptcy code results in high financial distress costs associated with restructuring, generally the firm is able to support a much lower level of long-term debt. The firm with the greater fraction of eligible collateral for pledging tends to use more short-term debt. In this case, we assume that $\alpha_2 = 0$ so that there are no deviations from APR. This implies that even in the absence of APR deviations, firms in our model have an incentive to use short-term debt. This incentive arises due to the fact that once the assets are pledged outside the code, the costs associated with recovery as summarized by β may be much less than the costs α_1 when the assets are inside the jurisdiction of the bankruptcy code.

The right panel of Figure 9 shows yet another role played by arrangements such as safe harbor and bankruptcy-remote SPVs: when the restructuring process is perceived to be very costly, moving assets outside the bankruptcy code can add value to the borrowing firm as a whole. To the extent that we believe that the bankruptcy and the financial distress resolution process faced by financial institutions is much messier than the ones faced by non-financial firms, then it is reasonable to expect financial firms to use more of these arrangements than non-financial firms. Their ability to use safe harbored debt and SPVs may also be further enhanced by the fact that they may be holding more eligible collateral.

[Insert Table 9 here.]

The left panel of Figure 10 plots the optimal liability structure for increasing levels of underlying asset volatility parameter σ. Note the the liability structure of less risky firms tend to have a greater proportion of short-term debt. In addition, if the firm has a greater fraction of eligible collateral, it is able to sustain a greater proportion of short-term debt in its liability structure.

The optimal leverage in our model is generally higher than Leland (1994b). This is due to the fact that the firm is able to trade off between short-term and long-term debt to optimally take advantage of any inefficiencies in the bankruptcy code. With a costly bankruptcy code, the firm will issue more short-term debt protected by safe harbor. Likewise when the firm has more eligible collateral, it can take advantage of that to increase its optimal leverage. The right panel of Figure 10 examines the relationship between optimal leverage and the volatility of the underlying assets of the borrower.

Note that at very low levels of asset volatility, the borrower tends to use higher levels of leverage, irrespective of the fraction of the assets that are eligible to be posted as collateral. This is due to the fact that at such low levels of σ the borrower's long-term debt capacity is rather high, and this compensates the inability to issue short-term debt when θ is low. This effect can also be appreciated by reviewing the optimal liability structure in the left panel of Figure 10, for various levels of θ. In the right panel of Figure 10, we also report the level of optimal leverage in an otherwise identical Leland (1994b) economy with a single issue of unprotected debt. It is clear that the firm's value in our economy is higher due to the increased level of optimal leverage.

[Insert Table 10 here.]

3.3.1 Creditor's Rights and the Relevance of Safe Harbor Debt

In this section we formalize the economic intuition that with a bankruptcy code, which admits lesser deviations from APR, and lower dead-weight losses, there is no role for safe harbor, unless the costs of liquidating the collateral under safe harbor are lower than the costs under the bankruptcy process. Hence we begin with the assumption that APR is enforced. When Absolute priority rule (APR) is respected, we have $\alpha_2 = 0$. In this case, by virtue of Proposition 3, we get

$$C/r = \frac{S}{f(\theta)(1-\beta)\theta}$$

where,

$$1 + \frac{1}{f(\theta)(1-\beta)\theta} = \frac{1+x}{x(1-\tau)}\frac{1}{\theta(1-\beta)}$$

This implies that $C/r + S = S(1 + \frac{1}{f(\theta)(1-\beta)\theta}) = V_B \frac{1+x}{x(1-\tau)}$. We can now write the total value of the borrower's firm as follows:

$$v(V) = V + \left(V_B \frac{\tau(1+x)}{x(1-\tau)}(1-p)\right) + pV_B\Big(\theta((1-\alpha_1)-\beta) - (1-\alpha_1)\Big) \tag{3.7}$$

Recall that when $\alpha_2 = 0$, $(1-\alpha_1)$ becomes the total loss from the bankruptcy, i.e., $\alpha = (1-\alpha_1)$ and β is the cost of liquidating collateral outside of the bankruptcy code. Then the last term of the Equation (3.7) becomes $pV_B(\theta(\alpha-\beta)-\alpha)$. Note that when $\alpha = \beta$, the firm's value is *independent* of θ. This leads to our Theorem 1, which is stated next.

Theorem 3.1. *When the bankruptcy code protects creditor's rights and the recovery rates to the creditor under the code are identical to the recovery rates when the debt is protected by safe harbor, then the firm's value is unaffected by the presence of safe harbor rights. The value of the firm is independent of the liability structure.*

□

An implication of the theorem is that when $\alpha > \beta$, which is a more natural assumption, the firm will secure all its eligible assets for pledging in safe harbor to issue riskless short-term debt, and will only issue unsecured long-term debt.

Now we examine the problem of designing the optimal liability structure facing the borrowing firm when APR is not respected, so that $\alpha_2 > 0$. Here, there are two interesting cases: The first case wherein $\alpha_1 + \alpha_2 = 1$ implying that the code in the background results in a restructuring that avoids dead-weight losses. The second case is one in which $\alpha_1 + \alpha_2 < 1$, so that there are some dead-weight losses associated with restructuring in the shadow of bankruptcy code. The value of the firm is

$$v(V) = V + \left(V_B \frac{\tau(1+x)}{x(1-\tau)}(1-p)\right) + pV_B\left(\theta\left[\frac{1-\beta}{1-\alpha_2(1-\theta)} - (\alpha_1+\alpha_2)\right] - (1-(\alpha_1+\alpha_2))\right) \tag{3.8}$$

It is easy to show that $\frac{\partial v(V)}{\partial \theta} > 0$ when the bankruptcy code violates creditor's rights and the total bankruptcy leakage is equal or larger than the pure market friction, i.e., $1 - (\alpha_1 + \alpha_2) = \alpha > \beta$. It is interesting to see that even though the dead-weight loss from the bankruptcy is equal to the liquidation cost ($\alpha = \beta$), the equity holder wants to pledge as much as he could. This is a stark contrast to the first case when APR is fully respected. In that case, when $\alpha = \beta$, the firm value is independent of θ. We summarize this result in the following theorem.

Theorem 3.2. *When the bankruptcy code violates creditor's rights and $\alpha > \beta$, and it is optimal to set $\theta = \bar{\theta}$ and issue short-term debt protected by safe harbor. When $\alpha = \beta$, it is optimal to issue secured debt within the bankruptcy code. The optimal liability structure will have secured, short-term debt with or without safe harbor protection and unsecured or partially secured long-term debt.*

□

In the specification above, there are no explicit costs to securing assets outside the bankruptcy code. In reality, however, we may expect both explicit and implicit costs: securing assets outside may require the borrowing form to set up a collateral management program, monitor covenants that long-term creditors may impose by way of negative pledges, restrictions on "sale" of assets, etc. Although, once we model these costs, it is possible to make the optimal level of θ less than $\bar{\theta}$, our existing specification is simple enough to deliver the basic intuition.

Theorem 3.1 and 3.2 suggest that the short-term liability will be, in fact, not only senior to unsecured long-term debt but also secured debt, depending on the nature of the underlying costs of restructuring debt. This has an important implication in our model if we were to calibrate the model to explain the credit spreads. Our framework is potentially capable of mitigating the credit spread puzzle in structural models of default as the existing models do not consider a) the subordination of long-term debt, and b) the higher spreads that long-term creditors would demand since they do not have access to the assets that have been pledged outside the bankruptcy process. Moreover, the existing models do not calibrate to the liability structure of firms.[8]. In the special case, where there are APR violations, i.e. , $\alpha_2 > 0$, and $\alpha = \beta$, there will be an incentive to issue secured debt inside the bankruptcy code, even though there is no incentive for safe harbor.

In Figure 11 we examine the optimality of issuing secured short-term debt within the bankruptcy code. The left panel plots the firm value as a function of θ for different levels of APR violations. When there are no APR violations, there is no advantage to issuing short-term, secured debt within the bankruptcy code in our model: note that the value of the firm is unaffected by θ when $\alpha_2 = 0$. On the other hand, for $\alpha_2 > 0$, there is an advantage to issuing short-term, secured debt, as the value of the firm is increasing in θ.

[8]A number of authors have appealed to macro-economic factors, and time varying risk aversion to help explain the credit spread puzzle. Our argument would be that the issuance of senior short-term debt will automatically increase the spreads at which longer-term debt will be issued. This dimension has not been explored in the credit spread literature. This is a topic of ongoing research.

The right panel plots the ratio of short-term debt to long-term debt as a function of $\bar{\theta}$ for different levels of α_1, under the assumption that there are APR violations. The greater the value of α_1 is, the higher are the benefits of issuing short-term, secured debt.

Theorems 3.1 and 3.2 have strong predictions as to how the secondary market liquidity of the eligible collateral might influence the desirability safe harbored short-term debt. We take this issue up in section 4.

[Insert Table 11 here.]

3.3.2 Linking Restructuring to the Underlying Bankruptcy Code

In the formulation above, we operated in a reduced-form setting and did not establish a direct link between the sharing rules proposed in the restructuring rules in Equation (3.3) and (3.4) and the provisions of the underlying code as discussed by Mella-Barral (1999), François et al. (2004), and in Broadie et al. (2007). We illustrate that link in this section, by using the approach of Franois and Morellec (2004) to illustrate how the provisions of the bankruptcy code influence the choice of the restructuring boundary and the payoffs to borrowers and lenders at the boundary. Two key parameters of the bankruptcy code that are modeled by François et al. (2004), and Broadie et al. (2007) are the following: a) the length of the automatic stay, denoted as d, and b) the flow rate of costs, ϕ, associated with the firm being in the chapter 11 process, attempting to restructure its loans. Using the approach of François et al. (2004), we can link the parameters α_1 and α_2 to these parameters and the bargaining power η of the borrowers as implied by the provisions of the bankruptcy code as in Fan and Sundaresan (2000).

In Figure 12, we plot the implied α_2 for different values of d in years, and for different bargaining powers η (left panel) and for different flow rate of costs (dissipative dead-weight losses of being in the chapter 11 process) ϕ (right panel). Note that if the code allows the borrower to remain in the chapter 11 process for a long period with automatic stay in effect, then the implied deviations from APR can be rather high. As seen in the left panel, the greater the bargaining power of the borrower, the higher is the implied violations of APR. The right panel shows that, as the costs associated with the chapter 11 process decrease, there is more room for shareholder's strategic behavior, hence the APR violations increase. These are fairly intuitive conclusions.

[Insert Table 12 here.]

3.4 Asset Liquidity & Incentives to Use Safe Harbor

The liquidity of the collateral in the secondary market and its appropriateness for backing a safe harbor debt, which is exempt from automatic stay has received some discussion in the literature. Duffie and Skeel (2012) have argued the following: ".. repos [and certain closely related (Qualified Financial Contracts) – QFCs] that are backed by liquid securities should be exempt from automatic stays, or receive an effectively similar treatment. Repos backed by illiquid assets, on the other hand, should not be given this safe harbor." In our model, we can address this question formally: will the borrower optimally choose not to issue safe harbored debt when the secondary market liquidity of its eligible collateral falls below a certain threshold? Intuitively, if β (which represents the secondary market friction parameter in our model) is higher than a certain threshold level, it might not be optimal for the borrower to issue any safe-harbored debt at all. Theorem 1 says that if there are no APR violations and the restructuring process is no more costly than liquidating collateral in the safe harbor, then the firm value is independent of the amount pledged. In fact, if the restructuring cost $1 - \alpha_1 = 0$ then, Theorem 1 implies that $\theta = 0$ as well to prevent a welfare loss. This implies that there is no place for safe harbor under such conditions.

We examine the incremental effect of secondary market friction on the firm's value. We find that there exists $\bar{\beta}$, such that $\frac{\partial v^\star(V,\beta)}{\partial\theta} < 0$ if β ¿ $\bar{\beta}$. This threshold value $\bar{\beta}$ is a function of α_1, α_2 and θ. This implies that if $\beta > \bar{\beta}$, then it is optimal not to use safe-harbor. In other words, the collateral has to be at least more liquid than what is implied by $\bar{\beta}$, given the basic parameters of the bankruptcy code. We can show that it is a decreasing function of α_1 and α_2. If the bankruptcy code implies a costly restructuring (α_1 is high) then the constraint on secondary market liquidity becomes less binding. In a similar vein, if the code results in more APR violations, the constraint on market liquidity becomes more relaxed. This is to say that if the code is efficient, only very liquid asset with very low values of β can be used as the collateral. In this sense, our model implies that the recommendation of Duffie and Skeel (2012) may be based on some desirable properties for the underlying bankruptcy code. This result is summarized in the following corollary.

Corollary 3.1. *If $\beta > \bar{\beta}$, it is optimal not to use safe harbored debt, where*

$$\bar{\beta} = \frac{(1-(\alpha_1+\alpha_2))(1+x\alpha_2(1-\theta)-\tau)+\alpha_2((1-\theta)(1-(\alpha_1+\alpha_2))+((1-\theta)\alpha_1+\theta)(x+1))\tau}{(1-\alpha_2(1+x\theta))(1-\tau)}$$

□

Figure 13 characterizes the region of $\bar{\beta}$ for different levels of frictions (α_1) associated with restructuring under the shadow of bankruptcy code and the possible range of violations of APR that the code admits as captured by α_2.

Note from the left panel of Figure 13 that for α_1 close to 1 (high recovery rates for long-term creditors) and α_2 close to zero (low violations of APR), the value maximizing $\bar{\beta}$ is close to zero, implying that it is only optimal for the firm to use extremely liquid collateral in safe harbored debt. This provides a theoretical context for the recommendation of Duffie and Skeel (2012). On the other hand, if the code admits significant APR violations (high α_2), and the recovery rates to long-term creditors are low, then the firm might wish to use even relatively illiquid collateral in issuing safe harbor debt. Note that in our model the firm is not internalizing the costs associated with the systemic risk implications of issuing safe harbored debt, and any policy action in addressing that question should also take into consideration the nature and efficiency of the bankruptcy code under which the firms are operating.

The right panel of Figure 13, plots the value of the firm with respect to β and θ. It is important to note that a higher θ may either have a beneficial or a negative effect on the total value of the firm. The lighter region indicates that the total firm value increases in θ. On the other hand, the darker region indicates that the total firm value decreases in θ, which occurs precisely when $\beta > \bar{\beta}$, the vertical cut-off point in β axis.

[Insert Table 13 here.]

3.4.1 Debt Capacity

The firm may lose some long-term debt capacity by issuing short-term debt backed by collateral that is under safe harbor. This is due to the fact that the long-term lenders will demand an extra spread to lend when they know that some assets have been pledged away. What about the overall debt capacity of the firm, when the firm decides to use both short-term and long-term debt? This is characterized in the following corollary.

Corollary 3.2. *With short-term debt and long-term debt, the maximum debt capacity is given as:*

$$C_{MAX} = \frac{rV}{f(\theta)} \left[\left(\frac{1}{1+x} \right) \left(\frac{1+\theta(1-\beta)\cdot f(\theta)}{1-(1-\theta)\alpha_1 \cdot f(\theta)} \right) \right]^{\frac{1}{x}}$$

□

It is easy to show that when $\theta = 0$ and $\alpha_2 = 0$, then the firm takes no short-term debt and we recover the debt capacity results of Leland (1994b) setting. Using this as benchmark model (dotted line), in Figure 7, we compare the debt capacity from our model (blue line; $\theta = 1$):

From Figure 14, we see that the debt capacity with short term debt is higher than the benchmark setting. We know that when $\theta = 0$ and $\alpha_2 = 0$, the optimal level of the debt is same as the benchmark model (see the expression for $C^{\star}$).

But this result suggests yet another motivation for firms to use short-term debt with safe harbor: it enables the firm to potentially raise more debt capital at time $t = 0$ and take on bigger projects that might be otherwise not feasible. This will be especially relevant if the code is very inefficient.

[Insert Table 14 here.]

The next figure shows the difference of the maximum debt capacity between the benchmark model ($\theta = 0$) and our model with θ =1 when there is APR violation. We vary α_1 to give some insights about the incremental debt capacity:

For three different levels of α_2, Figure 15 shows that the difference becomes bigger as α_2 gets larger. The dotted line is the case without APR violation ($\alpha_2 = 0$) and the difference becomes 0 when there is no dead-weight loss of the bankruptcy, i.e, $\alpha_1 = 1$.

[Insert Table 15 here.]

3.5 Empirical Implications & Empirical strategy

3.5.1 Empirical implications of the model

The model developed in the paper has several empirical implications. We focus on two specific implications of the model and explore them empirically to examine whether the model's predictions are consistent with the data.

First, the model implies that an adverse shock to the market value of eligible collateral, $\bar{\theta}V$, will lead to both a decrease in leverage [Figure 10, right panel] *and* a decrease in the use of secured short-term debt relative to long-term debt [Figure 10, left panel]. This implication occurs through the following channel: a sudden and unanticipated drop in the value of collateral, increases the probability of a "run" by the suppliers of short-term credit. This is due to the fact the borrower is not able to instantaneously de-lever and lower the short-term debt as predicted by our model. This causes the probability of default/run to go up as well. Since the short-term creditors continue to remain risk-free, the increased probability of default causes the long-term credit spreads to increase. One way to think about this outcome is to note that the short-term creditors do not adjust the price of their credit via higher credit spreads, but they simply refuse to lend if their loans are not risk-free. This captures the behavior of many money market mutual funds during the crisis: many simply refused to lend short-term at any price during the crisis. Gorton and Metrick (2012) provide a detailed treatment of such repo runs. The long-term creditors, in our model, make a price adjustment in response to a crisis, and are prepared to lend, but require high credit spreads. As a result, the borrower would like to reduce the level of short-term debt in response to an adverse shock to the value of the collateral.

Second, the model predicts that an increase in the volatility of assets causes the ratio of short-term debt to long-term debt to go down [Figure 10, left panel] and the leverage to go down [Figure 10, right panel]. When the volatility increases, the default boundary (and hence the "run" boundary") goes up triggering a higher probability of a run. By our earlier arguments, once again, the borrower will wish to lower the short-term debt.

In addition, an increase in the volatility of assets coupled with a sudden drop in the value of the assets operate in our model through two channels: a sudden drop in the value of assets causes $\bar{\theta}$ to go down. This increase the "run" risk by short-term creditors, and causes a natural drop in the ability of firms to issue short-term debt. When the drop in the value of the assets is coupled with an increase in the volatility of the assets, there is an amplification mechanism: both the ratio of short-term debt to long-term debt as well as the leverage go down rather significantly.

In view of the fact that financial firms rely much more on collateralized short-term borrowings such as repo, asset-backed commercial paper, etc. (we provide evidence to this effect in Figure 17). We expect the shocks to $\bar{\theta}V$ and the increased volatility of assets to have a disproportionately bigger impact on financial firms than non-financial firms. Note that, as shown in Proposition 3.3, the optimal capital structure is stable over the state of the economy. Firms do change their capital structure when there are significant changes in the state of the economy and when the firm characteristics such as volatility of assets change significantly. This is consistent with Leary and Roberts (2005) and Strebulaev (2007) who show empirical evidence and intuition that firms adjust their capital structure only infrequently in the presence of adjustment costs.

3.5.1.1 Simulating shocks to $\bar{\theta}V$ and σ in the model

Our model differentiates financial firms from non-financial firms in terms of their ability to pledge assets to raise short-term debt. This variation is modeled by the parameter $\bar{\theta}$ in our framework. We assume in our simulation that $\bar{\theta}$ is drawn from a normal distribution, truncated between 0 and 1 with variance η. Financial firms are expected to have a higher level of pledging capacity than non-financial firms, in general. Hence we set the mean of the distribution for financial firms (denoted by μ_F) to be higher than that of non-financial firms (denoted by μ_{NF}).

In this exercise, financial firms differ from non-financial firms only on two dimensions: $\bar{\theta}$ and σ. We proxy the σ from the monthly return volatility of the equity in the past 12 months to the each observation in the pre-crisis period. In the model σ is the asset return volatility, whereas in the simulation we use equity volatility, for illustrative purposes. We expect asset volatility to be lower than equity volatility due to leverage. It is worth noting that, empirically, average firm-year equity volatility for financial firms is lower than that for non-financial firms. Moreover, financial firms are more heavily levered than non-financial firms. Combining these two facts, it is reasonable to assert that the average firm-year asset volatility of financial firms is lower than that of non-financial firms. Hence, our simulation results essentially proceed on this basic fact.

The hypothetical distribution of $\bar{\theta}$ would in turn determine in our model the distribution of optimal leverage ratios and and the optimal maturity structure. In our simulation, we define the leverage ratio as $(D+S)/(D+S+E)$ and the maturity structure as $S/(S+D)$. These definitions are consistent with our empirical counterparts that we use in the following section. The two figures in top panel of Figure 16 illustrate the derived model-implied distribution before the financial crisis [9]. The lighter (darker) bars indicate the distribution of non-financial (financial) firms. The dashed (solid) vertical bar is the mean of the each distribution.

[Insert Table 16 here.]

The crisis results in a contraction of the pledging capacity, $\bar{\theta}$. We show in the two figures in lower panel of Figure 16 what would happen to the model-implied optimal leverage and optimal maturity structure if there is a reduction of $\bar{\theta}$. We assume that there is a 20% reduction of $\bar{\theta}$ due to the crisis. Again, we use the past 12 month equity volatility (monthly return) in post-crisis period to proxy the σ.

[9] We assume the crisis start from Jan 2007, which we discuss in detail in the following section.

Figure 16 shows the consequence of a decrease in $\bar{\theta}$ and an increase in σ to the model-implied optimal leverage and optimal liability structure. Note that the distance between the means of the distributions (indicated by vertical bars) shrinks after the shocks. Considering the fact that there is no common time trend for these quantities in the way we conducted our simulation, we should expect the financial firms to reduce the optimal leverage and the optimal maturity structure much more than non-financial firms. In reality, we would expect some common time trends and other cross-sectional variations of firms that our simulation does not consider. Our simulation thus provide a useful counter-factual, in terms of holding everything fixed, and is intended to give some intuition about the kind of the effects we may see in real life.

The goal of the empirical strategy is to try tease out from the data whether there is some support for these implications of our model. Rather than pursuing a structural estimation of our model, we rely on a difference-in-differences approach by using the 2007 credit crisis as an instrument for shocks to the value of collateral as well as to its riskiness. In our empirical work, we address the common time trend and other cross-sectional variations.

3.5.2 Financial crisis as an instrument

We use 2007 financial crisis as an instrument to explore the empirical implications of the model. This strategy allows us to capture the "run risk" of short-term debt from an empirical perspective. In our theory, the run risk plays a key role in the way in which firms select their liability structure and leverage. The credit crisis of 2007 had two effects in the context of our model: first, the crisis dramatically reduced the value of certain types of collateral such as mortgages, and mortgage-related collateral. In addition to mortgage related collateral, the crisis generally rendered most risky collateral to be ineffective to obtain secured short-term funding. We interpret this consequence of the credit crisis, in the context of our model, as an adverse (negative) shock to $\bar{\theta}V$. We further hypothesize that this shock will affect financial firms much more severely than non-financial firms.

The credit crisis, in addition to adversely impacting $\bar{\theta}V$, also increased the riskiness of certain types of collateral. This is captured by σ in our model or liquidity cost of collateral, β. We posit that the financial crisis caused the volatility of the assets, σ, of financial firms to increase much more than that of non-financial firms in addition to a negative shock to $\bar{\theta}$ as discussed earlier. Krishnamurthy et al. (2011) documents that there was a significant drop in repo with non-agency MBS/ABS and ABCP funding after the crisis (Figure 4 of their paper), which is consistent with our assumption.

