Procyclical Credit Rating Policy

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Abstract

This paper 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.

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1 Introduction

Credit ratings convey pricing-relevant information to investors (Klinger 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 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

¹Title 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.

²Standard & Poor’s (2008), p.28

³“Credit ratings are expressions of opinion about credit risk”, Standard & Poor’s (2012). Also see Manso et al. (2010) for related discussions.
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 debt servicing cost becomes higher (Leland (1994a,b)), the procyclical rating policy contributes to an even greater re-
duction 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 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. 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.

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

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7Those accounting ratios are interest coverage, operating margin, long-term debt, and total debt.
8They 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.
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. 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 likely to reduce investment when the cost of capital is higher. Auh (2013) 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 2 formalizes the motivation. Section 3 describes the data. Section 4 develops a base structural model and explains the procedure used to estimate credit quality. Sections 5 provides a quantitative measure of procyclical rating policy and its effect in the cross-section of firms. Section 6 considers several robustness checks. Section 7 studies the implication of the procyclical rating standard on the aggregate economy, and Section 8 concludes.

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9For 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.
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.
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.** 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 $E_g[\theta | p_g \leq \theta \leq q_g] > E_f[\theta | p_f \leq \theta \leq q_f]$ 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 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, I obtain the following corollary.

**Corollary.** 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 $f$, $(g \overset{\text{FOSD}}{\succ} f)$. 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. 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.]

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 within a month. Also, if there are cross-sectional differences in ratings across agencies at the same time, I

\(^{10}\)Table C.1 in the Appendix shows the same pattern in finer rating categories.
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.
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.\footnote{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 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.} These variables indicate that (1) the monthly rating panel has the average 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.\footnote{For the trading yield, I winsorize the yield at 1 percent level to remove extreme values.} 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.
4 Estimation Process

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 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 7 explains in detail the implication of credit rating policy.

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

$$dV = (\mu - \delta)V dt + \sigma V dW$$

where, $\mu$ is a drift of the asset value, $\delta$ is the dividend ratio, and $\sigma$ 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 $V$

\(^{13}\)For detailed derivation, see Leland (1994b).
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 $\alpha_1$ as the fraction of available asset value that the creditors recover, and $\alpha_2$ 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 $\alpha$ 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 $\alpha_1$ and $\alpha_2$. 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 2.** Consider that the asset process follows Equation (1). Suppose that, upon the credit event ($V \downarrow V_B$), the creditors recover the fraction $\alpha_1$ and the equity holders receive the fraction $\alpha_2$ of asset value. At that moment, the debt and equity valuations are:

\[
D(V|V_B) = \left( \frac{C + mP}{r + m} \right) (1 - (V/V_B)^{-y}) + \alpha_1 V_B (V/V_B)^{-y} \tag{2}
\]

\[
E(V|V_B) = V + \left( \frac{\tau C}{r} \right) (1 - (V/V_B)^{-x}) - (\alpha - \alpha_2) V_