Therefore, the effect of the crisis was to impose a much tighter limitation on a financial firm's capacity to pledge assets to secure short-term funding. In turn, short-term lenders to financial firms will have an incentive to run, and that effect itself will cause adjustments to liability ratio and leverage. In addition, the borrowers may also wish to lower the level of short-term debt and leverage after the crisis in order to reflect the altered market conditions after the crisis.

3.5.3 Sample Period & Dating the Crisis

Our sample period spans 2003 to 2011. Most observers would agree that the period 2003 through the end of 2006 was one in which credit spreads were extremely low. We provide evidence in C.2.2 of Appendix concerning the credit spreads during this period. We wish to use this period to document the differing entry states of financial and non-financial firms when the credit crisis began. The dating as to precisely when the crisis began has to be necessarily subjective. Although the worst period of the crisis was the post-September 2008 period when Lehman Brothers filed for bankruptcy, it is reasonable to argue that the crisis had began well before that. Bear-Stearns experienced problems with its hedge funds as early as in June 2007, and the Federal Reserve began to initiate its policy actions (directed at the crisis) in June 2007. To achieve exogeneity, we need to select the starting point of the crisis such that the crisis was not reasonably anticipated in the period prior to the date that we select. We think that it is reasonable to assume that market did not fully anticipate the full extent of the credit crisis at the end of 2006.

In our data, more than 78% of the financial statements were filed at the end of the calendar year as shown in Table C.2.3 in Appendix. Accordingly we select pick January 2007 as the starting point of the post crisis. We performed some robustness checks on our results using other reasonable choices for the dating of the credit crisis. We find that our results are qualitatively similar.

3.5.4 Data description & Characterization

We start with all the public firms traded on the three major exchanges in the U.S. (NYSE, Nasdaq and AMEX). We impose the criteria that they must have been listed for at least for one year and covered by intersection of Compustat and CRSP database (46,514 observation) from 2003 to 2011. We remove firms with missing information regarding total assets or total liabilities (40,961 remaining). We then match the resulting data with the Capital IQ database, resulting in 21,974 matched observations. Following Colla et al. (2013), we remove firms from our data set if the difference in the total asset values reported by these two databases is greater than 10% (2,204 removed).

We provide in Table C.2.1 the distribution of firms in terms of their liability structure from several different angles. We use the industry classification of Fama and French (1997) to define financial firms. Using their classification, our definition of financial firms comprises of Banking (SIC 6000-6099, 6100-6199), Real Estate (SIC 6500-6553) and Trading (SIC 6200-6299, 6700-6799).

From Table C.2.1, we note that a much higher fraction of financial firms uses multiple classes of debt in terms of their time to maturity. Noticeably larger fraction of financial firms employ short-term debt relative to non-financial firms (93% versus 83%). It is also of interest to see that a number of firms do not have any debt liability at all. These firms have no explicit debt and their liabilities consist of non-debt liabilities such as account payable to vendors or tax liability to the government. Since the focus of our analysis here is to empirically examine the changes in the liability structure when there is a shock to collateral values and the riskiness of the collateral, firms that have no debt are removed from the sample. However, to avoid any selection bias, we include firms that have either only short-term debt or only long-term debt. This way of filtering the data leaves us with 19,244 firm-year observation and 2,961 unique firms. This is our baseline database and it includes 15,208 observations for non-financial firms and 4,036 observations for financial firms: clearly non-financial firms form a much bigger share of our sample.

We further match SNL database to the resulting sample. SNL database provides us with a more detailed information about debt structure and asset composition of financial institutions. Unfortunately, the financial firms in our baseline database are not fully covered by SNL database: SNL covers only 3,139 firms out of 4,036 financial firms in the baseline database. In the formal tests that we present, we use the baseline database but we use the combined data base to provide more disaggregated information about the liability structure.

Since we are interested in analyzing how the firm leverage ratio and debt structure, S/D, interacts with $\bar{\theta}V$ and σ, we have to define the empirical counterparts for these variables. We proxy our theoretical ratio of debt structure S/D by the short-term debt (NP) over total debt (DLTT+DLC) ratio. This definition of short-term debt (NP) and long-term debt (DLTT+DLC) is widely used in the literature: see for example, Baker et al. (2003). We use this variable instead of short-term debt over long-term debt which might look like a more direct measure. Our choice is motivated by the following considerations: first, our choice bounds the ratio from 0 to 1 and allows us to use more observations. Had we chosen the ratio of short-term debt over long-term debt, for the firms which use lots of short-term debt, the ratio measure would have take on very high values. Also, if a firm has no long-term debt and has only short-term debt, the ratio will approach infinity, and would have to be removed from any analysis, introducing a possible sampling bias. However our results are robust to this alternative way of measuring the liability structure. For the $Leverage$, we use total debt (DLTT+DLC) over total asset (AT). Table C.2.2 presents summary of selected variables for financial firms and non-financial firms.

Table C.2.2 makes it is clear that non-financial firms differ in many important respects on observable characteristics such as market capitalization, market to book ratio, proportion of firms that have long-term debt ratings, and the extent of Government support that they received after the onset of credit crisis. In our empirical work we will explicitly control for these observable characteristics on which these two groups differ. In addition, financial firms as a group may also differ from non-financial firms as a group on unobserved characteristics as well. Such unobserved characteristics could be costs of financial distress, differential growth opportunities, etc. We nevertheless believe that our results are sufficiently strong so that they are unlikely to be overturned due to such differences.

In our model, the short-term debt is collateralized debt either within or outside the safe harbor provisions. Although a high proportion of short-term debt issued by financial firms is indeed secured debt such as repo and ABCP, they can also issue unsecured short-term debt as well. Commercial paper (CP) is a typical short-term debt without any explicit security. However, in fact, there is *implicit security* for CP as they are typically backed by a letter of credit or a credit line from banks. Likewise, some long-term debt might have secured debt as well. It would be ideal to disentangle the maturity structure on the dimension of security but we have serious limitations of data. Compustat information for the debt structure in term of underlying collateral is far from complete.

As a remedy, Capital IQ data provide a slightly different angle by grouping debt into secured and unsecured debt, but they do not further sub-classify such debt into long-term and short-term debt. Given the limitation of the data, we use Capital IQ information to see if our definition of short-term debt is a reasonable proxy for the secured debt and vice versa. The Figure C.2.1 in the Appendix shows that the correlation between our measure of short-term debt and total secured debt as reported by Capital IQ is 92%. Likewise, the correlation is 95% for our measure of long-term debt and total unsecured debt in Capital IQ. Also we look at the correlation between the changes in short-term (long-term) and that of secured debt (unsecured debt). The correlation is reasonably high and these results indicate that when the secured debt (unsecured debt) increases, this variation is very well captured by the change in our measure of short-term (long-term) debt definition. Therefore, despite the data limitations, we have some comfort that our measure of short-term debt and long-term debt captures the spirit of the definitions of short-term and long-term debt in our model

3.5.5 Some Motivating Evidence

3.5.5.1 Evolution of S/D ratio, Leverage & Default Likelihood

The model developed here has implications as to how the liability structure and leverage responds with respect to the asset volatility σ. It is intuitive to posit that the asset volatility of firms becomes higher when the economy enters into recession. Our model predicts that firms when confronted with an increase in asset volatility will de-lever *and* reduce the proportion of short-term debt in their liability structure. In Figure 17, we show the time-series of the liability structure of financial and non-financial firms during the period 2003 to 2011. We have also plotted the ABX prices, which serve as a proxy for the collateral value of assets supporting short-term debt.

[Insert Table 17 here.]

The left graph shows the corresponding information for the evolution of leverage for both financial firms and non-financial firms. The right graph shows the evolution of the liability structure for both financial firms and non-financial firms.The time series pattern of changes in the liability structure is much more stable for non-financial firms. It is clear that both financial and non-financial firms lower the fraction of the short term debt after the crisis. For financial firms, the proportion of repo debt increases within the short-term debt, shortly after the crisis. Figure 18 summarizes the empirical implication of our model in relation with σ and $\bar{\theta}$. We will use this figure as a lens to interpret our empirical evidence.

[Insert Table 18 here.]

3.5.5.2 S/D ratio and $Leverage$ with respect to σ and $\bar{\theta}V$ (2007 financial crisis)

The financial crisis of 2007 imposed a significant negative shock to $\bar{\theta}V$, the value of collateral eligible for securing short-term debt. This was, in our view, particularly severe for financial firms relative to non-financial firms as the latter relied, on average, much less on secured short-term debt, and the former relied a great deal on repo and ABCP. The crisis also caused a significant deterioration in the quality of the assets that financial firms could pledge: mortgages and mortgage-related collateral are obvious examples of such assets. In the context of our model, this is captured by σ. Our model predicts that both S/D ratio and $Leverage$ should decrease once the economy has been battered by the credit crisis. Since financial firms as a group experienced a relatively bigger shock than non-financial firms, we may expect to see a higher reduction on both short-term debt to long-term debt ratio as well as the leverage for financial firms when compared to non-financial firms.

It is well known that the Federal Reserve, FDIC and the Treasury mounted a coordinated response to the credit crisis. These interventions could have had a significant impact on both leverage and liability structure of firms in general and financial firms in particular. In this section, we provide a brief summary of those interventions and examine the extent to which they could be driving our results. Fed's interventions that are of direct consequence to our empirical work are the following: a) the Term Auction Facility (TAF), b) the ABCP money markets mutual funds facility, (AMLF), c) Commercial paper funding facility (CPFF), and d) Money markets investor funding facility (MMIFF). These facilities were instrumental in providing a backstop for short-term funding availability to financial firms. These interventions would have had an important impact on the liability structure as well as the leverage of firms in general, and financial firms in particular. In the absence of these facilities, we conjecture that the short-term funding might have collapsed even further than what we have documented in our empirical work.

The Treasury under the Troubled Assets Relief Program or TARP program provided funding to re-capitalize many banks. See Glasserman and Wang (2011) for a detailed treatment of TARP and their valuation issues. Under TARP, about \$450 billion was provided, overall. A significant part of the TARP funding went to banks and automobile industry. TARP was a hybrid security: it provided the borrowers with a redemption option to repay the loans in two years. In this sense, they could be viewed as debt. On the other hand, if the borrowers chose not to pay at the end of two years, TARP funds become preferred stock with very onerous terms to the borrowers. TARP is treated as equity capital in accounting statements, and in the way in which Compustat records TARP. Accordingly, we report our results in Tables 11 and 12 treating TARP as equity. Therefore having more TARP would negatively affect to the leverage ratio. The $TARP$ variable is defined as $TARPamount/TotalCapital(DTC + DLTT + SEQ + MIB)$ and it is used to address the concern that our leverage definition includes TARP, hence suppressing the leverage of financial firms who received the TARP fund. The qualitative results are unaffected if we treated TARP as debt, instead. Also, under the Temporary Liquidity Guarantee Program (TLGP) banks were able to issue both short-term and long-term debt (with a maturity of more than a year) with FDIC-guarantee for a fee.

As noted earlier, the Federal Reserve also actively supplied short-term credit through its various money market oriented programs such as the Term Auction Facility (TAF) introduced in December 2007, Commercial Paper Funding Facility (CPFF) introduced in October 2008, and the short-term portion of the TDGP facility. We mapped in our sample of firms those which received short-term credit from the Fed, and created the variable $Fund$, which measured the proportion of the firm's short-term debt accounted by the Fed's supply. The list of borrowers and amount of loan/ debt is available at the Fed and the FDIC web sites. Unfortunately, the information available for verifying the borrowers' identification is very limited; only the entity names and states are given. This poses a difficulty when we hand-match the borrowers with our sample of firms; the program debt borrowers are often private firms or foreign institutions that are not part of our sample, and therefore the existence of a borrower in the borrower's list does not necessarily mean that there is a matching firm. Given this limitation, we use the borrower's address as the second identifier when the borrower's name is not clear enough to find a match. If neither identifier gives us a confidence for the matching, we assume that there is no matching firm. Note that we have not accounted for all the supply of short-term credit by the Fed in our analysis and mapped them to each firm in our sample: for example, we have not accounted for the ABCP Money Markets Mutual Funds Facility (AMLF) introduced in September 2008, shortly following the Lehman bankruptcy.

We examine these predictions using the following regression specification:

$$Y = \beta_0 + \beta_1 \cdot Fin + \beta_2 \cdot Post + \beta_3 \cdot (Fin \cdot Post) + \beta_4 \cdot (Fin \cdot Post \cdot Fund) + \overrightarrow{\beta} \cdot X + e \tag{3.9}$$

where, Y can be our variable of interest: S/D or $Leverage$ as defined above, Fin is 1 if the firm is classified as financial firm, otherwise 0, $Post$ is 1 if the time is in the post-crisis period, otherwise 0. The variable $Fund$ is the proportion of Fed's short-term credit availed by the firm as a fraction of its total short-term debt. In this regression we use the sample period from January 2003 to December 2011. We report result with and without the triple interaction term ($Fin \cdot Post \cdot Fund$) in the result table. X is a vector of control variable. For the control variable, we use M/B , $log(MV)$, the rating status of the firms, and whether the firm used TARP money. In this specification, the coefficient of interest is β_3 that measures the different reaction of the financial firms in post-crisis period. To deal with outliers, all the ratio variables are winsorized at 1% and we use robust standard error clustered at the industry level for the statistical inference.

Per our theory, we expect that $\beta_3 < 0$, as financial firms which experienced significant run risk in the crisis, to significantly lower their leverage and their short-term debt. In our model, this adjustment occurs at the time of issuance only. But in the empirical context, financial firms arriving at the crisis face a sharp drop in collateral value and face an increased probability of run. This would cause them to reduce short-term debt. In addition, the volatility during the crisis went up. This would cause them to reduce long-term debt as well.

We expect $\beta_4 > 0$ if there is a strong supply (of credit) effect. The run by short-term creditors will leave a hole in the supply of short-term credit to financial firms. Therefore, the Fed's supply of short-term credit will be availed very actively by financial firms if they continue to have demand for it.

[Insert Table 11 here.]

Table 11 tabulates the results of our analysis on leverage ratios as specified in Equation (3.9). We have a total of eight specifications, to account for year fixed-effects, control variables, and government interventions following the credit crisis. While specifications in columns (1B) to (4B) in Table 11 use the triple interaction terms in Equation (3.9), columns (1A) to (4A) do not use the this term. For all the specifications, the coefficient β_3 is negative and significant at 1% level. The point estimates across all eight specifications are of very similar magnitude. The first row confirms the fact that financial firms, as a group, are much more heavily levered than their non-financial counterparts. The coefficient β_2 suggest that, at the aggregate level, there was no de-leveraging activities due to the crisis. Although they are not consistent, they suggest that the leverage ratio has either remained invariant or slightly increased after the crisis. The control variables that we have used (market-to-book, credit rating indicator variable, and market capitalization all load significantly. The coefficients on M/B are consistently negative, indicating that growth firms use less level of leverage. The coefficient on $log(MV)$ and *Rated* suggest an interesting interaction. In the specification (2) and (3) the coefficients on $log(MV)$ is positive, indicating high market cap firms use higher leverage. However, when it is conditioned on whether the firm is rated, it shows the opposite sign. This means that, conditioning on having been rated, bigger market cap firms use less leverage. The coefficients on the rating is also intuitive that having rating opens up the access to the public debt market, the leverage increases. One might argue that rating itself is an endogenous variable because the credit rating depends on the leverage ratio and also debt maturity structure. However we use an indicator variable to flag whether a firm has a rating or not. Hopefully this would mitigate this problem, while controlling the variation of firms' access to the public debt market.

The coefficient of interest is β_3. This captures how the financial firms adjusted their leverage, relative to that of non-financial firms. Across all the specifications, these coefficients are consistently negative and significant. This means that financial firms reduced their leverage, much more when compared to the non-financial firms, in response to the crisis.

The result that the coefficient β_3 is negative and significant is consistent with our model's predictions: the credit crisis represented a major adverse shock to the collateral values (see Figure 17) and their riskiness. The financial firms were much more adversely affected than non-financial firms. As a result, their leverage fell much more significantly than non-financial firms.

The coefficient β_4 is positive and significant across all specifications. This points to the existence of a supply effect: the run in the money markets left a hole in the supply of short-term credit. The Fed's supply allowed financial firms, on average, to reduce their leverage less.

[Insert Table 12 here.]

Table 12 shows the results of our analysis for debt maturity structure. Similar to the previous case, columns (1B) to (4B) in Table 12 use the triple interaction terms in Equation (3.9) whereas columns (1A) to (4A) do not use the this term. Note that financial firms use a much higher level of short-term debt than non-financial firms, which is picked up by the coefficient β_1. One noticeable fact is that the coefficient of *Rated* is consistently negative, suggesting that firms without long-term rating does not have access to the long-term debt market and must rely on private funding such as bank debt which is likely to be classified as short-term debt.

Again, the coefficient β_3 is the main interest of the analysis. They are consistently negative and significant across all the eight specifications. We interpret this evidence as being strongly consistent with our model's prediction: when the parameter $\bar{\theta}$ contracts due to the crisis, financial firms were much more adversely affected than non-financial firms, resulting in more than proportionate reduction in the short-term debt. Our model would have predicted that the probability of a run by short-term creditors would have increased as a result of the crisis. This in turn, would lead rational borrowers to lower short-term debt: thus, our model would have predicted that the suppliers of short-term credit will reduce credit, and the borrowers will demand less as well. The $Fund$ variables is included to address the effect of the supply of short-term credit by the Fed, and the effect that the government guarantee program (TDGP) might have had on the liability structure decisions of the firms. Since the guarantee program spans only a year (Oct 2008 to Oct 2009), maturities of most of issues are less or equal to the end date of the guarantee period. There are usually multiple issues through the program with different principal amounts and maturity from each issuer. We aggregate these issues for each firm. We classify the aggregated issued amount as long-term if the par-value-weighted maturity is longer than 1 year. To compute $TARP$ variable, we divide this aggregate issue amount, classified as long-term, by the total capital of the firm. In this respect, the fact that $TDGP$ has a positive and significant coefficient is interesting. Issuing more long-term bond using the facility would have reduced the debt maturity but it appears that these firms also increased their short-term debt. This might be because there are very small number of firms who issued the long-term bond through this program (only 28 firms). The coefficient β_3 is unaffected by these interventions.

The result that the coefficient β_3 is negative and significant is consistent with our model's predictions: the credit crisis represented a major adverse shock to the collateral values and their riskiness, causing a greater probability of a "run" by short-term lenders. The financial firms were much more adversely affected than non-financial firms by the run risk. As a result, their short-term debt to long-term debt ratio fell much more significantly than non-financial firms.

These results are broadly consistent with our model's predictions. The coefficient β_4 is positive and significant across all specifications: this implies that those financial firms which received short-term funding from the Fed, post crisis, reduced their short-term debt less in their liability structure. Once again, this suggests the presence of a supply effect. Fed's supply of short-term credit appears to have made a big difference to the liability structure of financial firms, on average.

Our results here should be also viewed in the context of the following observations: The credit spreads in money markets, as captured by the LIBOR to OIS spreads and CP to T-bill spreads are reported in Figure C.2.2 in Appendix. We note that after the interventions by the Fed, FDIC and Treasury, the spreads returned to nearly pre-crisis levels. Moreover, many of the Fed's short-term lending facilities were closed as there was no demand at these facilities for short-term credit. For example, TAF closed on March 2010, CPFF on February 2010, and so on. Our results show that the short-term debt and leverage of financial firms fell even after these facilities closed. This is evidence that borrowers were also reducing their demand for short-term debt, and leverage. While this is consistent with the theory's implication that a fall in collateral values should lead firms to de-lever and demand less short-term debt, the result may also be driven by unobserved factors such as the reduced opportunity set after the crisis.

3.5.5.3 S/D ratio and $Leverage$ of Financial Firms with Significant Mortgage Exposure

In this section, we focus just on financial firms. In so doing, we are hoping to tease out the effects of shocks to $\bar{\theta}$ on a subset of financial firms with a higher exposure to mortgage related activities. Since we restrict our analysis to only financial firms, we may expect that the shocks to the σ of the assets are relatively less variable, in cross-section, than in our previous specification where we compared financial firms with non-financial firms. Consider a financial firm which holds a significant amount of mortgage related assets. Given that the mortgages were at the heart of the credit crisis, the ability of this subset of financial firms to secure assets to raise short-term debt shrinks, when the economy is battered by the crisis. Therefore, this subset of financial firms will experience a greater decline in leverage. Furthermore, their debt structure will experience a greater decline in the use of short-term debt. Capital IQ provides some level of disaggregated security-class break-down for financial firms. One of the categories of assets is mortgages. We define the variable $Mortgage$ by dividing the amount of the mortgage related security held by the firm by the total assets of the firm. Our empirical specification is as follows.

$$Y = \beta_0 + \beta_1 \cdot Post + \beta_2 \cdot Mortgage + \beta_3 \cdot (Post \cdot Mortgage) + \overrightarrow{\beta} \cdot X + e \tag{3.10}$$

The coefficient of interest is β_3. If the amplification mechanism is present, the value should be negative because a firm with higher mortgage security delevers and reduces the S/D ratio more dramatically than other firms. Since this analysis is within financial sector, we only have 3 different industry classification. Having too few cluster groups could cause potential downward bias on the standard error. Therefore, in this regression, we use both unclusterd robust standard errors and robust standard errors clustered at the firm level. The results are qualitatively similar and we report the unclustered version. For the control variable X, we use same control variables as above: M/B, $log(MV)$ and $Rated$ variable.

[Insert Table 13 here.]

Table 13 provides the evidence. We have used each firm's fraction of mortgage backed securities to their total assets to capture the differential effect of the crisis. The regression specification we use is as in Equation (3.10), where we define $Mortgage = MBS/TotalAsset(AT)$.

The negative and significant coefficient β_1 indicates that financial firms universally de-lever after the crisis. The coefficients β_2 are positive and highly significant, implying that firms with a higher ownership of mortgages are more highly levered.

The coefficient β_3 would pick up the diff-in-diffs of leverage ratio between financial firms with high level of mortgage related asset and firms without. As model predicted, they are negative when they are significant. Although every specification does not show significance, this generally seems to support the prediction.

[Insert Table 14 here.]

We present the regression analysis of debt maturity structure using only financial firms in Table 14. As in Table 13, we use the regression specification in Equation (3.10). In this case the coefficient β_3 is more consistently negative and significant than the case of leverage. This is strongly supportive of the hypothesis that financial firms with a higher level of mortgage security suffered a greater reduction in $\bar{\theta}$ and hence decreased their short-term debt much more than other financial firms.

It is also of interest to compare these results with those of leverage reported in Table 13, where the effect was much weaker. Keeping the σ constant, our model shows that the S/D ratio is far more sensitive to $\bar{\theta}$ than leverage as shown in the left panel of Figure 18. We may assume that, since these specifications are within the financial industry, the shocks to σ associated with the crisis did not vary too much cross-sectionally.

However, comparing Table 11 and Table 12 does not give us the same pattern: the effect on leverage was very significant with large magnitude. This is because the shock in σ was presumably very different to financial and non-financial firms. The financial crisis triggered larger uncertainty on financial firms. In other words, the crisis imposed a greater shock to σ and negative shock to $\bar{\theta}$ to all firms, but the magnitude of the shock was much more severe on financial firms. Our model implies that the cross-derivatives $\frac{\partial^2(Leverage)}{\partial\theta\partial\sigma} > 0$, under very reasonable assumption of $\beta < 1 - (\alpha_1 + \alpha_2)$, i.e., the liquidation cost of collateral asset is less than the total bankruptcy loss. This implies that when the shock simultaneously causes σ to go up and $\bar{\theta}$ to go down, the leverage drops much dramatically. While the cross-derivatives $\frac{\partial^2(S/D)}{\partial\theta\partial\sigma} < 0$, indicating the impact of decreasing $\bar{\theta}$ is partly mitigated by rise of σ.

Finally, we examine more directly the nature of the shock to collateral values of assets, which supported short-term credit. Since we do not have cross-sectional information on the actual collateral posted by financial firms, we use the ABX prices to proxy for the sub-prime mortgage value. Our goal is to interact the ABX prices with the financial firms in our regression specifications to examine whether firms tended to behave differently when the sub-prime mortgage prices fell dramatically . The regression specification is shown below:

$$Y = \beta_0 + \beta_1 \cdot Fin + \beta_2 \cdot (Fin \cdot ABX) + \overrightarrow{\beta} \cdot X + e \tag{3.11}$$

Table 15 shows the results for the leverage variable. Note that the coefficient $\beta_2 > 0$ across all specifications and is statistically significant. Since the fall in ABX prices coincided with the onset of the credit crisis, our results support the view that the fall in the values of sub-prime mortgages is an important channel for the delevering outcomes that we document.

Table 16 documents the results with respect to the debt maturity structure. We note that the coefficient $\beta_2 > 0$ across all specifications and is statistically significant. Our results suggest that negative shocks to the collateral was an important factor in explaining the drop in short-term debt after the crisis.

[Insert Table 15 here.]

[Insert Table 16 here.]

3.6 Conclusion

We have developed a structural model of optimal liability structure and optimal leverage in which the borrower internalizes the risk of a run by short-term lenders in choosing his liability structure and leverage. When there are violations of APR and dead-weight losses associated with the underlying restructuring process, we show that the borrower has an incentive to use safe harbored debt such as secured repo debt or asset-backed commercial paper. The model has some predictions about how firms will change their liability structure and leverage when there are shocks to eligible collateral that is used for securing short-term debt and when the riskiness of the collateral increases due to an exogenous shock. Using the credit crisis of 2007 as an exogenous shock to the value and riskiness of collateral, we examine the changes in the liability structure and leverage decisions of financial firms relative to the changes in those variables by non-financial firms. The evidence that we report is in broad agreement with the theoretical results developed in this paper.

Using the ABX prices as a proxy for collateral value, we show that the financial firms, post-crisis, significantly reduced their leverage and short-term debt, when they are exposed to ABX risk. We map the Fed's provision of credit to the cross section of firms in our sample, and demonstrate a supply effect: the Fed's provision of short-term credit buffered the financial firms' decline in leverage and the use of short-term debt. Even after accounting for the Fed's interventions. which brought the credit spreads in the money markets to the pre-crisis levels, there was still a fall in the use of short-term debt and leverage after the crisis for financial firms. This evidence suggests the presence of a demand effect as well.

Some caveats are in order: our model does not consider dynamic adjustments to leverage and liability structure. This is clearly an important question. He and Xiong (2011) have considered a framework to include this possibility. We do not allow for variations in the investment opportunity set to the borrower. Clearly, these issues warrant further research.

Tables and Figures

Panel A: Issue-Level Summary

	Mean	St.Dev.	25th Pct.	Median	75th Pct.	N
Coarse Issue Rating	4.47	1.54	3.00	4.00	6.00	487,803
Portion of HY Bonds	0.47	0.50	-	-	-	487,871
EDF	0.08	0.15	0.01	0.02	0.07	487,871
Distance-to-Default	5.14	2.67	3.13	4.91	6.96	487,871
Nbr. of CRA at Issuance	2.13	1.22	1.00	2.00	3.00	487,871
Seniority	4.88	0.51	-	-	-	468,663
Credit Enhancement	0.16	0.36	-	-	-	487,847
Preferred Shares	0.02	0.14	-	-	-	487,847
Callablity	0.78	0.42	-	-	-	487,871
Puttability	0.08	0.27	-	-	-	487,526
Covenant	0.55	0.50	-	-	-	487,762
Coupon Type	2.90	0.36	-	-	-	487,871
Par Value at Issuance	306,702	940,781	75,000	200,000	375,000	487,871
Bond Yield	0.06	0.04	0.04	0.06	0.07	176,372
Bond Age	5.47	4.58	2.08	4.50	7.67	487,871
Time to Maturity	8.53	9.64	2.67	5.58	9.83	484,176
Duration	6.09	4.36	3.15	5.17	7.58	176,031

Panel B: Issuer-Level Summary

	Mean	St.Dev.	25th Pct.	Median	75th Pct.	N
Coarse Long-term Issuer Rating	4.60	1.11	4.00	5.00	5.00	4,977
Assets (in mil. USD)	8,050	15,127	1,211	2,766	7,782	5,370
Equity Market Value (in mil.USD)	8,342	20,391	717	2,067	6,647	5,336
Leverage Ratio	0.51	0.23	0.33	0.47	0.64	4,566
Short-term Debt Ratio	0.03	0.07	0.00	0.00	0.02	5,356
Average Maturity	11.16	4.53	8.04	11.50	14.43	5,372
Book/Market	1.90	1.56	0.83	1.37	2.32	5,336
Undrawn Credit Ratio	0.08	0.18	0.00	0.00	0.00	3,287
Private Debt Ratio	0.19	0.24	0.00	0.07	0.32	3,311
Industry Correlation	0.20	0.17	0.10	0.19	0.30	5,372
Nbr. of CDS dealer (among total firms)	0.35	1.32	0.00	0.00	0.00	5,372
Nbr. of CDS dealer (among firms with CDS)	4.09	2.25	2.00	4.00	5.50	460

Table 1: **Summary Statistics:** This table reports summary statistics of selected variables. There are two layers of data: (1) issue-level and (2) issuer-level. Panel A describes the data in issue-level and Panel B exhibits summary statistics of issuer-level data. In the issue-level data (Panel A), Coarse Issue Rating is a categorical variable which take the following values: AAA=1, AA=2, A=3, BBB=4, BB=5, B=6 and CCC=7. Seniority is also a categorical variable that assigns higher value on more senior bonds: Subordinate = 1, Junior Subordinate = 2, Junior = 3, Senior Subordinate = 4, Senior Unsecured = 5 and Senior Secured = 6. Coupon type assigns following values: Zero coupon = 1, Variable = 2 and Fixed = 3. For Credit Enhancement, Callablity, Puttability, and Covenant take value of 1 when a bond has the corresponding feature, otherwise 0. Bond Age and Time to Maturity are in year. Duration is a Macaulay Duration. In the issuer-level data (Panel B), Coarse Long-term Issuer Rating is from S&P with the same value assignment. Leverage Ratio is total debt over total capital. Short-term debt ratio is a fraction of debt with less than 1 year maturity over total debt. Average maturity is the amount-weighted time-to-maturity. Book/Market is book asset over market equity. Undrawn Credit Ration and Private Debt Ratio are a fraction of associating debt type over total debt. Industry correlation is the industry-wide average correlation of firms' profitability (= Net Income/Total Revenue) with GDP growth rate. Nbr. of CDS dealer is the average number of CDS quote providers.

	Distance-to-Default			EDF		
	Mean	Median	St.Dev	Mean	Median	St.Dev
AAA	8.95	9.10	1.16	0.11%	0.07%	0.17%
AA	7.60	7.30	1.43	0.49%	0.41%	0.45%
A	6.99	6.90	2.02	1.08%	0.74%	1.13%
BBB	5.48	5.14	2.12	2.46%	1.48%	3.40%
BB	3.93	3.72	2.28	11.04%	4.82%	14.32%
B	2.96	2.59	1.81	22.31%	15.17%	20.79%
CCC	1.74	1.18	2.03	44.62%	46.94%	25.24%

Table 2: **Result of Distance-to-Default Estimation:** This table presents estimation results of the distance-to-default in the left 3 columns, and 5-year Expected Default Frequencies (EDF) in the right 3 columns, per rating class. The distance-to-default is estimated from the procedure described in Section 1.4.1 and EDF is obtained from KMV Moody's.

	Distance-to-Default				EDF			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Metric	-0.24***	-0.26***	-0.26***	-0.26***	3.97***	3.97***	4.10***	4.10***
	(-47.31)	(-40.51)	(-41.34)	(-41.11)	(64.54)	(49.59)	(50.12)	(49.69)
Metric·Regime	0.01***	0.01***	0.01***	0.01***	0.68***	0.44***	0.38***	0.38***
	(6.28)	(5.73)	(5.82)	(4.83)	(6.12)	(3.44)	(2.94)	(2.89)
Issuer Industry	N	Y	Y	Y	N	Y	Y	Y
Nbr of CRA	N	Y	Y	Y	N	Y	Y	Y
Seniority	N	N	Y	Y	N	N	Y	Y
Credit Enhance	N	N	N	Y	N	N	N	Y
Preferred	N	N	N	Y	N	N	N	Y
Callablity	N	N	N	Y	N	N	N	Y
Puttability	N	N	N	Y	N	N	N	Y
Covenant	N	N	N	Y	N	N	N	Y
Coupon Type	N	N	N	Y	N	N	N	Y
Cut-offs								
θ_1	-3.20***	-3.11***	-1.33***	-0.89***	-1.52***	-1.56***	0.55***	0.90***
	(-76.95)	(-45.30)	(-6.50)	(-4.00)	(-57.15)	(-32.36)	(2.81)	(4.18)
θ_2	-2.83***	-2.63***	-0.86***	-0.42*	-1.18***	-1.10***	1.00***	1.35***
	(-76.74)	(-41.52)	(-4.22)	(-1.90)	(-50.80)	(-25.33)	(5.11)	(6.33)
θ_3	-1.99***	-1.60***	0.18	0.63***	-0.42***	-0.13***	1.97***	2.33***
	(-64.54)	(-27.14)	(0.86)	(2.83)	(-23.75)	(-3.20)	(10.00)	(10.87)
θ_4	-1.14***	-0.57***	1.21***	1.68***	0.38***	0.82***	2.95***	3.31***
	(-42.51)	(-10.34)	(5.90)	(7.52)	(23.00)	(19.79)	(14.78)	(15.33)
θ_5	-0.65***	-0.02	1.78***	2.25***	0.86***	1.38***	3.52***	3.89***
	(-25.78)	(-0.33)	(8.61)	(10.03)	(49.79)	(31.60)	(17.50)	(17.86)
θ_6	0.43***	1.17***	2.99***	3.46***	2.01***	2.64***	4.82***	5.19***
	(16.91)	(19.71)	(14.14)	(15.16)	(81.57)	(52.25)	(23.34)	(23.38)
N	486850	486850	486826	486436	486850	486850	486826	486436
Pseudo R2	0.092	0.172	0.178	0.181	0.079	0.164	0.173	0.176

Table 3: **Result of Ordered Probit Regression:** This table presents the result of ordered probit regression specified in Equation (1.6). I present four specifications when distance-to-default and EDF are considered as a metric for the credit risk, respectively, in each column (1) to (4). Among Z, Issuer industry is a set of dummy variable according to Fama-French 49 industry classification. Nbr of CRA is the number of CRA that covers this bond at the time of issuance. Seniority is a categorical variable that indicates seniority of the issue (Senior Secured, Senior Unsecured, Senior Unsubordinated, Junior Secured, Junior or Subordinated). Credit enhance and Preferred are sets of dummy variable that indicate the bond has such feature that enhances credit quality or gives preferable treatment to the bond, respectively. Callablity and Puttability are sets of dummy variables that indicate the bond has call or put feature, respectively. Covenant is a dummy variable that assigns 1 if the bond is protected by covenants. Coupon Type is a categorical variable that assigns value depending on the type of coupon of the bond (Fixed, Variable or Zero). The usage of these issue/issuer-specific control variables Z are indicated by yes (Y) or no (N). *Regime* is defined to have 1 in the recession period that is chosen from Jun 2007 to Jan 2009. Numbers inside of parenthesis are the z-value. Standard errors are clustered at issue level. Asterisks denote statistical significance at the 0.01(***), 0.05(**) and 0.1(*).

	$Prob(R = \text{AAA})$	$Prob(R \geq \text{AA})$	$Prob(R \geq \text{A})$	$Prob(R \geq \text{BBB})$
	(1)	(2)	(3)	(4)
Diff. at Most Likely DD	6.61%	5.88%	4.31%	2.46%
Range of Most Likely DD	18-19	13-14	10-11	6-7
Max.Diff.	7.32%	6.38%	4.77%	3.29%
Range of DD for Max Diff.	14-15	14-15	9-10	7-8

Table 4: **Cumulative Probability of Achieving Credit Rating:** This table shows the probability of receiving a rating at or higher than a reference rating in an expansion and a recession. Column (1) displays the probability of having a rating of AAA, the highest rating. Columns from (2) to (4) present the probability of receiving a rating at of higher than AA, A and BBB rating, respectively. First row show the difference in the probability for associated ratings in an expansion and a recession, when the distance-to-default is at a range that gives the highest probability of attaining the associated rating. The second row is those ranges of distance-to-default that is related to the first row. The third row shows the maximum difference of the probability under rating policy under two regimes. The last row indicates the range of distance-to-default when the difference of the probabilities is at the maximum. Recession period that is chosen from Jun 2007 to Jan 2009.

	Rating Difference				Pct. Difference in Default Boundary			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Pct. of retiring debt (m)	1.28	0.57	1.03	0.24	1.33	1.35	1.26	1.27
	4.55***	1.98**	3.76***	0.87	18.44***	16.59***	19.19***	17.12***
Nbr. of CDS dealer	-0.04	-0.02	-0.04	-0.03	-0.01	-0.01	0.00	-0.01
	-1.83*	-0.91	-2.07**	-1.34	-1.65*	-2.15**	-1.06	-1.68*
Ind.-wide corr. with GDP	0.75	0.50			0.09	0.11		
	3.44***	2.13**			2.30**	2.53**		
Book to market	-0.14	-0.26	-0.12	-0.24	0.01	0.01	0.02	0.02
	-6.84***	-8.73***	-5.59***	-8.32***	2.80***	2.55**	5.18***	4.01***
Ln(Market Cap)		-0.29		-0.31		0.00		0.00
		-8.83***		-9.48***		0.49		0.64
Leverage Ratio		-0.76		-0.65		-0.02		0.01
		-3.58***		-2.88***		-0.70		0.34
Industry FE	N	N	Y	Y	N	N	Y	Y
R2	0.05	0.16	0.18	0.28	0.22	0.24	0.30	0.32
N	4204	3508	4204	3508	4239	3508	4239	3508

Table 5: **Cross-Sectional Analysis:** This table presents a regression result for the cross-sectional analysis specified in Equation (1.7). The first dependent variable Rating Difference is the difference of the actual rating and most likely rating under the benchmark rating policy. The second dependent variable Pct. Difference in Default Boundary is defined $\frac{V_B - V_B'}{V_B'}$, capturing the percentage difference of the estimated default boundary relative to counterfactual level. The Pct. of retiring debt is a inverse of average maturity of the existing debt. Nbr. of CDS dealer (N^{CDS}) is average number of quote contributors per firm. This information is from Markit CDS database. Ind.-wide corr. with GDP ($Corr$) is to capture the cyclicality of the business in industry level. To obtain this number, correlation of 4-quarter average of GDP growth rate between firm's net incomes is calculated per firm and it is averaged over industry. Book to market is book value of asset / market value of equity. Ln(Market Cap) is the logarithm of market value of equity. Leverage Ratio is defined total debt/ total capital. Specification (1)-(2) has no industry fixed effect and specification (3)-(4) is controlled for industry fixed effect. The Industry-wide corr. with GDP is industry specific variable, hence it is omitted when industry fixed effect is used.

	Expansion		Expansion (excl. def. in rec.)		Recession	
	Def. Fraction	Total N. Bonds	Def. Fraction	Total N. Bonds	Def. Fraction	Total N. Bonds
AAA	0.00%	432	0.00%	176	0.00%	12
AA	0.00%	80	0.00%	51	0.00%	126
A	0.00%	522	0.00%	403	0.00%	101
BBB	0.09%	1077	0.14%	734	0.00%	268
BB	0.44%	900	0.54%	551	0.00%	158
B	1.02%	1767	1.09%	1370	0.00%	151
CCC	5.56%	701	8.44%	379	3.85%	182

Table 6: **Ex-post Analysis of Default Frequency:** This table presents a 3-year ex-post default event frequency. Each row of the table includes bonds that are initially or subsequently assigned to the corresponding credit rating. In the left and right column, Total Number of Bonds displays the number of bonds that are either issued or regraded at the corresponding rating in each regime (expansion on right, recession on left). In the middle column of the table, Total Number of Bonds include the number of bonds that are either issued or regraded at the corresponding rating in an expansion but that have credit events before the recession period. The credit events information is merged from Moody's Default & Recovery Database. Types of credit events defined in the database cover distress exchange, missed principal and/or interest payment, suspension of payments, Chapter 11 and prepackaged Chapter 11 filing event. Default Fraction column presents the ratio of bonds that have those credit events over the Total Number of Bonds for each rating category. Recession period that is chosen from Jun 2007 to Jan 2009.

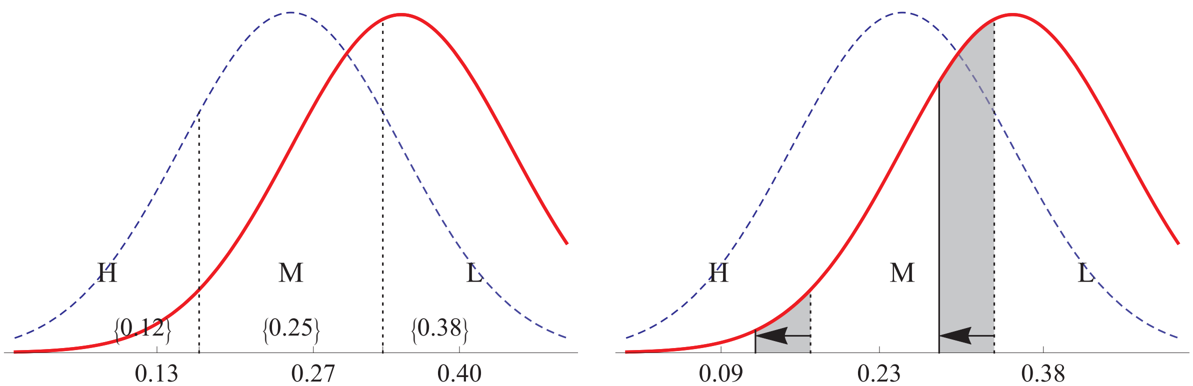


Figure 1: **Hypothetical Firm Distribution in Default Probability:** These plots illustrate the distribution of firms with respect to default probability. Average default probability of firms is reported for each rating category. Dashed curves present the distribution in an expansion while solid curves display the distribution in a recession when the credit quality of firms generally worsens. In the left panel, the dotted vertical lines imply the rating policy by indicating rating cut-off points. In the left panel, the numbers in brackets show the average default probability of each rating bucket when the firm distribution is the dashed curve (expansion) and the numbers under the horizontal axis exhibit mean probabilities when the firm distribution is the solid curve (recession). In the right panel, the solid vertical lines present the stricter rating policy in a recession. The numbers under the horizontal axis in this panel display the mean probabilities of default under the stricter policy.

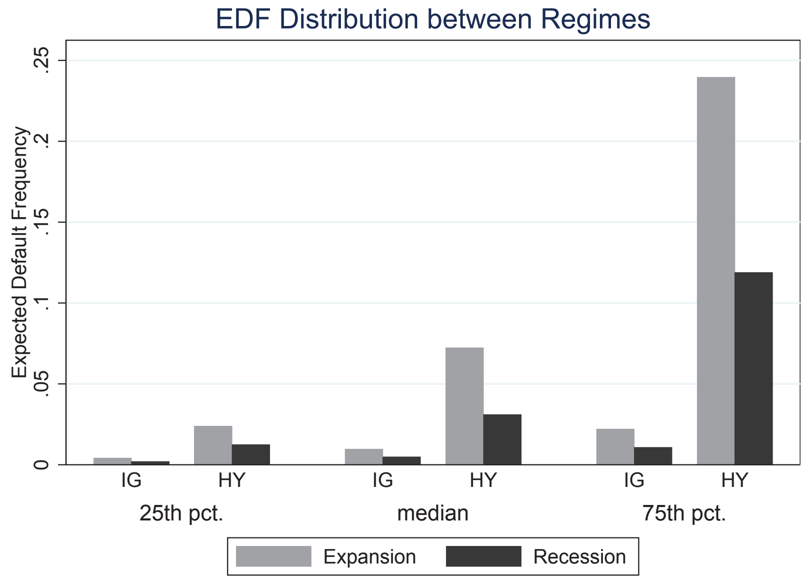


Figure 2: **Expected Default Frequency (EDF) within Rating:** This figure present 3 points (25th and 50th and 75th percentile) of the distribution of 5-year cumulative Expected Default Frequency (EDF), conditioned on two most coarse rating categories; Investment Grade (IG) and High Yield (HY). EDF measures probability that a firm will have a credit event in 5 years and it comes from KMV-Moody's. Recession is defined as a period from Jun 2007 to Jan 2009.

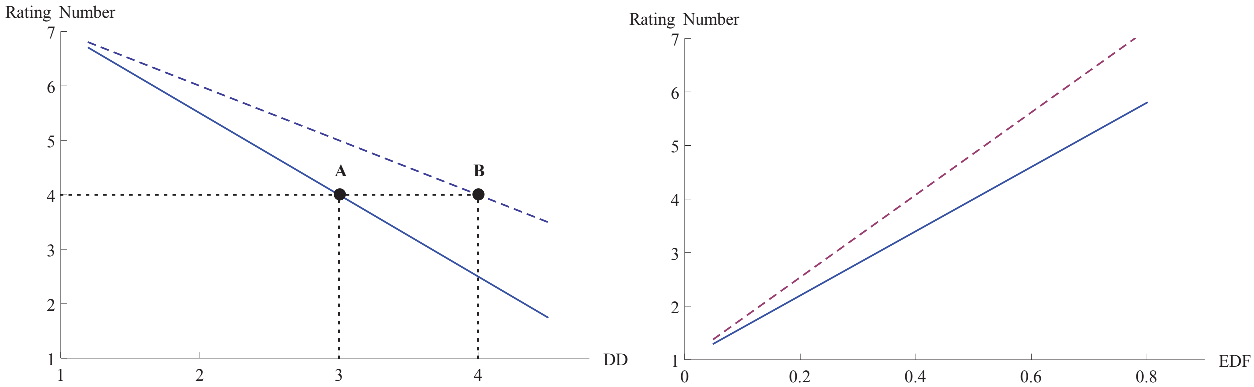


Figure 3: **Illustration of Rating Mapping:** These hypothetical plots illustrate how the credit risk metric is translated to the credit rating. The left panel is when the metric is the distance-to-default (DD) and the right panel is with the EDF. The solid lines represent the mapping functions under relaxed standard and the dashed lines indicate the mapping functions under stricter standard.

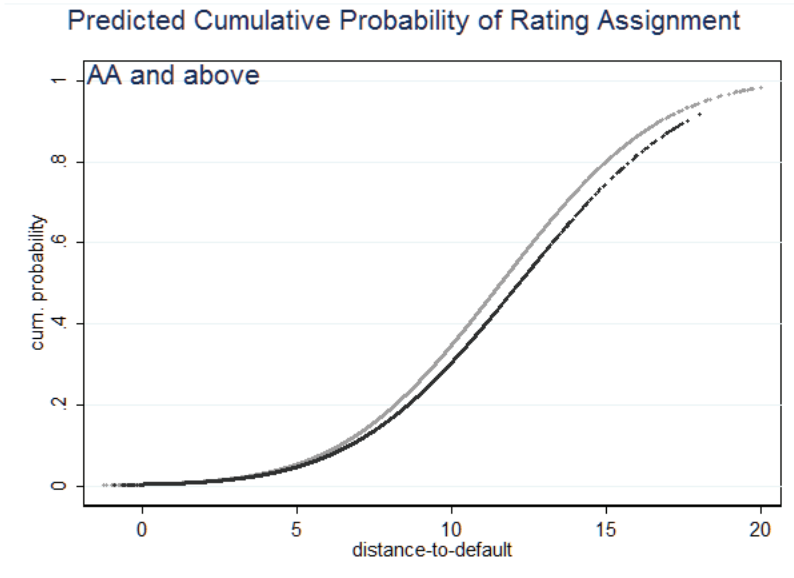


Figure 4: **Predicted Cumulative Probability of Gaining AA or Higher Rating:** This figure shows the probability of achieving a rating AA or higher in term of distance-to-default. The lighter curve is the probability under an expansion period and darker curve is under the policy in a recession period. The difference between these two curves when a firm is most likely to achieve AA rating is 5.9 percent as reported in the first row of Table 4. This is when firms' distance-to-default is between 13 and 14. The maximum difference between these two curves is about 6.4 percent as reported in the third row of the same table. The maximum difference exhibits at the distance-to-default when it ranges from 14 to 15. Recession period that is chosen from Jun 2007 to Jan 2009.

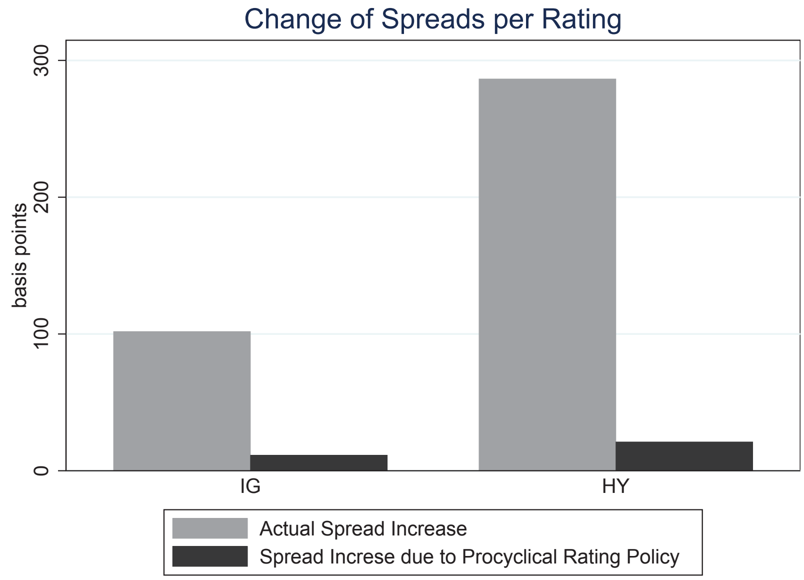


Figure 5: **Credit Spread Change due to Procyclical Rating Policy:** The lighter bars of this plot display changes of median spread between the expansion and the recession period across investment grade and high yield ratings. For example, median spread of investment bond increased by 102 basis points in the recession. The darker bars present the difference in model implied spread between estimated benchmark rating standards and rating standards used in the recession period. For example, the median spread of investment grade bond would have been lower by 11 basis points if the benchmark rating policy were used. Actual spread information is from primary and secondary yields of sample bonds from combination of FISD and TRACE database. The model implied yield is calculated by $\frac{C}{D(V|V_B)}$, where C is dollar coupon for total debt and $D(\cdot)$ is defined in Equation (1.2). In order to obtain spread, I subtracted 1 year constant maturity Treasury rate from actual yield and model implied yield. The recession period that is chosen from Jun 2007 to Jan 2009.

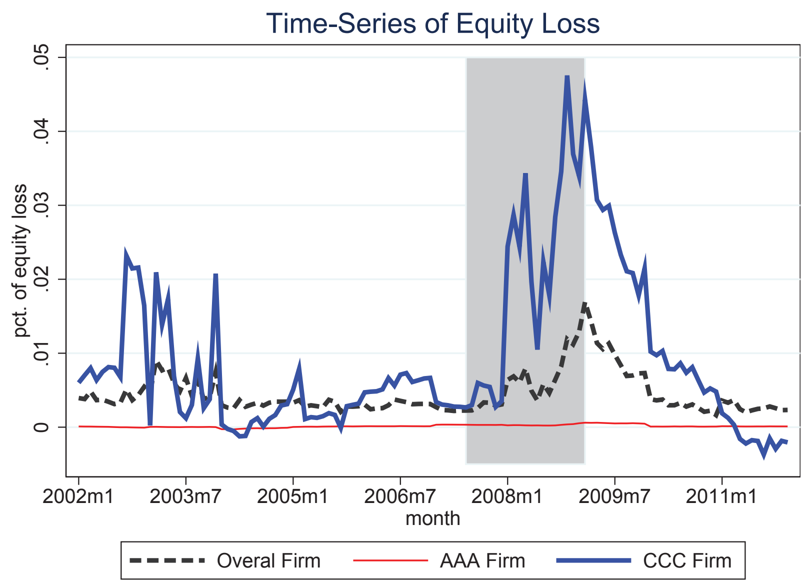


Figure 6: **Equity Loss due to Procyclical Rating Policy:** This figure shows the time-series of mean equity loss due to the procyclical rating policy. The dashed line is mean equity loss of overall firms, while the thick solid line stands for mean equity loss of CCC rated firms, and thin solid line indicates that of AAA rated firms. The equity loss is defined as $\frac{E(V|V_B')-E(V|V_B)}{E(V|V_B')}$, where $E(V|V_B')$ is an equity value under benchmark rating policy and $E(V|V_B)$ is an equity value under rating policy in recession. $E(\cdot)$ is defined in Equation (1.3). This number captures a fraction of reduction in equity value relative to equity value under the benchmark policy. The mean of this loss across firms is plotted over time. The shaded area is the recession period that is chosen from Jun 2007 to Jan 2009.

(I) Bond-level Data

	Mean	St.Dev.	25th Pct.	Median	75th Pct.	N
Quarterly Yield	7.8%	0.09	4.9%	5.8%	7.3%	408691
Quarterly Spread	4.8%	0.10	1.0%	2.3%	4.4%	408691
New Bond	2.7%	0.16	-	-	-	408691

(II) Issuer-level Data

	Mean	St.Dev.	25th Pct.	Median	75th Pct.	N
ΔCapex	8.6%	38.1%	-17.4%	4.8%	27.6%	2973
Leverage	49.8%	21.9%	33.5%	46.8%	62.0%	3328
Log(Market Cap)	8.15	1.54	7.07	8.19	9.34	3803
Log(Asset)	8.52	1.30	7.56	8.48	9.55	3958
Book/Market	1.77	1.30	0.85	1.36	2.22	3803
Tobin's q	1.24	0.54	0.83	1.08	1.49	3803
RBC_I	8.27	1.24	7.41	8.23	9.27	3958
Spread	4.1%	4.0%	1.7%	3.0%	5.0%	3958

Table 7: **Summary Statistics:** These tables present summary statistics of selected variables for (I) bond-level data and (II) issuer-level data. In the bond-level data, Quarterly Yield indicates the quarterly trading-volume weighted average of bond yield either from primary and secondary markets. Quarterly Spread means the quarterly trading-volume weighted average of bond spread in which the bond spread is the difference between the bond yield and benchmark yield in the same duration bucket. New Bond indicates the fraction of newly issued bonds in the sample. In the issuer-level data, ΔCapex is defined as: $\text{Cape}x_t/\text{Cape}x_{t-1} - 1$. Leverage is total debt over total capital (total debt + total equity). Tobin's q is defined as: (Market equity+Book value of debt)/ Book value of asset. RBC_I is the firm-wide variable that summarizes the RBC ratio of the firm's investors (insurance companies). *Spread* is the 4-quarter average of firm-wide bond spread in which firm-wide bond spread is the bond-size weighted average of individual bond spread of the firm.

	Low RBC (mean = 4.41)		High RBC (mean = 17.88)			
Variables	Mean	N	Mean	N	Diff.	t-stat
Inv. Ratio	7.2%	57417	7.3%	54858	-0.1%	-1.5969
NI Ratio	7.8%	84517	8.0%	80021	-0.2%	-0.4225
Notches Chg.	-0.0015	95037	-0.0013	90362	-0.0002	-0.2912
Tobin's q	1.2766	61870	1.2813	62024	0.00	-1.1087
Yield	6.0%	39461	5.6%	34673	0.4%	1.1062
Mkt. Val.	37059	64253	37270	64378	-211	-0.7684
Book / Mkt.	3.0	64243	2.9	64373	0.0	0.8347
Industry	30.6	92980	30.6	88038	0.0	0.1247

Table 8: **RBC ratio and Variables Relevant to Future Investment:** This table presents statistical difference of several variables relevant to future investment and characteristics of issuing firms between insurance companies with high RBC ratio and low RBC ratio at the time of purchasing bonds. Inv. Ratio is 4 quarter average of investment ratio = I_t/K_{t-1} where K_t is a level of property, plant, and equipment at the end of period t and I_t is investment during the period t. NI Ratio is defined as Net Income/Revenue. Notches Chg. is net change of ratings in the past 4 quarters. A positive number of Notches Chg. means the bond's rating has been downgraded in the period. Tobin's q = (Market Equity + Total Debt) / Book Asset. Yield is average yield of a bond in the past 4 quarters if any traded yields are available. Mkt. Val. is market value of equity of issuing firm. Book / Mkt. is defined as Book Value Asset / Market Value Equity. Industry is number-coded according to Fama-French 49 industry classification.

	OLS				2SLS-IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Spread	-0.02***	-0.02***	-0.03***	-0.03***	-0.13**	-0.12**	-0.12**	-0.12**
	(-11.88)	(-11.03)	(-10.24)	(-10.37)	(-2.30)	(-2.12)	(-2.05)	(-2.06)
Tobin's q		0.03**		0.09***		-0.05		0.04
		(2.28)		(2.70)		(-0.35)		(0.33)
Leverage			0.08*	0.02			0.72**	0.69*
			(1.94)	(0.32)			(1.98)	(1.94)
Log(MktValue)			0.03*	-0.03			-0.14	-0.16
			(1.84)	(-1.11)			(-0.87)	(-0.87)
Log(Asset)			-0.06***	-0.00			-0.00	0.02
			(-3.82)	(-0.00)			(-0.03)	(0.17)
Industry	N	N	Y	Y	N	N	Y	Y
N	2973	2865	2416	2416	494	472	414	414

Table 9: **Result of IV Regression:** This table presents the result of OLS and 2SLS-IV regression in Equation (2.1) and (2.2), respectively. The columns from (1) to (4) report the results from OLS regression and the columns from (5) to (8) report from the results from 2SLS-IV regression. The LHS variable ΔInvestment is defined as the percentage change of capital flow, $\Delta\text{Investment}_t = (\text{Capex}_t/\text{Capex}_{t-1}) - 1$. Spread is the value-weighted bond yield from TRACE less benchmark treasury yield (from same duration bucket). Tobin's q is defined as (Book value of debt + Market value of equity) / Book asset value. Leverage is a ratio of total debt over total capital. Log(MktValue) is logarithm of market value equity. Log(Asset) is logarithm of book asset value. The firm industry is controlled according to Fama-French industry classification when the Industry row indicates "Y".

	Cost of Borrowing			Decision to Issue		
	(1)	(2)	(3)	(4)	(5)	(6)
Secondary Yield (lagged 1)	0.58***	0.50***		-0.11***	-0.07***	
	(4.88)	(3.80)		(-4.68)	(-4.28)	
Secondary Yield (lagged 2)	-0.05	0.03		-0.02	-0.03**	
	(-1.60)	(0.43)		(-1.14)	(-2.03)	
Secondary Spread (lagged 1)			0.32**			-0.08***
			(2.56)			(-4.52)
Secondary Spread (lagged 2)			0.04			-0.03**
			(0.44)			(-2.32)
Time FE	N	Y	N	N	Y	N
R2	0.44	0.29	0.05	0.02	0.14	0.02
N	285	285	285	70739	21260	70714

Table 10: **Predictability of Secondary Bond Yield:** This table presents the regression specification in Equation (2.3) (column (1) to (3)) and Equation (2.4) (column (4) and (6)). The left hand side variable for the regression in the column (1) and (2) is the current bond yield at issuance. The left hand side variable for the regression in column (3) is the current bond spread at issuance. Columns (1) to (3) are estimated by OLS model. The left hand side variable for regression in the columns (4) to (6) is the indication variable about firms' decision of issuing a new debt in the quarter (1 if it issues; 0 otherwise) and they are estimated by logit model. Time fixed effect is used when the independent variables are yield to capture the time variation of the reference interest rate (column (2) and (5)). For logit model (column (4) to (6)), the pseudo R-square, calculated by the improvement of log likelihood, is reported.

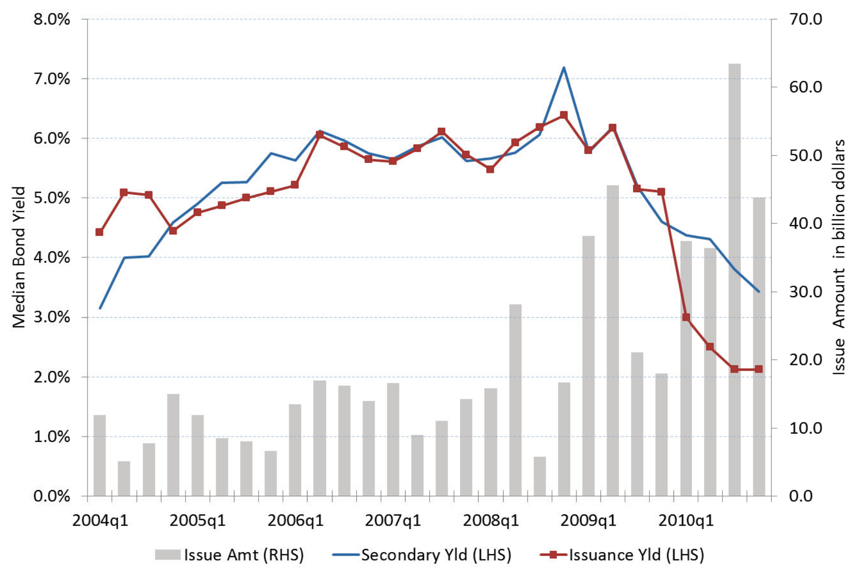


Figure 7: **The Time Series of Secondary Yield and Yield at Issuance:** This plot shows the time series of the median yield of bonds in the secondary market and yield of bonds at the issuance in the sample period from 2004 to 2010. Specifically, among firms that have at least one issuance of new bond in each quarter, I calculate the average firm-quarter bonds yield in the secondary market, weighted by trade volume, excluding the yield of bonds the firms issue in the quarter. The median of these secondary yield is presented in the solid line (LHS). Also, I calculate the average firm-quarter yield of new bonds in the quarter, weighed by issuance size. The median of these yields at issuance is presented in the line with square marker (LHS). Bars in the plot (RHS) indicate the total issue amount in the sample firms. The unit of bars is billion U.S. dollars.

	(1A)	(1B)	(2A)	(2B)	(3A)	(3B)	(4A)	(4B)
Fin	0.2240***	0.2240***	0.1784***	0.1784***	0.2362***	0.2362***	0.2364***	0.2364***
	(10.66)	(10.66)	(7.59)	(7.59)	(12.05)	(12.05)	(12.03)	(12.02)
$Post$	0.0249***	0.0249***	0.0005	0.0006	0.0164**	0.0164**	0.0149	0.0150
	(3.01)	(3.01)	(0.04)	(0.05)	(2.11)	(2.11)	(1.22)	(1.22)
$Fin{\cdot}Post$	-0.0683***	-0.0693***	-0.0511***	-0.0518***	-0.0713***	-0.0720***	-0.0604***	-0.0610***
	(-6.02)	(-6.12)	(-4.25)	(-4.32)	(-6.33)	(-6.40)	(-4.85)	(-4.90)
$Fin{\cdot}Post{\cdot}Fund$		0.4401***		0.2953***		0.2850***		0.2956***
		(11.83)		(7.08)		(9.36)		(6.23)
M/B			-0.0543***	-0.0543***	-0.0304***	-0.0304***	-0.0303***	-0.0303***
			(-4.31)	(-4.31)	(-2.90)	(-2.90)	(-2.86)	(-2.86)
$log(MV)$			0.0145***	0.0145***	-0.0188***	-0.0188***	-0.0190***	-0.0190***
			(3.68)	(3.67)	(-3.89)	(-3.89)	(-4.03)	(-4.03)
$Rated$					0.2122***	0.2122***	0.2127***	0.2126***
					(9.09)	(9.08)	(9.21)	(9.20)
$TARP$							-0.5239***	-0.5304***
							(-8.59)	(-8.90)
Constant	0.3477***	0.3477***	0.3372***	0.3373***	0.4232***	0.4232***	0.4274***	0.4275***
	(18.03)	(18.03)	(12.18)	(12.18)	(14.34)	(14.35)	(14.67)	(14.69)
Year FE	No	No	Yes	Yes	No	No	Yes	Yes
Observations	19244	19244	19237	19237	19237	19237	19237	19237
Adjusted R^2	0.070	0.070	0.124	0.124	0.190	0.190	0.192	0.192

Table 11: **Difference-in-differences analysis of leverage:** This table reports the result of panel regression of leverage using the regression equation specified in Eq. (3.9). The dependent variable *Leverage* which is defined in the text. Column (1A)-(4A) in each set use different combination of control variables X. Column (1B)-(4B) further add the triple interaction variable $Fin{\cdot}Post{\cdot}Fund$. Fin is 1 if financial firm otherwise 0. $Post$ is 1 if the data date is after the event date, which is Jan 2007. $Fund$ is the percentage of government short-term funding (TAF, CPFF and short-term portion of TDGP) in percentage of total capital. Details on the definition of other variables are provided in the Table C.2.2. The standard errors are robust to heteroscedasticity and clustered at the industry level. Asterisks denote statistical significance at the 0.01(∗∗∗), 0.05(∗∗) and 0.1(∗)

	(1A)	(1B)	(2A)	(2B)	(3A)	(3B)	(4A)	(4B)
Fin	0.2128***	0.2128***	0.2120***	0.2120***	0.1968***	0.1967***	0.1968***	0.1967***
	(15.02)	(15.02)	(13.51)	(13.51)	(12.98)	(12.97)	(13.02)	(13.01)
$Post$	-0.0030	-0.0030	0.0101	0.0106	-0.0046	-0.0046	0.0051	0.0054
	(-0.65)	(-0.65)	(1.04)	(1.05)	(-1.05)	(-1.05)	(0.58)	(0.60)
$Fin{\cdot}Post$	-0.0244***	-0.0264***	-0.0262***	-0.0282***	-0.0211***	-0.0233***	-0.0170***	-0.0187***
	(-4.06)	(-4.18)	(-4.45)	(-4.59)	(-3.86)	(-4.10)	(-2.83)	(-2.98)
$Fin{\cdot}Post{\cdot}Fund$		0.8934***		0.8803***		0.9244***		0.9179***
		(13.25)		(13.04)		(13.84)		(17.32)
M/B			0.0026	0.0026	-0.0037	-0.0037	-0.0037	-0.0037
			(0.58)	(0.58)	(-0.78)	(-0.77)	(-0.77)	(-0.77)
$log(MV)$			-0.0044	-0.0045	0.0041	0.0040	0.0040	0.0040
			(-0.68)	(-0.70)	(0.53)	(0.52)	(0.53)	(0.53)
$Rated$					-0.0552***	-0.0553***	-0.0550***	-0.0551***
					(-4.69)	(-4.66)	(-4.78)	(-4.76)
$TARP$							-0.1880	-0.2083
							(-1.33)	(-1.46)
Constant	0.0821***	0.0821***	0.1071**	0.1074**	0.0847*	0.0849*	0.0852*	0.0857*
	(13.18)	(13.18)	(2.55)	(2.58)	(1.85)	(1.87)	(1.93)	(1.96)
Year FE	No	No	Yes	Yes	No	No	Yes	Yes
Observations	19244	19244	19237	19237	19237	19237	19237	19237
Adjusted R^2	0.106	0.107	0.108	0.109	0.113	0.114	0.115	0.115

Table 12: **Difference-in-differences analysis of maturity structure:** This table reports the result of panel regression of leverage using the regression equation specified in Eq. (3.9). The dependant variable $Maturity$ which is defined in the text.Column (1A)-(4A) in each set use different combination of control variables X. Column (1B)-(4B) further add the triple interaction variable $Fin{\cdot}Post{\cdot}Fund$. Fin is 1 if financial firm otherwise 0. $Post$ is 1 if the data date is after the event date, which is Jan 2007. $Fund$ is the percentage of government short-term funding (TAF, CPFF and short-term portion of TDGP) in percentage of total capital. Details on the definition of other variables are provided in the Table C.2.2. The standard errors are robust to heteroscedasticity and clustered at the industry level. Asterisks denote statistical significance at the 0.01(∗∗∗), 0.05(∗∗) and 0.1(∗)

	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.0292***	-0.1068***	-0.0612***	-0.1065***	-0.0606***	-0.0461***
	(-2.59)	(-9.16)	(-3.72)	(-9.14)	(-3.68)	(-2.78)
Mortgage	0.3622***	0.3826***	0.3718***	0.3806***	0.3705***	0.3724***
	(5.69)	(6.81)	(6.53)	(6.77)	(6.50)	(6.48)
Post·Mortgage	-0.1660**	-0.1262*	0.0049	-0.1230*	0.0072	-0.0422
	(-2.01)	(-1.69)	(0.07)	(-1.65)	(0.10)	(-0.58)
M/B		-1.0566***	-1.1961***	-1.0331***	-1.1762***	-1.2523***
		(-18.46)	(-19.22)	(-17.05)	(-17.84)	(-17.92)
$log(MV)$		0.0266***	0.0273***	0.0238***	0.0249***	0.0238***
		(15.91)	(16.38)	(9.14)	(9.74)	(9.28)
Rated				0.0187	0.0158	0.0205*
				(1.54)	(1.38)	(1.83)
$TARP$						-0.6564***
						(-7.81)
$TDGP$						-0.1954
						(-0.54)
Constant	0.5363***	0.5783***	0.6011***	0.5876***	0.6085***	0.6287***
	(62.96)	(42.37)	(35.64)	(39.73)	(35.00)	(35.49)
Year FE	No	No	Yes	No	Yes	Yes
Observations	3194	3194	3194	3194	3194	3194
Adjusted R^2	0.034	0.179	0.272	0.179	0.272	0.291

Table 13: **Difference-in-differences analysis on leverage within financial firms:** This table reports the result of panel regression of leverage using the regression equation specified in Eq. (3.10). The dependent variable *Leverage* which is defined in the text. Column (1)-(6) in each set use different combination of control variables X. Fin is 1 if financial firm otherwise 0. *Post* is 1 if the data date is after the event date, which is Jan 2007. $Mortgage$ is the percentage of mortgage-related-asset to total asset. Details on the definition of other variables are provided in the Table C.2.2. Robust standard error is used. Asterisks denote statistical significance at the 0.01(∗∗∗), 0.05(∗∗) and 0.1(∗) levels.

	(1)	(2)	(3)	(4)	(5)	(6)
$Post$	-0.0037	0.0371**	0.0578**	0.0360**	0.0551**	0.0542**
	(-0.22)	(2.14)	(2.16)	(2.09)	(2.07)	(2.02)
$Mortgage$	0.1322	0.1051	0.1219	0.1124	0.1275	0.1272
	(1.50)	(1.25)	(1.42)	(1.34)	(1.49)	(1.49)
$Post{\cdot}Mortgage$	-0.2089*	-0.2716**	-0.2487**	-0.2834***	-0.2586**	-0.2554**
	(-1.88)	(-2.54)	(-2.29)	(-2.66)	(-2.39)	(-2.34)
M/B		0.0809	0.0358	-0.0046	-0.0493	-0.0454
		(1.01)	(0.43)	(-0.06)	(-0.59)	(-0.53)
$log(MV)$		0.0408***	0.0408***	0.0510***	0.0509***	0.0512***
		(15.67)	(15.76)	(12.49)	(12.49)	(12.52)
Rated				-0.0680***	-0.0675***	-0.0678***
				(-3.15)	(-3.13)	(-3.15)
$TARP$						0.0633
						(0.50)
$TDGP$						-0.5133
						(-0.81)
Constant	0.2919***	0.0420**	0.0403	0.0083	0.0084	0.0058
	(22.65)	(2.04)	(1.52)	(0.35)	(0.29)	(0.20)
Year FE	No	No	Yes	No	Yes	Yes
Observations	3194	3194	3194	3194	3194	3194
Adjusted R^2	0.003	0.076	0.080	0.079	0.082	0.082

Table 14: **Difference-in-differences analysis on maturity structure within financial firms:** This table reports the result of panel regression of maturity structure using the regression equation specified in Eq. (3.10). The dependent variable $Maturity$ which is defined in the text. Column (1)-(6) in each set use different combination of control variables X. Fin is 1 if financial firm otherwise 0. *Post* is 1 if the data date is after the event date, which is Jan 2007. $Mortgage$ is the percentage of mortgage-related-asset to total asset. Details on the definition of other variables are provided in the Table C.2.2. Robust standard error is used. Asterisks denote statistical significance at the 0.01($***$), 0.05($**$) and 0.1($*$) levels.

	(1)	(2)	(3)	(4)	(5)	(6)
Fin	0.1515***	0.1160***	0.1099***	0.1523***	0.1428***	0.1555***
	(7.21)	(5.03)	(4.63)	(8.07)	(7.36)	(7.93)
$Fin{\cdot}ABX$	0.0578***	0.0561***	0.0702***	0.0738***	0.0949***	0.0812***
	(6.36)	(6.97)	(5.19)	(9.38)	(7.29)	(5.88)
M/B		-0.0551***	-0.0542***	-0.0312***	-0.0300***	-0.0301***
		(-4.40)	(-4.30)	(-2.98)	(-2.85)	(-2.85)
$log(MV)$		0.0140***	0.0145***	-0.0188***	-0.0185***	-0.0190***
		(3.53)	(3.67)	(-3.94)	(-3.85)	(-4.05)
Rated				0.2117***	0.2120***	0.2127***
				(9.16)	(9.10)	(9.24)
$TARP$						-0.4771***
						(-8.12)
$TDGP$						0.7295**
						(2.50)
Constant	0.3628***	0.3368***	0.3368***	0.4348***	0.4244***	0.4272***
	(18.24)	(11.46)	(12.17)	(14.05)	(14.37)	(14.61)
Year FE	No	No	Yes	No	Yes	Yes
Observations	19244	19237	19237	19237	19237	19237
Adjusted R^2	0.069	0.123	0.124	0.190	0.191	0.192

Table 15: **Difference in leverage decisions between financial and non-financial firms:** This table reports the result of panel regression of leverage using the regression equation specified in Eq. (3.11). The dependant variable *Leverage* which is defined in the text. Column (1)-(6) in each set use different combination of control variables X. Fin is 1 if financial firm otherwise 0. ABX is ABX price level of A tranche, normalized to 1 at 2003. Details on the definition of other variables are provided in the Table C.2.2. Robust standard error is used. Asterisks denote statistical significance at the 0.01($***$), 0.05($**$) and 0.1($*$) levels.

	(1)	(2)	(3)	(4)	(5)	(6)
Fin	0.1746***	0.1712***	0.1734***	0.1618***	0.1649***	0.1686***
	(10.53)	(9.69)	(9.51)	(9.46)	(9.35)	(8.37)
$Fin{\cdot}ABX$	0.0439***	0.0465***	0.0428***	0.0419***	0.0364***	0.0325***
	(6.40)	(8.26)	(5.05)	(8.41)	(4.71)	(3.52)
M/B		0.0027	0.0027	-0.0035	-0.0035	-0.0035
		(0.60)	(0.61)	(-0.73)	(-0.74)	(-0.75)
$log(MV)$		-0.0046	-0.0044	0.0039	0.0041	0.0040
		(-0.71)	(-0.69)	(0.51)	(0.55)	(0.53)
$Rated$				-0.0546***	-0.0550***	-0.0548***
				(-4.70)	(-4.78)	(-4.80)
$TARP$						-0.1528
						(-1.04)
$TDGP$						0.7172***
						(2.83)
Constant	0.0803***	0.1077**	0.1063**	0.0824*	0.0835*	0.0846*
	(11.80)	(2.52)	(2.50)	(1.83)	(1.86)	(1.89)
Year FE	No	No	Yes	No	Yes	Yes
Observations	19244	19237	19237	19237	19237	19237
Adjusted R^2	0.106	0.108	0.109	0.114	0.115	0.115

Table 16: **Diff. in debt maturity structure decisions between financial and non-financial firms:** This table reports the result of panel regression of debt maturity structure using the regression equation specified in Eq. (3.11). The dependant variable $Maturity$ which is defined in the text. Column (1)-(6) in each set use different combination of control variables X. Fin is 1 if financial firm otherwise 0. ABX is ABX price level of A tranche, normalized to 1 at 2003. Details on the definition of other variables are provided in the Table C.2.2. Robust standard error is used. Asterisks denote statistical significance at the 0.01($***$), 0.05($**$) and 0.1($*$) levels.

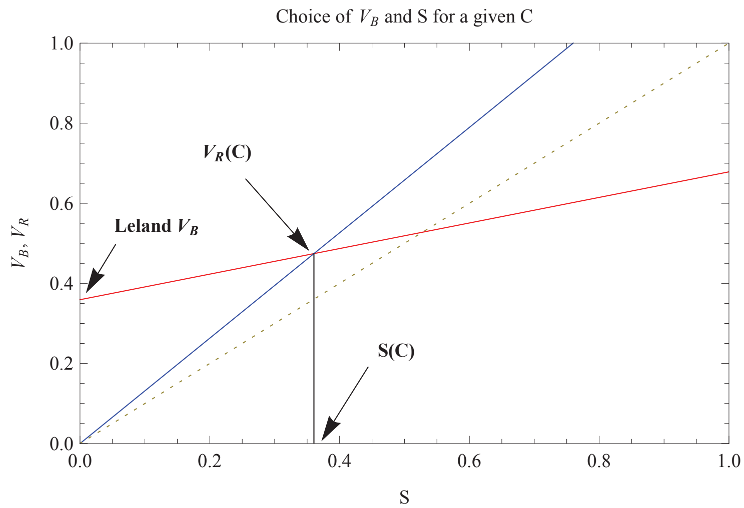
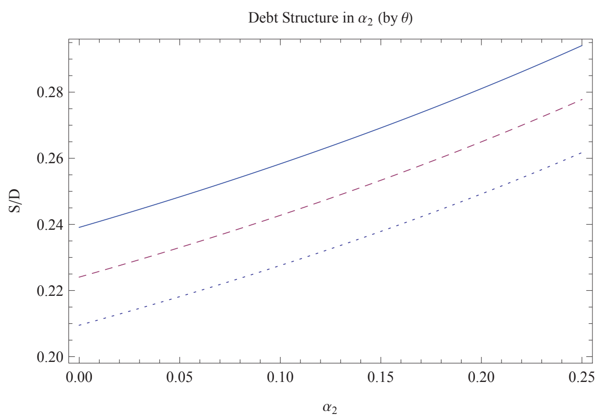


Figure 8: **Illustration of choosing V_B and S for a given C:** This figure illustrates the equity holder's optimal choice of restructuring boundary and the level of short-term debt. For a given level of C, equity holder chooses V_B and S. The solid line with steeper slope is V_R imposed by the short-term lender. The solid line with flatter slope is V_B the optimal restructuring boundary associated with each value of S. The dotted line is 45 degrees line. With a given C, the optimal choice is to pick S and V_B at the point where two solid lines cross. In this figure, $C = 0.045$, $\theta = 0.8$, $\alpha 1 = 0.7$ and $\alpha_2 = 0$ is assumed. Also the following deep parameter values have been assumed: $V_0 = 1$, $r = 0.04$, $\delta = 0.02$, $\tau = 0.35$, $\sigma = 0.25$, $\beta = 0.05$.



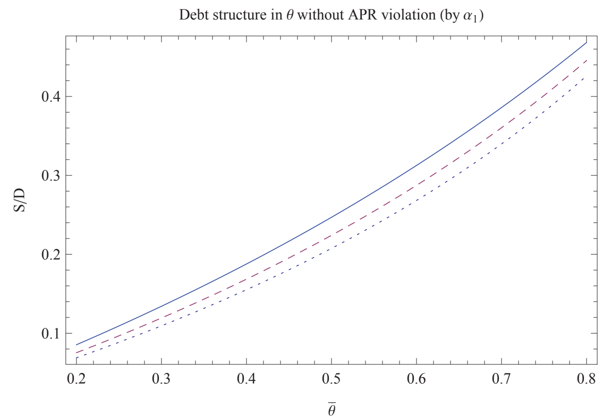
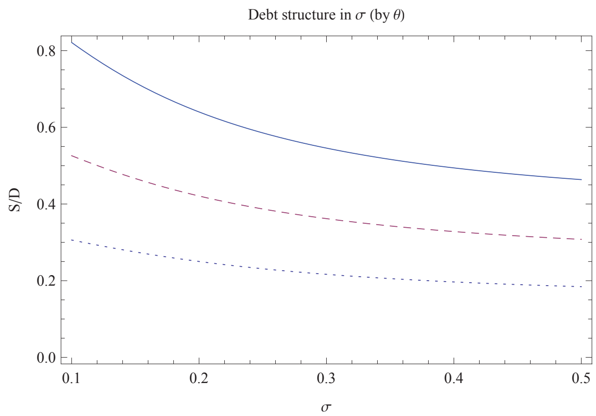


Figure 9: **Effect of APR violations and eligibility to pledge on optimal liability structure:** These figures plot short-term debt to long-term debt ratio (S/D) with respect to the APR violation, α_2 (left) and eligibility to pledge, $\bar{\theta}$ (right). The left figure is with three different value of $\bar{\theta} = 0.525$ (solid), 0.5 (dashed) and 0.475 (dotted), keeping $\alpha_1 = 0.5$. The right figure uses three different value of $\alpha_1 = 0.9$ (solid), 0.5 (dashed) and 0.1 (dotted), keeping $\alpha_2 = 0.0$. For both figures, the following deep parameter values have been assumed: $V_0 = 1$, $r = 0.04$, $\delta = 0.02$, $\tau = 0.35$, $\sigma = 0.5$ and $\beta = 0.05$.



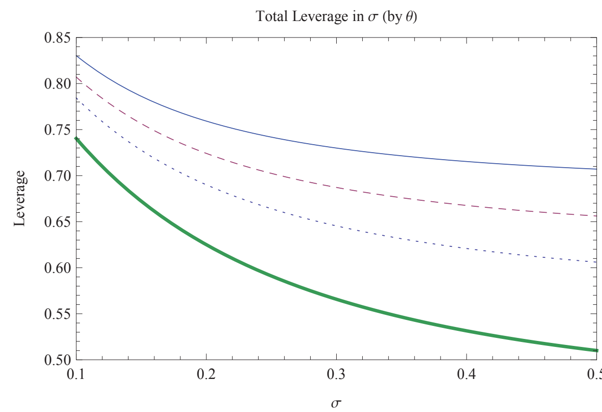
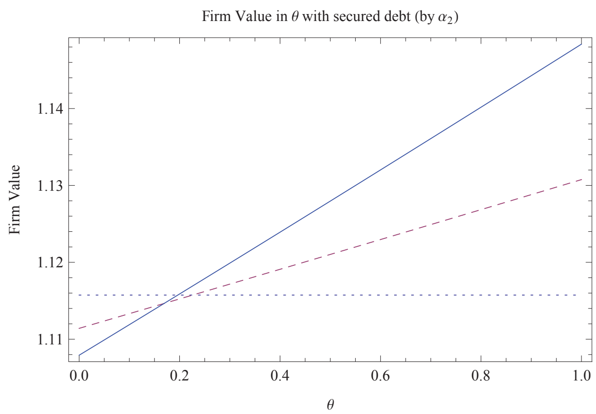


Figure 10: **Effect of asset volatility on optimal Liability structure and leverage:** These figures plot short-term debt to long-term debt ratio (left) and total leverage of a firm (right) with respect to the asset volatility (σ). The solid line uses $\theta = 0.8$ and the dashed and dotted line use $\theta = 0.6$, $\theta = 0.4$ respectively. In the right pane, thicker line represents the leverage in Leland (1994) with only unprotected long-term debt, keeping other parameters same. For all three lines, the following deep parameter values have been assumed: $V_0 = 1$, $r = 0.04$, $\delta = 0.02$, $\tau = 0.35$, $\beta = 0.05$, $\alpha_1 = 0.5$ and $\alpha_2 = 0.1$.



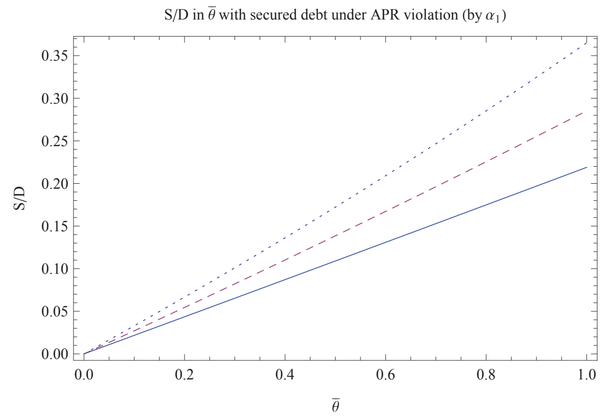


Figure 11: **Case of secured but not safe harbored debt:** These plots describe the case when the short-term debt is secured debt but not safe harbored. Since the short-term debt is under the bankruptcy code, they share the bankruptcy cost but there is no APR violation because it is secured. The left figure shows that firm value is increasing in θ when $\alpha_2 > 0$. Solid and dashed line use $\alpha_2 = 0.2, 0.1$, respectively and 0 for dotted line. The right figure is the corresponding debt structure with respect to $\bar{\theta}$ when $\alpha_2 = 0.2$ with three different values of $\alpha_1 = 0.3$ (dotted), 0.4 (dashed) and 0.5 (solid). For both figures, other parameters are used as follows: $V_0 = 1$, $r = 0.04$, $\delta = 0.02$, $\tau = 0.35$ and $\sigma = 0.25$.

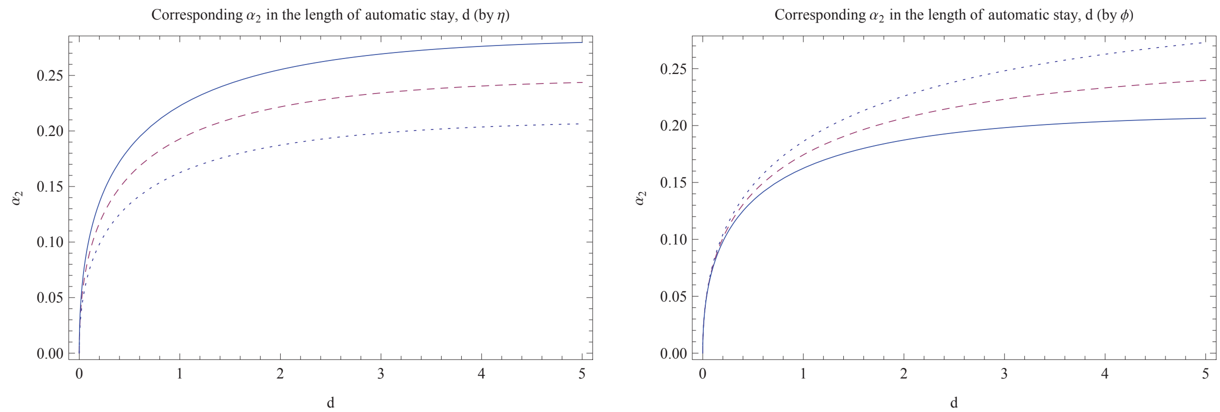
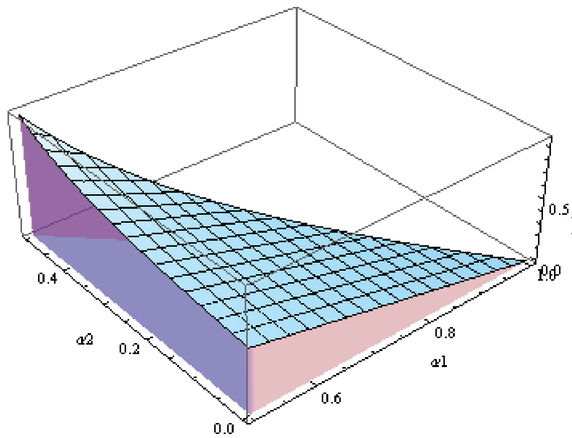


Figure 12: **Illustrations of APR violations arising from the provisions of the bankruptcy code:** These plots depict how our reduced form of APR violation parameter, α_2, is linked to the characteristics of the bankruptcy code at a more fundamental level, using the framework of Francois and Morellec (2004). Both figures map the length of automatic stay of the code to the parameter α_2, which captures APR violations. The left panel varies the bargaining power of share holder by using $\eta = 0.7$ (solid), 0.6 (dashed) and 0.5 (dotted), keeping $\phi = 0.03$. The right panel varies the cost of being in the Chapter 11 by using $\phi = 0.03$ (solid), 0.02 (dashed) and 0.01 (dotted), keeping $\eta = 0.5$. For both figures, total bankruptcy loss is fixed at 0.2 and other parameters are used as follows: $V_0 = 1$, $r = 0.04$, $\delta = 0.02$, $\tau = 0.35$, $\sigma = 0.25$, $\beta = 0.05$.



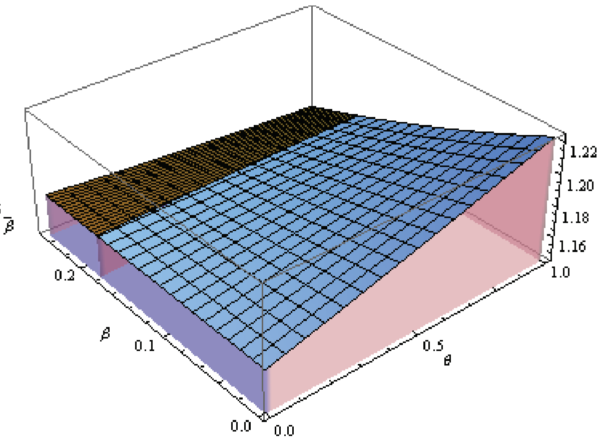


Figure 13: **Constraint on liquidity of pledged asset to justify safe harboring activity:** These figures visualize the minimum level of liquidity that collateralized asset should satisfy for safe harboring to be beneficial. In the left figure, the vertical axis represents $\bar{\beta}$, the maximum market friction the asset can afford, on different combinations of α_1 and α_2. The figure assumes $\alpha_2 \leq \alpha_1$ and α_1 takes value from 0.5 to 1, α_2 from 0 to 0.5. The right figure, the vertical axis plots the firm value in θ for different value of β, assuming $\alpha_1 = 0.8$ and $\alpha_2 = 0.1$. The lighter area is the region where the firm value increase in θ whereas it decreases in θ in darker region. The borderline of these regions pins down the value of $\bar{\beta}$. For both, the following deep parameter values have been assumed: $V_0 = 1$, $r = 0.04$, $\delta = 0.02$, $\tau = 0.35$, $\theta = 1$ and $\sigma = 0.5$.

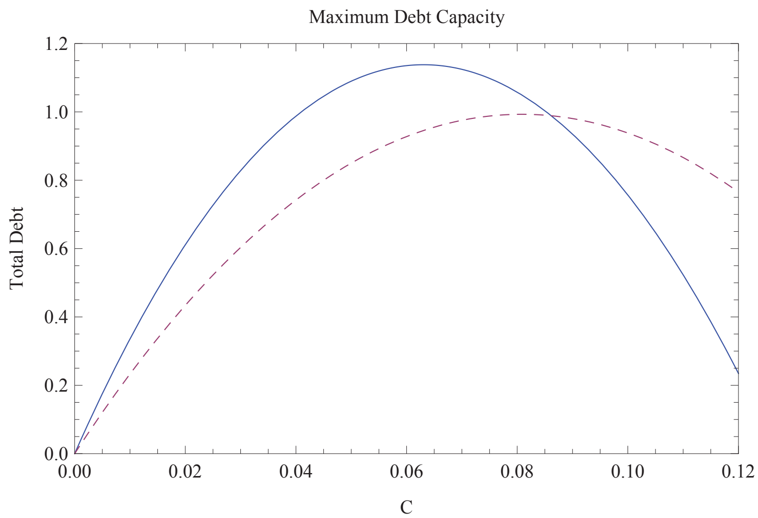


Figure 14: **Maximum debt capacity with Safe Harbor:** This figure plots maximum debt capacity when there is a short-term debt that a firm can borrow with pledging. The dashed line is the benchmark case where there is no short-term debt. To make a stark contrast, we assume $\theta = 1$ for the solid line when pledging activity is possible. So in this case, the total debt capacity comes from both long-term and short-term debt. We also assume that there is no APR violation. For all lines, the following deep parameter values have been assumed: $V_0 = 1$, $r = 0.04$, $\delta = 0.02$, $\tau = 0.35$, $\sigma = 0.25$, $\beta = 0.05$, $\alpha_1 = 0.7$ and $\alpha_2 = 0.0$.

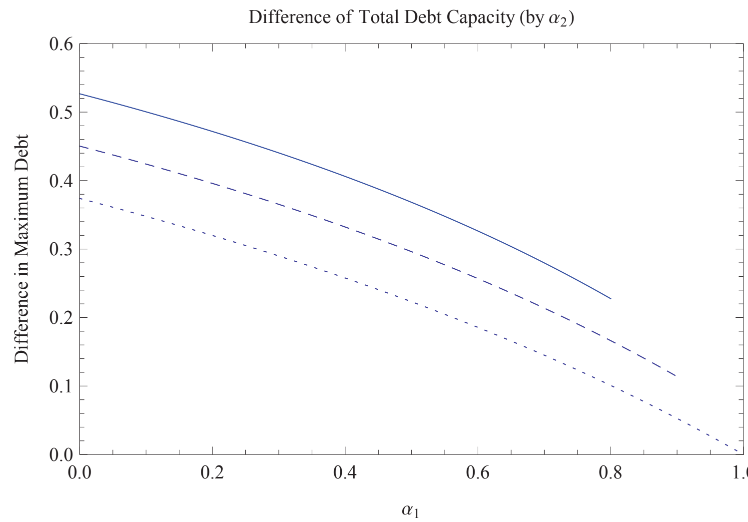


Figure 15: **Difference in debt capacity with APR violation:** This figure presents the difference of maximum debt capacity between the model with pledgibility and the benchmark model where there is no short-term debt. Each line represents different level of α_2. The blue line has $\alpha_2 = 0.2$, and $\alpha_2 = 0.1, 0.0$ for dashed and dotted line, respectively. The horizontal axis is α_1. Therefore, the plot depicts the difference of debt capacity with respect to the efficiency of the code, for a given α_2. For all three lines, the following deep parameter values have been assumed: $V_0 = 1$, $r = 0.04$, $\delta = 0.02$, $\tau = 0.35$, $\sigma = 0.25$, $\beta = 0.05$ and $\theta = 1$.

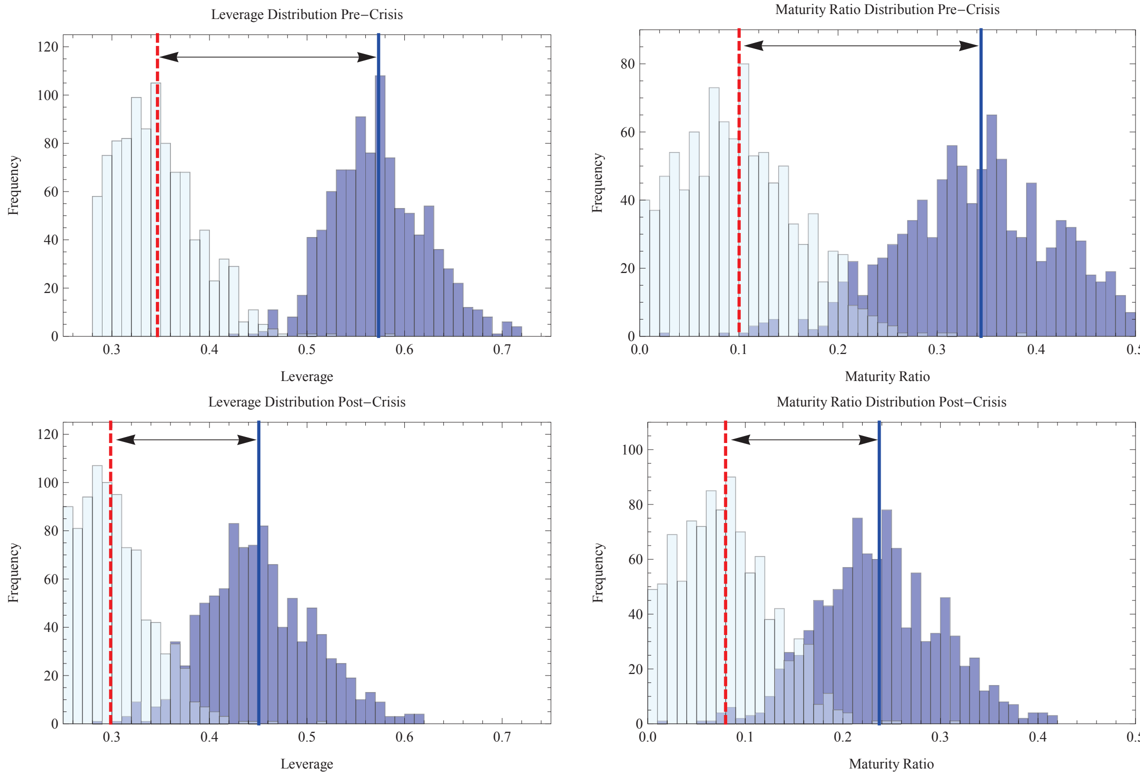
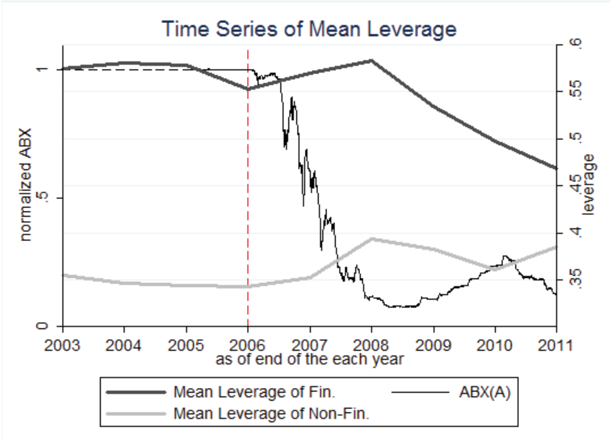


Figure 16: **Distribution of optimal leverage and optimal maturity structure:** These histograms illustrate the model-implied predictions of optimal leverage and optimal maturity ratio before and after the financial crisis. The lighter bars account for non-financial firms whereas darker bars denote financial firms. Each vertical line indicates the mean of the distribution. They differ in mean of truncated normal distribution of $\bar{\theta}$: $TN(\mu_{\{F,NF\}}, \eta)$ bounded by 0 and 1. We assume $\mu_F = 0.6, \mu_{NF} = 0.2$ and $\eta = 0.15$. We use the mean equity volatility of 12 month return as a proxy for σ. For financial firms $\sigma = 0.21, 0.39$ for pre and post crisis, respectively. For non-financial firms, we use $\sigma = 0.37, 0.47$ for pre and post crisis, respectively. Other parameters are assumed as follows: $V_0 = 1$, $r = 0.04$, $\delta = 0.02$, $\tau = 0.15$, $\alpha_1 = 0.5$, $\alpha_1 = 0.1$ and $\beta = 0.05$.



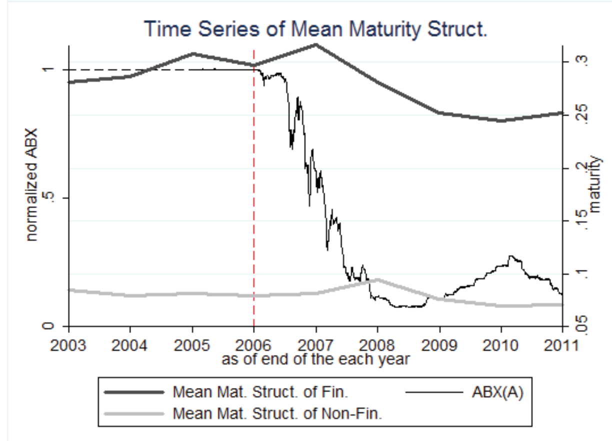


Figure 17: **Time series of debt maturity structure and leverage:** These figures plot the time series pattern of the mean leverage ratio (left) and mean debt maturity structure (right) of financial and non-financial firms. Thick darker lines stand for mean leverage (maturity structure) of financial (RHS axis). Thick lighter lines represent mean leverage (maturity structure) of non-financial firms (RHS axis). Thin solid line is the A-tranche ABX index which is normalized to 1 at its inception date, beginning of 2006 (LHS axis). The vertical dashed line is the starting point of the crisis period.

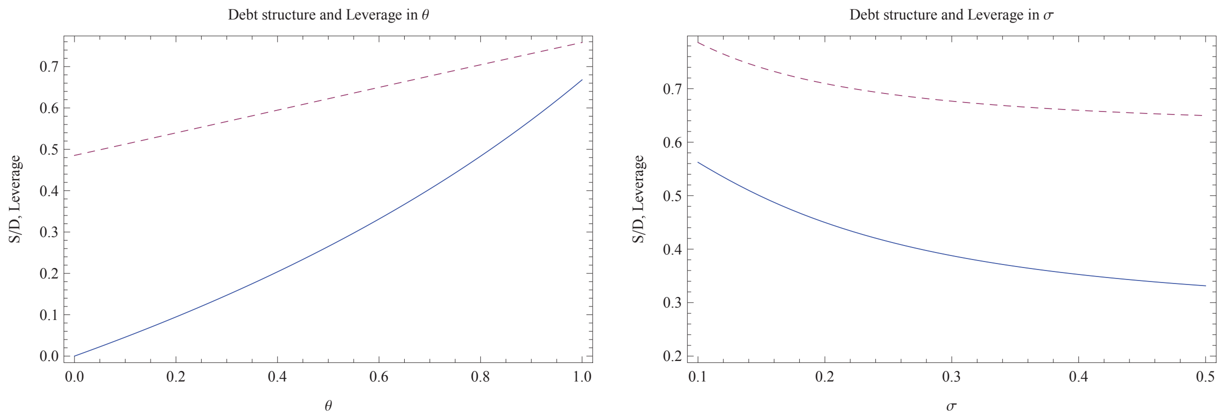


Figure 18: **Debt structure and leverage ratio:** These plots summarize the model implied prediction. Left panel shows Debt structure (solid) and Leverage ratio (dashed) in asset volatility (σ) and ability to pledging ($\bar{\theta}$). For both figures, the following deep parameter values have been assumed: $V_0 = 1$, $r = 0.04$, $\delta = 0.02$, $\tau = 0.35$, $\beta = 0.05$, $\alpha_1 = 0.5$ and $\alpha_2 = 0.2$. Additionally, the left figure uses $\sigma = 0.5$ and the right figure uses $\bar{\theta} = 0.6$.

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Appendices

Appendix A

Appendix for Chapter 1

A.1 Proofs

Proposition 1

Since $p_f - p_g = q_f - q_g = 0$, let us define $p \equiv p_f = p_q$ and $q \equiv q_f = q_g$. Note that the condition g first-order stochastically dominates f in $[p, q]$ ($g \overset{FOSD}{\succ} f$ in $[p, q]$) is a necessary and sufficient condition for g to dominate f in likelihood ratio, i.e., $\frac{g(\theta)}{f(\theta)}$ increases in $\theta \in \Theta$. By definition of conditional expectation, we have the following equation:

$$\begin{aligned}
\mathbb{E}_g[\theta | p \leq \theta \leq q] &= \int_p^q u \cdot h_g(u)\, du \\
&= [-u \cdot (1 - H_g(u))]_p^q + \int_p^q (1 - H_g(u))\, du \\
&= (q \cdot H_g(q) - p \cdot H_g(p)) - (q - p) + \int_p^q (1 - H_g(u))\, du
\end{aligned}$$

where, $h_i(\cdot)$ is a conditional density function and $H_i(\cdot)$ is a conditional cumulative distribution function for $i = \{f, g\}$ in $[p, q]$. Similarly,

$$\mathbb{E}_f[\theta | p \leq \theta \leq q] = (q \cdot H_f(q) - p \cdot H_f(p)) - (q - p) + \int_p^q (1 - H_f(u))\, du$$

Then,

$$\begin{aligned}
\mathbb{E}_g[\theta | p \leq \theta \leq q] - \mathbb{E}_f[\theta | p \leq \theta \leq q] &= p \cdot (H_f(p) - H_g(p)) \\
&\quad - q \cdot (H_f(q) - H_g(q)) + \int_p^q (H_f(u) - H_g(u))\, du
\end{aligned} \tag{A.1}$$

The condition $g \overset{FOSD}{\succ} f$ in $[p, q]$ implies $H_f(\cdot) > H_g(\cdot)$. Then the first terms in Equation (A.1) is positive. Since $H(\cdot)$ is monotonic in $[0, 1]$, it is Riemann-integrable. Hence, the second term has the following relationship:

$$\begin{aligned} q\cdot(H_f(q)-H_g(q)) &< \int_{q-\epsilon^+}^{q} q\cdot(H_f(v)-H_g(v))\,dv \\ &< \int_{p}^{q} q\cdot(H_f(v)-H_g(v))\,dv \end{aligned}$$

Then the second and third term of Equation (A.1) can be expressed as:

$$\begin{aligned} -q\cdot(H_f(q)-H_g(q))+\int_p^q (H_f(u)-H_g(u))\,du &= -q\cdot(H_f(q)-H_g(q))+\frac{1}{q}\int_p^q q\cdot(H_f(u)-H_g(u))\,du \\ &> \frac{1}{q}\int_p^q q\cdot(H_f(u)-H_g(u))\,du-\int_p^q q\cdot(H_f(v)-H_g(v))\,dv \\ &\geq 0 \end{aligned}$$

The last inequality is obtained from $q \in (0,1]$. Therefore, $\mathbb{E}_g[\theta|p \leq \theta \leq q] > \mathbb{E}_f[\theta|p \leq \theta \leq q]\square$

Corollary

Contraposition of Proposition 1.1 immediately yields that if $\mathbb{E}_g[\theta|p \leq \theta \leq q] \leq \mathbb{E}_f[\theta|p \leq \theta \leq q]$ for some $\theta \in \Theta$, then the cut-off points are not the same under each distribution ($p_f \neq p_g$). Suppose $p_f < p_q$ and let $p_f \to 0^+$. Then, for a given $p_g > \epsilon^+$, $\mathbb{E}_f[\theta|p \leq \theta \leq q] < \mathbb{E}_g[\theta|p \leq \theta \leq q]$. This is a contradiction. Therefore, $p_g < p_f$ and obtains the corollary $\square$

Proposition 2

I first find the price of state-dependent asset that pays 1 when $V \downarrow V_B$: $\mathbb{E}_0[e^{-r\tau_B}\cdot 1]$ where $\tau_B = inf\{t : V_t = V_B\}$. From the property of Geometric Brownian Motion in Equation (3.1), I can re-write the process V as follows:

$$ln(V_t/V_0) = (r-\delta-\sigma^2/2)t + \sigma W_t^{\mathbb{Q}} \tag{A.2}$$

where $W_t^{\mathbb{Q}}$ is the Standard Brownian Motion under the risk-neutral measure $\mathbb{Q}$. Then let us define the exponential martingale $M(t) = e^{(-rt+x\cdot ln(V_t/V_0))}$. Using the Equation (A.2),

$$M(t) = e^{(-rt+x(r-\delta-\sigma^2/2)t+x\sigma W_t^{\mathbb{Q}})} \tag{A.3}$$

Applying Ito's rule to Equation (A.3) yields:

$$\frac{dM(t)}{M(t)} = \left(-r + x(r-\delta-\sigma^2/2)+\frac{1}{2}x^2\sigma^2\right)dt + x\sigma dW_t^{\mathbb{Q}} \tag{A.4}$$

Since $M(t)$ is a $\mathbb{Q}$- martingale, the drift term of Equation (A.4) is zero. This restriction gives:

$$x = \frac{1}{\sigma^2}\left((r-\delta-\sigma^2/2)+\sqrt{(r-\delta-\sigma^2/2)+2\sigma^2 r}\right) \tag{A.5}$$

Then the expectation of $M(\tau_B)$ under $\mathbb{Q}$- measure is:

$$\begin{aligned}
\mathbb{E}_0^{\mathbb{Q}}[M(\tau_B)] &= \mathbb{E}_0^{\mathbb{Q}}[M(\tau_B)] \\
&= \mathbb{E}_0^{\mathbb{Q}}[e^{(-r\tau_B + x\cdot ln(V_B/V_0))}] \\
&= \mathbb{E}_0^{\mathbb{Q}}[e^{-r\tau_B}] \cdot e^{x\cdot ln(V_B/V_0)} \\
&= M(0) = 1
\end{aligned}$$

Therefore, I obtain:

$$\mathbb{E}_0^{\mathbb{Q}}[e^{-r\tau_B}] = e^{-x\cdot ln(V_B/V_0)} = (V_0/V_B)^{-x} \tag{A.6}$$

The price of state-dependent asset that pays $1 \cdot e^{mt}$ when $V \downarrow V_B$ can be similarly written as $\mathbb{E}_0[e^{-r\tau_B} \cdot e^{-m\tau_B} \cdot 1]$. Through a similar step this price can be expressed as:

$$\mathbb{E}_0^{\mathbb{Q}}[e^{-(r+m)\tau_B}] = (V_0/V_B)^{-y} \tag{A.7}$$

where

$$y = \frac{1}{\sigma^2}\left((r - \delta - \sigma^2/2) + \sqrt{(r - \delta - \sigma^2/2) + 2\sigma^2(r + m)}\right) \tag{A.8}$$

Then, from risk-neutral valuation, the individual debt value is

$$d(0) = \frac{c + mp}{r + m} \cdot (1 - (V_0/V_B)^{-y}) + m\alpha_1 V_B (V_0/V_B)^{-y} \tag{A.9}$$

The reason that Equation (A.9) uses Equation (A.7) rather than Equation (A.6) for the state-dependent asset price is creditors are repaid at the rate of m over time. Therefore the money owed to them at the default is already decayed at the same rate. The total debt D consists of continuum of individual debt d with different time to maturity. Integrating over time to maturity, I obtain Equation (1.2) for the total debt D. The firm value v can be found by adding the present value of tax benefit to and subtract the present value of bankruptcy cost from the unlevered asset value V:

$$v = V + (\tau C/r) \cdot (1 - (V/V_B)^{-x}) - \alpha V_B (V/V_B)^{-x} \tag{A.10}$$

From the accounting identity $v = E + D$, the equity value, E, can be calculated from $v - D$ which yields Equation (1.3) $\square$

A.2 Estimation procedure for Leland (1994b) model

Set-up

I use MCMC methodology, following Korteweg and Polson (2010) to estimate the model parameters. Recall that Proposition 1.2 provides valuation equation for equity and debt as follows:

$$D_t = \left(\frac{C+mP}{r+m}\right)\left(1-(V_t/V_B)^{-y}\right)+\alpha_1 V_B (V_t/V_B)^{-y} \quad \text{(A.11)}$$

$$E_t = V_t + \left(\frac{\tau C}{r}\right)\left(1-(V_t/V_B)^{-x}\right)-(\alpha-\alpha_2)V_B(V_t/V_B)^{-x} - D_t \quad \text{(A.12)}$$

where,

$$\begin{aligned}
C &= \text{dollar coupon} \\
P &= \text{debt principal} \\
m &= \text{fraction of retiring debt} \\
\alpha_1 &= \text{share for creditor} \\
\alpha_2 &= \text{share for equity holder} \\
\alpha &= 1-(\alpha_1+\alpha_2) \\
x &= \left[(r-\delta-\sigma^2/2)+\sqrt{(r-\delta-\sigma^2/2)^2+2r\sigma^2}\right]/\sigma^2 \\
y &= x+\sqrt{2m}/\sigma
\end{aligned}$$

For each firm, I estimate the following system:

$$Y_t \equiv ln(f_E^{-1}(E_t,\Theta)) = X_t + \epsilon_t,\ \epsilon_t \sim N(0,\nu^2) \quad \text{(A.13)}$$

$$X_t = X_{t-1} + (\mu-\delta-\sigma^2/2)+\sigma\eta_t,\ \eta_t \sim N(0,1) \quad \text{(A.14)}$$

The Equation (A.13) is the observation equation where $f_E^{-1}(E_t,\Theta)$ provides an inverse mapping of $E_t \to V_t$, given $\Theta = \{\mu,\sigma,\delta,r,C,F,m,\tau,\alpha_1,\alpha_2\}$. Therefore X stands for log asset value. Following the asset value process in Equation (1.3), the evolution of X is characterized in Equation (A.14).

Objectives

I need to estimate $\{V_t\}$and Θ in Equation (A.13) and (A.14) and ν. Among the parameter set Θ, I can easily observe $\{\delta,r,C,F,m\}$. δ is defined as dividend pay from CRSP divided by average market cap of the year. For r, I used the yield of 1 year constant maturity treasury security. The interest payment for debt C and book value of the debt P are both observable in Compustat. m is the inverse of the average tenor of outstanding bonds weighted by the face value. Compustat breaks down the debt amount by time to due from 1 to 5 years (variable DD1 to DD5). For the bond amount maturing beyond 5 year, I use 18 years for average maturity to make the average maturity of the sample firm close to 10.8 years as reported in SIFMA for the sample period. If these information is not available in Compustat, I use FISD database to use average maturity of the debt issued in the sample period, weighted by the face value. For τ, I use 35 percent as suggested by Korteweg and Polson (2010). For $\alpha_1^{j=\{E,R\}}$, I use Moody's DRD/URD database and use mean recovery rate for bond holder in the sample a recession and an expansion period. I approximate the rent extraction of equity holders from the credit event,$\alpha_2^{j=\{E,R\}}$, by calculating the equity value at the time of the credit event over the most recent reported asset value in the sample recession and expansion period.

Now the problem is reduced to estimate $\{V_t\}$ and parameter set $\{\mu, \sigma, \nu\}$. In other words, the objective is to obtain the joint posterior $p(\{X_t\}, \mu, \sigma^2, \nu^2 | \{E_t\})$. For calculation convenience, I modify Equation (A.14) to $X_t = X_{t-1} + (\mu^\star - \delta) + \sigma\eta_t$, where I define $\mu^\star = \mu - \sigma^2/2$.

Estimation procedure

The estimation steps in big picture are as follows:

(1) $X_{(g+1)} \sim p(X|\sigma^2_{(g)}, \mu^\star_{(g)}, \nu^2_{(g)}, E) \sim FFBS$

(2) $\sigma^2_{(g+1)} \sim p(\sigma^2|X_{(g+1)}, \mu^\star_{(g)}, \nu^2_{(g)}, E) \sim IG$

(3) $\mu^\star_{(g+1)} \sim p(\mu^\star|X_{(g+1)}, \sigma^2_{(g+1)}, \nu^2_{(g)}, E) \sim N$

(4) $\nu^2_{(g+1)} \sim p(\nu^2|X_{(g+1)}, \sigma^2_{(g+1)}, \mu^\star_{(g+1)}, E) \sim IG$

I use burn-in period of 30 and draw 300 samples. For all firms in the sample, at the end of each month, I calculate $DD_t = (log(V/V_B) + (\mu^\star - \delta))/\sigma$ and compute the mean of the distribution. This measure provides proxy for the credit quality of the firm in monthly frequency.

Asset value $X = ln(V)$

I implement Filter Forward Backward Sampling algorithm.

Filter Forward (FF)

Initialize the Equation (A.13):

$$X_0 = Y_0 - \epsilon_0 \Rightarrow (X_0|Y_0) \sim N(Y_0, \nu^2)$$

The Equation (A.14) gives the forecasting of X_1:

$$X_1 = X_0 + (\mu^\star - \delta) + \sigma\eta_t \Rightarrow (X_1|Y_0) \sim N(Y_0 + (\mu^\star - \delta), \nu^2 + \sigma^2)$$

Using the Bayes rule I update the X_1 given Y_0, Y_1:

$$\begin{pmatrix} X_1 \\ Y_1 \end{pmatrix} | \, Y_0 \sim N\left(\begin{pmatrix} Y_0 + (\mu^\star - \delta) \\ Y_0 + (\mu^\star - \delta) \end{pmatrix}, \begin{pmatrix} \nu^2 + \sigma^2 & \cdot \\ \nu^2 + \sigma^2 & \sigma^2 + 2\nu^2 \end{pmatrix}\right) \Rightarrow (X_1|Y_0,Y_1) \sim N(M, V)$$

where the updated mean M and updated variance V are:

$$\begin{aligned} M &= Y_0 + (\mu^\star - \delta) + \frac{\nu^2 + \sigma^2}{\sigma^2 + 2\nu^2} \cdot [Y_1 - (Y_0 + (\mu^\star - \delta))] \\ V &= (\nu^2 + \sigma^2) - \frac{(\nu^2 + \sigma^2)^2}{\sigma^2 + 2\nu^2} \end{aligned}$$

Now I can formulate for the t:

$$\begin{aligned} \mathbb{E}[X_t|Y^t] &= \mathbb{E}[X_t|Y^{t-1}] + \frac{Var[X_t|Y^{t-1}]}{Var[X_t|Y^{t-1}] + \nu^2} \cdot \left(Y_t - \mathbb{E}[X_t|Y^t]\right) \\ Var[X_t|Y^t] &= Var[X_t|Y^{t-1}] - \frac{Var[X_t|Y^{t-1}]^2}{Var[X_t|Y^{t-1}] + \nu^2} \end{aligned}$$

Backward Sampling (BS)

I sample X from backward using quantities generated from the FF step. For given t, the joint distribution $p(X_t, X_{t+1}|Y^t)$ is

$$\begin{pmatrix} X_t \\ X_{t+1} \end{pmatrix} \mid Y^t \sim N\left(\begin{pmatrix} \mathbb{E}[X_t|Y^t] \\ \mathbb{E}[X_{t+1}|Y^t] \end{pmatrix}, \begin{pmatrix} Var[X_t|Y^t] & \cdot \\ Cov[X_t, X_{t+1}|Y^t] & Var[X_{t+1}|Y^t] \end{pmatrix}\right)$$

Therefore the conditional distribution is:

$$p(X_t|X_{t+1}, Y^t) \sim N\left(\mathbb{E}[X_t|Y^t] + \frac{Var[X_t|Y^t]}{Var[X_{t+1}|Y^t]} \cdot \left(X_t - \mathbb{E}[X_{t+1}|Y^t]\right), Var[X_t|Y^t] - \frac{Var[X_t|Y^t]^2}{Var[X_{t+1}|Y^t]}\right)$$

I star sampling from $X_T \sim N(\mathbb{E}[X_T|Y^T], Var[X_T|Y^T])$ and moving backwards to sample:

$$\begin{aligned} X_{T-1} &\sim p(X_{T-1}|X_T, Y^{T-1}) \\ X_{T-2} &\sim p(X_{T-2}|X_{T-1}, Y^{T-2}) \\ &\vdots \\ X_1 &\sim p(X_1|X_2, Y^1) \end{aligned}$$

Also, in order to impose a condition that $X_t > ln(V_B(t))$, I use truncated normal distribution bounded by $ln(V_B(t))$ for the sampling.

Asset volatility σ^2

From Bayes rule, I obtain the following equality:

$$p(\sigma^2|X, \mu^\star, \nu^2, E) \cdot p(X, \mu, \nu^2, E) = p(E|\sigma^2, X, \mu, \nu^2) \cdot p(\sigma^2|X, \mu, \nu^2) \cdot p(X, \mu, \nu^2)$$

The third term in the RHS of the above equation is independent of σ^2. So I can rewrite:

$$p(\sigma^2|X, \mu^\star, \nu^2, E) \propto p(E|\sigma^2, X, \mu^\star, \nu^2) \cdot p(\sigma^2|X, \mu^\star, \nu^2) \tag{A.15}$$

where, $p(\sigma^2|X, \mu^\star, \nu^2) \sim IG\left(a + \frac{T}{2}, b + \frac{1}{2}\Sigma_{t=2}^{T-1}(X_{t+1}^{(g+1)} - X_t^{(g+1)} - \mu^{(g)})^2\right)$ with prior of $a = 2.1$ and $b = 300$. Since distribution in Equation (A.15) is not a standard one, I use independent Metropolis-Hastings algorithm such that:

(1) Draw $\sigma^2_{(\star)} \sim IG\left(a + \frac{T}{2}, b + \frac{1}{2}\Sigma_{t=2}^{T-1}(X_{t+1}^{(g+1)} - X_t^{(g+1)} - \mu^{(g)})^2\right)$

(2) Generate $u \sim U[0,1]$

(3) If $u < \bar{A}$, then accept $\sigma^2_{(g+1)} = \sigma^2_{(\star)}$, otherwise $\sigma^2_{(g+1)} = \sigma^2_{(g)}$. where, the acceptance rule $\bar{A}$ is :

$$\bar{A} = min\left\{1, \frac{\pi(\sigma^2_{(\star)})}{\pi(\sigma^2_{(g)})} \cdot \frac{q(\sigma^2_{(g)})}{q(\sigma^2_{(\star)})}\right\} = min\left\{1, \frac{p(E|\sigma^2_{(\star)}, X_{(g+1)}, \mu^\star_{(g)}, \nu^2_{(g)})}{p(E|\sigma^2_{(g)}, X_{(g+1)}, \mu^\star_{(g)}, \nu^2_{(g)})}\right\}$$

Note that $p(E|\sigma^2_{(g)}, X_{(g+1)}, \mu^\star_{(g)}, \nu^2_{(g)})$ and $p(E|\sigma^2_{(\star)}, X_{(g+1)}, \mu^\star_{(g)}, \nu^2_{(g)})$ are easy to calculate by $\Pi_{t-1}^T p\left(ln(f_E^{-1}(E_t, \sigma^2_{(g)}, \mu^\star_{(g)}, \nu^2_{(g)}))\right)$ and $\Pi_{t-1}^T p\left(ln(f_E^{-1}(E_t, \sigma^2_{(\star)}, \mu^\star_{(g)}, \nu^2_{(g)}))\right)$, respectively.

Drift of log asset value $\mu^\star$

Note that in risk neutral measure, drift of asset process does not matter for prices. So I can ignore the condition from E. From the normal prior of $(\mu^\star|\sigma^2) \sim N(A, \sigma^2/B)$ with $A = 0.15$ and $B = 5$, the posterior distribution is

$$p(\mu^\star_{(g+1)}|X_{(g+1)}, \sigma^2_{(g+1)}, \nu^2_{(g)}) \sim N\left(\frac{1}{B^\star}(AB + (X_T^{(g+1)} - X_1^{(g+1)})/2), \sigma^2_{(g+1)}/B^\star\right)$$

where, $B^\star = B + (T-1)/2$.

Pricing error ν^2

Given prior $\nu^2 \sim IG(a, b)$, the posterior is:

$$p(\nu^2|\sigma^2_{(g+1)}, X_{(+1)}, \mu^\star_{(g+1)}, E) \sim IG\left(a + \frac{T}{2}, b + \frac{1}{2}\Sigma_{t=2}^{T-1}(ln(f_E^{-1}(E_t, |\mu^\star_{(g+1)}, \sigma^2_{(g+1)})) - X_t^{(g+1)})^2\right)$$

A.3 Supplemental Tables and Figures

	EDF				Distance-to-Default			
	Mean		Median		Mean		Median	
	Exp.	Rec.	Exp.	Rec.	Exp.	Rec.	Exp.	Rec.
AA+	0.9%	0.5%	0.4%	0.1%	7.53	7.19	7.41	7.09
A	1.3%	0.8%	0.8%	0.4%	6.94	7.02	6.84	7.03
BBB	3.1%	2.0%	1.6%	0.8%	5.52	5.77	5.18	5.55
BB	9.4%	6.6%	3.9%	1.9%	4.42	4.81	4.21	4.63
B	16.4%	9.6%	7.9%	2.6%	3.59	3.96	2.98	3.44
CCC	28.5%	24.5%	21.7%	11.7%	2.89	2.74	2.27	2.27

Table A.1: **Expected Default Frequency (EDF) and Distance-to-Default (DD) within Rating:** This table presents the credit quality measured by EDF and DD per rating group during the expansion and the recession. The rating format of the coarse rating used here follows S&P, and ratings from other CRAs (Fitch, Moody's, and Duff & Phelps) are translated to equivalent S&P ratings. Further, I pool AAA rating into AA, making AA+ category. Recession period is chosen from Jun 2007 to Jan 2009.

	Distance-to-Default			
	(1)	(2)	(3)	(4)
Metric	-0.25***	-0.27***	-0.27***	-0.27***
	(-49.16)	(-41.70)	(-42.59)	(-42.28)
Metric·Regime	0.01***	0.01***	0.01***	0.01***
	(5.22)	(4.43)	(4.51)	(3.57)
Issuer Industry	N	Y	Y	Y
Nbr of CRA	N	Y	Y	Y
Seniority	N	N	Y	Y
Credit Enhance	N	N	N	Y
Preferred	N	N	N	Y
Callablity	N	N	N	Y
Puttability	N	N	N	Y
Covenant	N	N	N	Y
Coupon Type	N	N	N	Y
Cut-offs				
θ_1	-3.16***	-3.15***	-1.21***	-0.81***
	(-78.97)	(-45.99)	(-5.77)	(-3.56)
θ_2	-2.79***	-2.66***	-0.73***	-0.33
	(-78.89)	(-42.15)	(-3.50)	(-1.46)
θ_3	-1.94***	-1.61***	0.33	0.73***
	(-66.57)	(-27.59)	(1.57)	(3.25)
θ_4	-1.07***	-0.57***	1.38***	1.80***
	(-43.07)	(-10.40)	(6.59)	(7.89)
θ_5	-0.57***	0.00	1.97***	2.40***
	(-24.33)	(0.05)	(9.36)	(10.45)
θ_6	0.52***	1.19***	3.18***	3.60***
	(21.40)	(20.19)	(14.77)	(15.45)
N	480961	480961	480937	480531
Pseudo R2	0.098	0.178	0.185	0.188

Table A.2: **Result of Ordered Probit Regression with Borrowers' Strategic Behavior:** This table presents the result of ordered probit regression specified in Equation (1.6). I present four specifications when distance-to-default in each column (1) to (4). In this case, borrowers' strategic behaviors described in Section 1.6.2 are considered, by using $\alpha_1 = 0.44$, $\alpha_2 = 0.045$ in an expansion and $\alpha_1 = 0.41$, $\alpha_2 = 0.064$ in a recession. Among Z, Issuer industry is a set of dummy variable according to Fama-French 49 industry classification. Nbr of CRA is the number of CRA that covers this bond at the time of issuance. Seniority is a categorical variable that indicates seniority of the issue (Senior Secured, Senior Unsecured, Senior Unsubordinated, Junior Secured, Junior or Subordinated). Credit enhance and Preferred are sets of dummy variable that indicate the bond has such feature that enhances credit quality or gives preferable treatment to the bond, respectively. Callablity and Puttability are sets of dummy variables that indicate the bond has call or put feature, respectively. Covenant is a dummy variable that assigns 1 if the bond is protected by covenants. Coupon Type is a categorical variable that assigns value depending on the type of coupon of the bond (Fixed, Variable or Zero). The usage of these issue/ issuer-specific control variables Z are indicated by yes (Y) or no (N). *Regime* is defined to have 1 in the recession period that is chosen from Jun 2007 to Jan 2009. Numbers inside of parenthesis are the z-value. Standard errors are clustered at issue level. Asterisks denote statistical significance at the 0.01(***), 0.05(**) and 0.1(*).

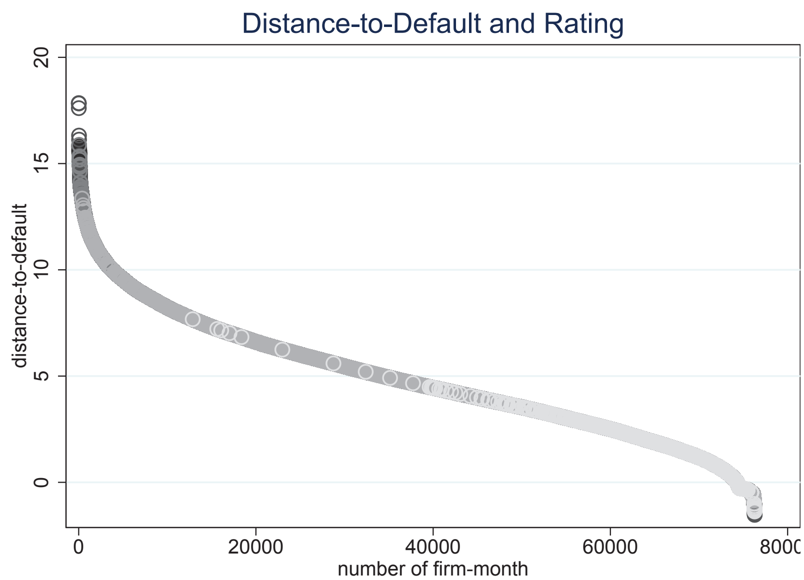

Figure A.1: **Distance-to-Default and Bond Rating:** This plot shows how distance-to-default measure and credit ratings are correlated. Each point in the plot stands for one bond in the sample and it delivers two pieces of information: (1) the distance-to-default of the bond by it vertical location and (2) the bond credit rating by its color. Higher vertical points indicate a bond with higher distance-to-default. Darker points indicate a bond with better credit rating. All points are sorted in descending order of distance-to-default.

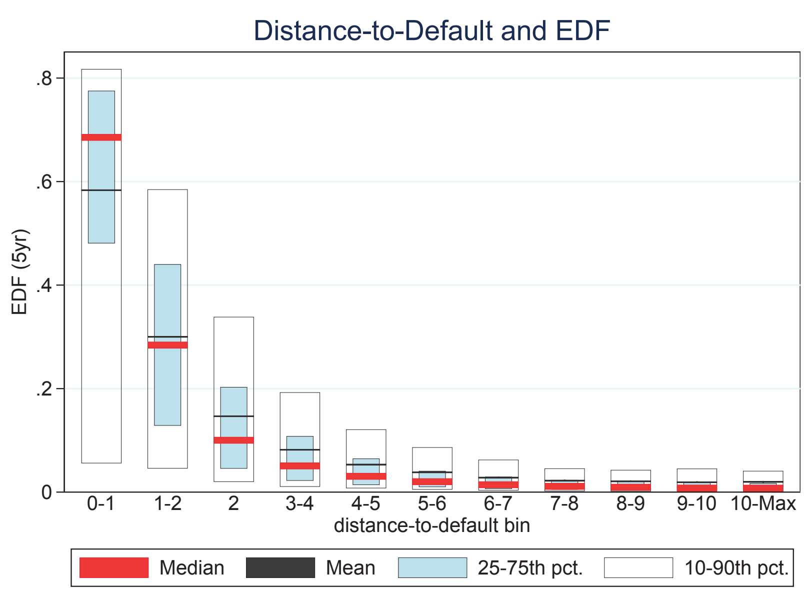

Figure A.2: **Relationship between Distance-to-Default and EDF:** This scatter chart plots the relationship between two metrics of credit quality: the distance-to-default and 5-year Expected Default Frequency (EDF). For each bin of distance-to-default, the plot shows (1) median (thicker horizontal lines), (2) mean (thinner horizontal lines), and (3) distributions of 25th to 75th percentile and 10th to 90th percentile (blue boxes and white boxes, respectively).

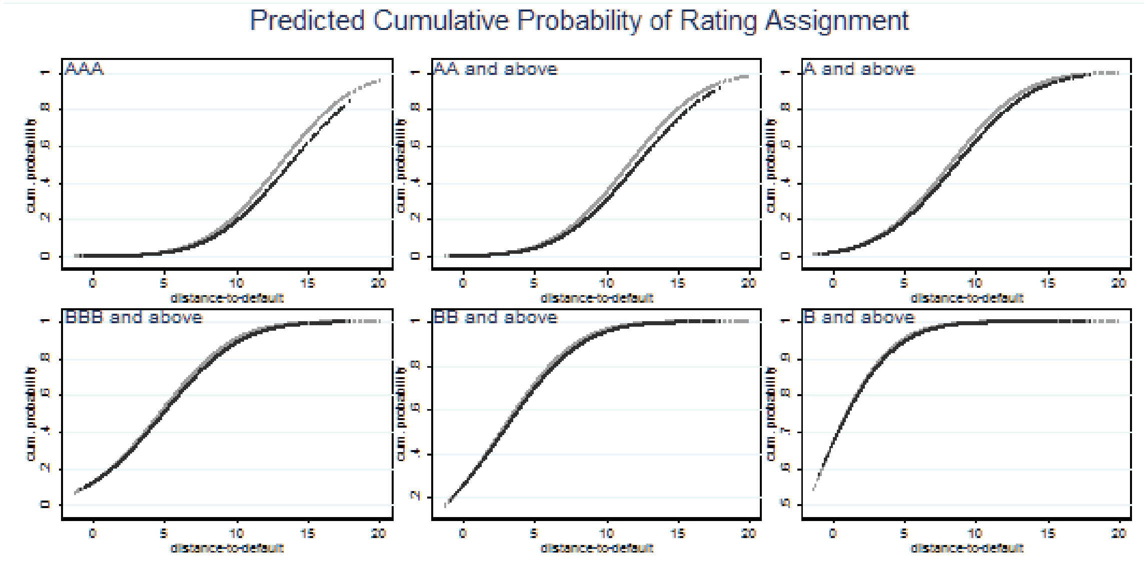

Figure A.3: **Predicted Cumulative Probability of Gaining per Each Rating:** This figure shows the probability of achieving a reference rating or higher in term of distance-to-default. The lighter curves are the probability under the expansion period and darker curves are under the policy in the recession period. Each reference rating is displayed in the upper left corner of each plot. Recession period that is chosen from Jun 2007 to Jan 2009.

Appendix B

Appendix for Chapter 2

B.1 RBC Ratio Calculation

I present the RBC ratio formula for Life and Property&Casualty insurance companies. The following calculation shows that RBC ratio is determined by various factors including bond ratings in their portfolio. More detailed information can be found at NAIC's Risk-Based Capital for Insurers Model Act (Volume II-312). RBC ratio is define as:

$$\text{RBC ratio} = \frac{\text{Statutory Surplus}}{\text{Risk Charges}}$$

where Statutory Surplus is a capital of the insurance company and Risk Charges are calculated as follows:

1. Life Insurance Risk Charges $= C0 + \sqrt{(C1o + C3a) + (C1cs + C3c)^2 + (C2)^2 + (C3b)^2 + (C4b)^2} + C4a$

   $C0$ = Insurance affiliate investment and (non-derivative) off-balance sheet risk

   $C1cs$ = Invested common stock asset risk

   $C1o$ = Invested asset risk, plus reinsurance credit risk except for assets in C1cs

   $C2$ = Insurance risk

   $C3a$ = Interest rate risk

   $C3b$ = Health provider credit risk

   $C3c$ = Market risk

   $C4a$ = Business risk - guaranty fund assessment and separate account risks

   $C4b$ = Business risk - health administrative expense risk

2. Property and Casualty Insurance Risk Charges $= R0 + \sqrt{(R1)^2 + (R2)^2 + (R3)^2 + (R4)^2 + (R5)^2}$

   $R0$ = Insurance affiliate investment and (non-derivative) off-balance sheet risk

   $R1$ = Invested asset risk - fixed income investments

$R2$ = Invested asset risk - equity investments

$R3$ = Credit risk (non-reinsurance plus one half reinsurance credit risk)

$R4$ = Loss reserve risk, one half reinsurance credit risk, growth risk

$R5$ = Premium risk, growth risk

Appendix C

Appendix for Chapter 3

C.1 Proofs

Proof of Proposition 3.1

The value of equity satisfies the following ODE:

$$\frac{1}{2}\sigma^2 E_{VV} + (r-\delta)VE_V - rE + \delta V - (C+Sr)(1-\tau) = 0 \tag{C.1}$$

The boundary conditions are:

$$\begin{aligned} E(V \uparrow \infty) &= V - (C/r+S)(1-\tau) \\ E(V_B) &= (1-\theta)\alpha_2 V_B \\ E_V(V_B) &= (1-\theta)\alpha_2 \end{aligned}$$

The general solution of the Equation (C.1) is known as

$$a_0 + a_1 V + a_2 V^{-x} \tag{C.2}$$

where, $x > 0$ is the root of the characteristic equation below:

$$\frac{1}{2}x^2\sigma^2 - x\left(r - \delta - \frac{\sigma^2}{2}\right) - r = 0 \tag{C.3}$$

Using the boundary conditions, we determine a_0, a_1, a_2 and V_B. Defining $p \equiv (V/V_B)^{-x}$, we obtain the valuation function for the equity, $E(V)$:

$$E(V) = V - (C/r+S)(1-\tau)(1-p) - (1-(1-\theta)\alpha_2)V_B p \tag{C.4}$$

V_B can be determined from maximizing Equation (C.4) such that $\frac{\partial E}{\partial V}|_{V=V_B} = 0$ giving the expression in the Proposition 3.1:

$$V_B = (1-\tau)(C/r+S)\left(\frac{x}{1+x}\right)\frac{1}{1-(1-\theta)\alpha_2} \tag{C.5}$$

□

Proof of Proposition 3.2

We start from our equilibrium where the equity holder triggers restructuring simultaneously when the run happens. From Equation (C.4), we know the equity pricing formula when there is no run risk. We denote the equity in this case $E^\star$ and it has the following form:

$$E^\star(V) \quad = \quad V - (C/r + S)(1-\tau)(1 - (V/V_B)^{-x}) - (1 - (1-\theta)\alpha_2) \cdot V_B \cdot (V/V_B)^{-x} \tag{C.6}$$

where, the optimal restructuring boundary is

$$\begin{aligned} V_B &= (1-\tau)(C/r + S)\left(\frac{x}{1+x}\right)\frac{1}{1-(1-\theta)\alpha_2} \\ &= V_R = \frac{S}{\theta(1-\beta)} \end{aligned} \tag{C.7}$$

Consider now an off-the-equilibrium case where the equity holder picks an arbitrary S such that $\frac{S}{\theta(1-\beta)} > V_B$. The short-term lender will run when $V_R = \frac{S}{\theta(1-\beta)}$ is reached which is the minimum point of asset value that they can recover the full amount. This would imply that the equity holder allows the short-term lender to liquidate the pledged assets when $V \downarrow V_R$. At that time, the short-term lender will take out θV_R, leaving only $(1-\theta)V_R \equiv \hat{V}_R$ in the firm. With this left-over asset, the equity holder can operate the firm until their new restructuring boundary $\hat{V}_B$ is hit. Let us define a state-price $\hat{p}$, that pays out \$1 when $\hat{V}_R \downarrow \hat{V}_B$:

$$\hat{p} = \left(\frac{\hat{V}_R}{\hat{V}_B}\right)^{-x} \tag{C.8}$$

After the point when short-term lender stops rolling over at V_R, the firm only has long-term debt. The equity value at V_R, therefore follows the standard expression as in Leland (1994). Let us denote it $\hat{E}$ and it can be written as follows. At $V = V_R$:

$$\hat{E}(\hat{V}_R) = \hat{V}_R - (C/r)(1-\tau)(1-\hat{p}) - (1-\alpha_2)\hat{V}_B \cdot \hat{p} \tag{C.9}$$

Using standard techniques, the optimal post-run restructuring boundary $\hat{V}_B$ can be easily found:

$$\hat{V}_B = (C/r)(1-\tau)\left(\frac{x}{1+x}\right)\left(\frac{1}{1-\alpha_2}\right) \tag{C.10}$$

So, when $\alpha_2 = 0$, we recover the standard Leland equity valuation. Now the off-the equilibrium equity claim has the following PDE:

$$\frac{1}{2}\sigma^2 V^2 E_{VV} + (r-\delta)VE_V - rE + \delta V - (C + Sr)(1-\tau) = 0 \tag{C.11}$$

with the boundary conditions:

$$E(V_R) \quad = \quad \hat{E}(\hat{V}_R) \tag{C.12}$$

$$E(V \uparrow \infty) \quad = \quad V - (C/r + S)(1-\tau) \tag{C.13}$$

We can interpret (A.12),which is the value matching condition, as follows: It says that the equity value immediately after the short-term lenders run, is equal to the continuation value associated with the firm operating with only long-term debt after the run by short-term lenders. We guess the following form for $E(\cdot)$:

$$E(V) = a_0 + V + a_1 V^{-x} \tag{C.14}$$

The second boundary condition in (C.13) immediately pins down $a_0 = -(C/r+S)(1-\tau)$. The first boundary condition (C.12) and Equation (C.9) yield the following equation:

$$V_R - (C/r + S)(1-\tau) + a_1 V_R^{-x} = \hat{V}_R - (C/r)(1-\tau)(1-\hat{p}) - (1-\alpha_2)\hat{V}_B \cdot \hat{p} \tag{C.15}$$

We solve for $a_1 V_R^{-x}$:

$$\begin{aligned}
a_1 V_R^{-x} &= (\hat{V}_R - V_R) + (1-\tau)\left[(C/r + S) - (C/r)(1-\hat{p})\right] - (1-\alpha_2)\hat{V}_B \cdot \hat{p} \\
&= -\frac{S}{1-\beta} + (1-\tau)\left[S + (C/r)\hat{p}\right] - (1-\alpha_2)\hat{V}_B \cdot \hat{p} \\
&= -S\left[\frac{\beta}{1-\beta} + \tau\right] + \left[(1-\tau)(C/r) - (1-\alpha_2)\hat{V}_B\right]\hat{p} \\
&= -S\left[\frac{\beta}{1-\beta} + \tau\right] + \left[(C/r)(1-\tau)\left(\frac{1}{1+x}\right)\right]\hat{p}
\end{aligned}$$

The last equality uses the expression in (C.10). Therefore, we can pin down a_1:

$$a_1 = \left(-S\left[\frac{\beta}{1-\beta} + \tau\right] + \left[(C/r)(1-\tau)\left(\frac{1}{1+x}\right)\right]\hat{p}\right) \cdot V_R^x \tag{C.16}$$

Plugging (C.16) to (C.14), we obtain off-the-equilibrium equity valuation:

$$E(V) = V - (C/r + S)(1-\tau) + \left(-S\left[\frac{\beta}{1-\beta} + \tau\right] + \left[(C/r)(1-\tau)\left(\frac{1}{1+x}\right)\right]\hat{p}\right) \cdot \left(\frac{V}{V_R}\right)^{-x} \tag{C.17}$$

At $t = 0$, equity holder decides whether they would deviate from the equilibrium by computing:

$$\begin{aligned}
E^{\star}(V_0) - E(V_0) \;&=\; (C/r)(1-\tau)\left(\frac{1}{1+x}\right)\left[(V_0/V_B)^{-x} - \hat{p} \cdot (V_0/V_R)^{-x}\right] \\
&\quad + S(1-\tau)\left(\frac{1}{1+x}\right) \cdot (V_0/V_B)^{-x} + S\left[\frac{\beta}{1-\beta} + \tau\right] \cdot (V_0/V_R)^{-x}
\end{aligned} \tag{C.18}$$

From the definition of $\hat{p}$ in (C.8) and the fact that when V_R is hit, the asset value immediately drops to $\hat{V}_R$, $\hat{p} \cdot (V_0/V_R)^{-x}$ is the price of the state contingent claim at $t = 0$ that pays \$1 when $V \downarrow \hat{V}_B$. Hence, this value must be smaller than $(V_0/V_B)^{-x}$ which is the value of a state contingent claim that pays \$1 when $V_0 \downarrow V_B$, because $V_B > \hat{V}_B$. Therefore, $[(V_0/V_B)^{-x} - \hat{p} \cdot (V_0/V_R)^{-x}] > 0$, resulting $E^{\star}(V_0) - E(V_0) > 0$. Hence, we conclude that the equity holder has no incentive to deviate from the equilibrium of $V_R = V_B$ and this equilibrium will sustain.

□

Proof of Proposition 3.3

First, we solve the ODE satisfied by the value of long-term debt.

$$\frac{1}{2}\sigma^2 D_{VV} + (r-\delta)VD_V - rD + C = 0 \tag{C.19}$$

with boundary conditions:

$$\begin{aligned} D(V \uparrow \infty) &= C/r \\ D(V_B) &= (1-\theta)\alpha_1 V_B \end{aligned}$$

The second boundary condition specifies that short term debt is secured by a fraction θ of assets and short-term lenders have seniority to long-term debt holders. The debt value is:

$$D(V) = C/r(1-p) + p(1-\theta)\alpha_1 V_B \tag{C.20}$$

Next, the valuation function for the short-term debt, B, is always S due to the fact that the short-term lender can always recover the full amount.

$$B(V) = S \tag{C.21}$$

Now, we add up Equation (C.4), (C.20), and (C.21) to compute the firm value, v: **??**)

$$\begin{aligned} v(V) &= E(V) + D(V) + B(V) \\ &= V + \tau(C/r+S)(1-p) + Sp - pV_B + p(1-\theta)(\alpha_1+\alpha_2)V_B \end{aligned} \tag{C.22}$$

Note that when the restructuring boundary is reached the firm's value becomes:

$$v(V_B) = S + (1-\theta)(\alpha_1+\alpha_2)V_B \tag{C.23}$$

In other words, in restructuring, short-term creditors get back their principal S from liquidating the θV_B and the amount $(1-\theta)(\alpha_1+\alpha_2)V_B$ is split between long-term creditors and borrowers.

We now start from the rational belief that the short-term lender must make their claim risk free. That is, for any given restructuring boundary V_B, they should be able to recover everything they lent. Also, we assume that the short-term lender is better off staying with the firm as long as they can recover everything. This beliefs form the following equilibrium, as shown in Proposition 3.2:

$$S = V_B(1-\beta)\theta \tag{C.24}$$

Plugging (C.24) to (C.5) results the following:

$$V_B = \left(\frac{C}{r}\right) \cdot f(\theta) \tag{C.25}$$

where,

$$f(\theta) = \left(\frac{(1-\tau)(\frac{x}{1+x})(\frac{1}{1-(1-\theta)\alpha_2})}{1-(1-\beta)\theta(1-\tau)(\frac{x}{1+x})(\frac{1}{1-(1-\theta)\alpha_2})} \right) \tag{C.26}$$

Then substituting S and V_B in (C.22) with (C.24) and (C.25) gives us:

$$v(V) = V + \tau(C/r)(1 + (1-\beta)\theta \cdot f(\theta) - p) + pV_B \cdot g(\theta) \tag{C.27}$$

where,

$$g(\theta) = ((1-\tau)(1-\beta)\theta + (1-\theta)(\alpha_1 + \alpha_2) - 1) \tag{C.28}$$

The first order condition of (C.27) with respect to C determines the optimal $C^\star$ and $S^\star$:

$$\begin{aligned} C^\star &= \frac{rV}{f(\theta)}\left[\frac{1 + f(\theta)\cdot(1-\beta)\theta}{(1+x)(1 - f(\theta)\cdot g(\theta)/\tau)}\right]^{\frac{1}{x}} \\ S^\star &= (C^\star/r)\cdot f(\theta)\cdot(1-\beta)\theta \end{aligned}$$

□

Proof of Theorem 3.1

When $\alpha_2 = 0$ and $\alpha = \beta$, that is $1 - \alpha_1 = \beta$, the third term of the Equation (3.7) becomes $-pV_B(1-\alpha_1)$. Also V_B in Equation (C.5) becomes independent of θ. Therefore, the firm value is independent of θ. This means we can replicate the firm value with only using long-term debt, hence the optimal liability structure is not uniquely pinned-down.

□

Proof of Theorem 3.2

The result is very intuitive. When $\alpha > \beta$, there is a saving in dead-weight loss of restructuring. Therefore, to engage more into safe-harboring activity improves the firm value. As a result, the equity holders pledge as much as possible, setting $\theta = \bar{\theta}$ where, $\bar{\theta}$ is the maximum level of portion of asset that they can pledge.

□

Proof of Corollary 3.1

Plugging in optimal $C^\star(\theta)$ and $S^\star(\theta)$ found in 3.3 into Equation (C.22) provides the the optimized level of the firm value, $v^\star(\theta)$. It is straight forward to show, with positive α_1 and α_2 such that α_1+α_2¡1, $(\frac{\partial v^\star(\theta)}{\partial \theta}|\beta = 0 > 0)$ and $(\frac{\partial v^\star(\theta)}{\partial \theta}|\beta = 1 < 0)$. Since β is continuous between 0 and 1, there exists a point in β such that $\frac{\partial v^\star(\theta)}{\partial \theta} = 0$. We denote this point by $\bar{\beta}$. Note that $\bar{\beta}$ is a function of parameters that are related to bankruptcy code such as α_1 and α_2 and the pledging capacity θ. Thus, we express $\bar{\beta}$ in terms of these parameters:

$$\begin{aligned} \bar{\beta}(\alpha_1, \alpha_2, \theta) &= \frac{(1 - (\alpha_1 + \alpha_2))(1 + x\alpha_2(1-\theta) - \tau)}{(1 - \alpha_2(1 + x\theta))(1-\tau)} \\ &+ \frac{\alpha_2((1-\theta)(1 - (\alpha_1 + \alpha_2)) + ((1-\theta)\alpha_1 + \theta)(x+1))\tau}{(1 - \alpha_2(1 + x\theta))(1-\tau)} \end{aligned} \tag{C.29}$$

Therefore, in any level of $\beta > \bar{\beta}$, the firm value is decreasing in θ, making safe-harboring activity sub-optimal. It is also clear that $\bar{\beta}$ is a increasing in α and α_2 (keeping α same). Hence, as the code gets messier (higher α) and as there is more APR violation (higher α_2), this constraints on liquidity becomes more relaxed (higher $\bar{\beta}$). This is to say that if the code is very efficient, only very liquid asset with tiny β can be used as the collateral.

□

Proof of Corollary 3.2

We know that the valuation formula for the long-term debt is:

$$D = (C/r)(1-p) + p(1-\theta)\alpha_1 V_B \tag{C.30}$$

and the short-term debt is always S. Therefore, the total debt is $D+S$. From the equilibrium result where $V_B = V_R$, we can express the total debt in terms of C.

$$D + S = (C/r)(1-p) + (p(1-\theta)\alpha_1 + \theta(1-\beta))V_B \tag{C.31}$$

where,

$$V_B = \left(\frac{C}{r}\right) \cdot f(\theta) \tag{C.32}$$

and

$$f(\theta) = \left(\frac{(1-\tau)(\frac{x}{1+x})(\frac{1}{1-(1-\theta)\alpha_2})}{1-(1-\beta)\theta(1-\tau)(\frac{x}{1+x})(\frac{1}{1-(1-\theta)\alpha_2})}\right) \tag{C.33}$$

Differentiating (C.31) with respect to C gives us the dollar-coupon that delivers maximum total debt capacity:

$$C_{MAX} = \frac{rV}{f(\theta)}\left[\left(\frac{1}{1+x}\right)\left(\frac{1+\theta(1-\beta)\cdot f(\theta)}{1-(1-\theta)\alpha_1 \cdot f(\theta)}\right)\right]^{\frac{1}{x}} \tag{C.34}$$

□

C.2 Supplemental Tables and Figures

(Whole sample)	Has debt $\geq$ 1 year					
	Yes		No		Total	
Has debt $<$ 1 year	N.	(%)	N.	(%)	N.	(%)
Yes	15,974	(87)	889	(62.8)	16,863	(85.3)
No	2,381	(13)	526	(37.2)	2,907	(14.7)
Total	18,355	(100)	1,415	(100)	19,770	(100)

(Financials)	Has debt $\geq$ 1 year					
	Yes		No		Total	
Has debt $<$ 1 year	N.	(%)	N.	(%)	N.	(%)
Yes	3,632	(93.3)	143	(85.6)	3,775	(93)
No	261	(6.7)	24	(14.4)	285	(7)
Total	3,893	(100)	167	(100)	4,060	(100)

(Non-Financials)	Has debt $\geq$ 1 year					
	Yes		No		Total	
Has debt $<$ 1 year	N.	(%)	N.	(%)	N.	(%)
Yes	12,342	(85.3)	746	(59.8)	13,088	(83.3)
No	2,120	(14.7)	502	(40.2)	2,622	(16.7)
Total	14,462	(100)	1,248	(100)	15,710	(100)

Table C.2.1: **Distribution of debt structure in maturity:** This table presents the distribution of the firms in terms of the debt structure. The top panel covers all the firms in our sample. The middle panel covers only financial firms under our definition and the bottom panel covers only non-financial firms. Column under $N.$ stands for the number of observation and number in parenthesis is the corresponding percentage of observations.

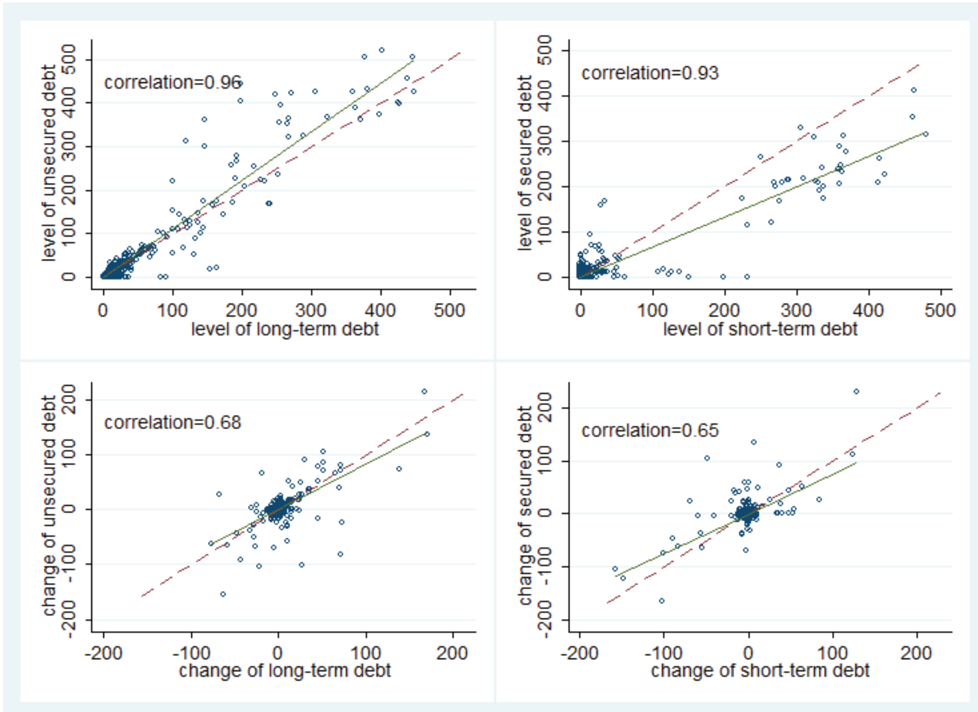

Figure C.2.1: **Correlation of debt by maturity and security:** These plots present the correlation between our definition of short-term (long-term) debt and total secured (unsecured) debt defined by Capital IQ. The top two graphs use levels of variables and bottom two use the change. Solid line is the fitted line of those observations and dashed line is 45 degrees line.

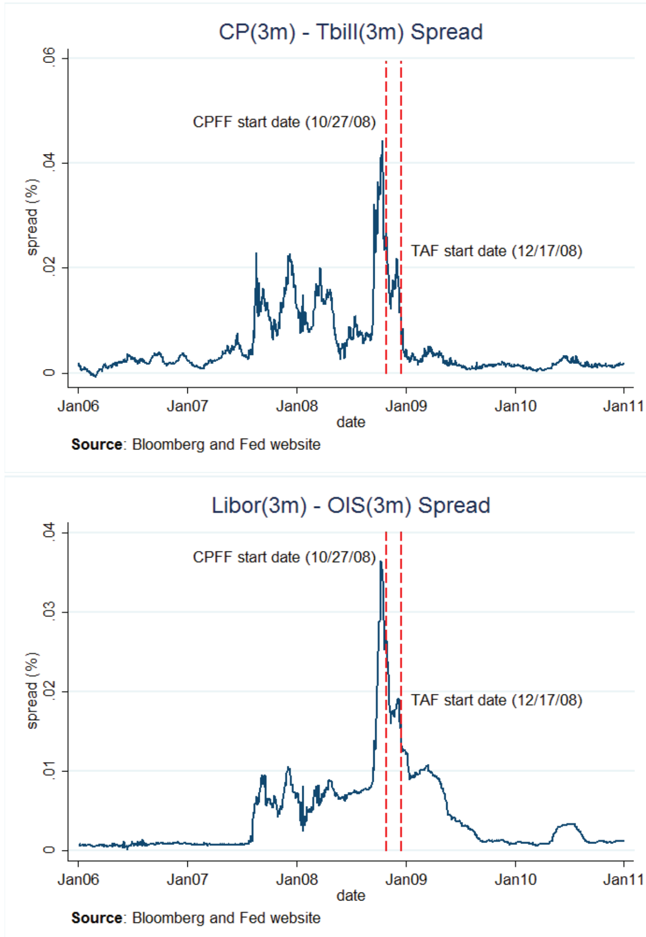

Figure C.2.2: **Short-term debt spread during the crisis:** These plots show the spread between Commercial Paper and 3m T-bill rate (left) and the spread between the 3m LIBOR (right) and Overnight Index Swap (OIS) rate. Two vertical lines indicate the starting point of the each short-term facility.

	Non-Fin						Fin					
Variables	Mean	St.Dev.	25th Pct.	Median	75th Pct.	N	Mean	St.Dev.	25th Pct.	Median	75th Pct.	N
Total asset	7,586	37,509	236	974	3,704	15,208	24,914	158,851	613	1,348	4,201	4,036
Total liability	5,375	31,999	96	529	2,309	15,208	22,684	145,858	525	1,165	3,716	4,036
Total debt	1,812	12,582	22	216	982	15,208	8,061	57,379	69	192	676	4,036
Short-term debt	182	2,813	0	0	3	15,208	3,999	32,885	0	26	156	4,036
Total secured debt	340	2,294	0	7	111	15,206	3,076	22,736	29	110	404	4,036
Total unsecured debt	1,400	11,341	0	97	639	15,206	4,355	32,407	0	21	125	4,036
Market value of equity (MV)	5,428	20,058	213	847	2,991	15,208	3,031	15,741	67	206	836	4,029
Stock volatility for 12 mo	44.2%	31.7%	25.0%	36.7%	54.1%	15,208	32.9%	24.1%	17.6%	26.1%	40.6%	4,036
Leverage ratio ($Leverage$)	36.3%	28.8%	14.7%	32.3%	51.1%	15,208	54.5%	22.3%	40.0%	56.7%	69.5%	4,036
ST / Total Debt ($Maturity$)	8.0%	21.4%	0.0%	0.0%	2.2%	15,208	27.8%	30.0%	0.0%	18.1%	46.7%	4,036
Mortgage fraction ($Mortgage$)	8.8%	4.1%	4.0%	9.4%	12.7%	16	12.0%	9.2%	5.2%	10.2%	16.1%	3,194
TARP / Total Cap ($TARP$)	-	-	-	-	-	0	10.54%	5.53%	6.97%	9.72%	12.64%	502
TDGP / Total Cap ($TDGP$)	-	-	-	-	-	0	3.44%	4.80%	0.00%	1.62%	4.38%	40
ST Funding / Total Cap ($Fund$)	4.33%	5.47%	1.14%	2.53%	5.42%	15	7.28%	10.12%	0.00%	4.32%	10.90%	80
Market to book (M/B)	123.6%	125.8%	50.3%	88.3%	151.8%	15,208	28.8%	64.2%	8.5%	13.9%	21.6%	4,029
Dur. of LT debt repayment	2.7	1.1	1.9	2.8	3.5	13,849	1.4	0.8	1.0	1.0	1.0	2,946
Years from IPO	11.1	6.3	6.0	11.0	15.0	7,841	8.8	5.1	5.0	9.0	12.0	1,765
Rating ($Rating$)	3.4	1.1	3.0	3.0	4.0	6,679	2.8	1.0	2.0	3.0	3.0	640
Firms with rating ($Rated$)	43.9%	-	-	-	-	15,208	15.9%	-	-	-	-	4,036

Table C.2.2: **Summary Statistics:** This table show summary statistics of the sample firms for selected variables. We divided them into financial group and non-financial group according to our definition. Total asset and total liability are the Compustat variables, AT and LT, respectively. Total debt is from Compustat $DLTT+DLC$. Short-term debt is the Compustat variable, NP. Total secured debt and total unsecured debt are from Capital IQ. Leverage ratio ($Leverage$) is from Compustat variables, $(DLTT+DLC)/(DLTT+DLC+MIB+SEQ)$. ST / Total Debt ($Maturity$) is from Compustat variables, $NP/(DLTT+DLC)$. Mortgage fraction ($Mortgage$) is the Mortgage related asset / AT where, Mortgage related asset is from the Capital IQ database. TARP/Total Cap ($TARP$) is the TARP money received in percentage over total capital $(DLTT+DLC+MIB+SEQ)$. TDGP ($TDGP$) is the long-term portion (>1 year) of issuance through TDGP over total capital. ST Funding / Total Cap ($Fund$) is the amount received via TAF and CPFF program and short-term portion of TDGP issuance over total capital. Statistics for $TARP$ and $TDGP$ and $Fund$ are only within firm-year observations that have matched value to the funding program. Stock volatility for past 12 month uses monthly equity return from CRSP for the past 12 month period from the data reporting month. Market value of equity (MV) is the from the Compustat variable $CSHO * PRCC_F$ and Market to book (M/B) is defined as MV/AT. Dur. of LT debt repayment is the weighted average of the number of year to repay the long-term debt within 5 years: $(\sum_{i=1}^{5} i \cdot DD_i)/(\sum_{i=1}^{5} DD_i)$ where DD_i is the portion of long-term debt due in "i"th year from Compustat. Rating is numerically assigned Standard and Poor's long-term domestic issuer rating where 1 = CC, 2=CCC, 3=B, 4=BB, 5=BBB, 6=A, 7=AA and 8=AAA. The number of observations are not same for all variables because some of variables uses subset of our sample firms. For example, rating variable only uses firms which have rating the agency. Firm with rating ($Rated$) is percentage of firms that have domestic long-term issuer rating from S&P.

Fiscal Month	Freq.	Percent	Cum.
1	38	1.7%	1.7%
2	8	0.4%	2.1%
3	36	1.6%	3.7%
4	17	0.8%	4.5%
5	12	0.6%	5.1%
6	118	5.4%	10.5%
7	23	1.1%	11.5%
8	29	1.3%	12.8%
9	132	6.0%	18.8%
10	35	1.6%	20.4%
11	22	1.0%	21.4%
12	1,722	78.6%	100.0%
Total	2,192	100.0%	

Table C.2.3: **Fiscal month frequency in 2007:** This table shows the filing month distribution of our sample firms in 2007. Most of firms (78.6%) are reporting at the year-end. This patter of distribution is almost constant across all sample year.

Name	Non-Fin	Fin	Diff	Non-Fin	Fin	Diff	DD
Leverage	34.8%	57.2%	22.4%	37.3%	52.8%	15.6%	-6.8%
(t-stat)			10.66			10.66	(6.02)
Leverage (ex TARP)	34.8%	57.2%	22.4%	37.3%	54.0%	16.7%	-5.7%
(t-stat)			10.66			10.66	(4.71)
Leverage (ex TDGP)	34.8%	57.2%	22.4%	37.3%	52.8%	15.5%	-6.9%
(t-stat)			10.66			10.66	(6.08)
Leverage (ex TARP ex TDGP)	34.8%	57.2%	22.4%	37.3%	53.9%	16.7%	-5.7%
(t-stat)			10.66			10.66	(4.76)
Leverage (treating TARP as debt)	34.8%	57.2%	22.4%	37.3%	56.4%	19.1%	-3.2%
(t-stat)			10.67			10.67	(2.22)
Maturity	8.2%	29.5%	21.3%	7.9%	26.8%	18.9%	-2.4%
(t-stat)			15.02			15.02	(4.02)
Maturity (ex TDGP)	8.2%	29.5%	21.3%	7.9%	26.8%	18.8%	-2.4%
(t-stat)			15.02			15.02	(4.06)
N	5,929	1,515		9,279	2,521		

Table C.2.4: **Unconditional Diff-in-Diffs for different variable definition:** This table exhibits unconditional Diff-in-Diffs results with different *Leverage* and *Maturity* definition associated with the government funding program. *Leverage* is our baseline definition: $(DLTT + DLC)/(DLTT + TLC + MIB + SEQ)$. *Leverage* (ex TARP) is leverage without having TARP fund in the firm's equity: $(DLTT+DLC)/(DLTT+TLC+MIB+SEQ-TARP)$. *Leverage* (ex TDGP) does not include long-term debt issued through TDGP: $(DLTT - TGDP + DLC)/(DLTT - TGDP + TLC + MIB)$.*Leverage* (ex TARP ex TDGP) does not include niether TARP money nor TDGP debt: $(DLTT + DLC)/(DLTT + TLC + MIB + SEQ - TARP)$. *Leverage* (treating TARP as debt) treats TARP money as a debt for its calulation: $(DLTT + DLC + TARP)/(DLTT + TLC + MIB + SEQ - TARP)$. *Maturity* is our baseline definition for the maturity structure: $(NP)/(DLTT + DLC)$. *Maturity* (ex TDGP) subtracts TDGP debt from the long-term debt: $(NP)/(DLTT - TDGP + DLC)$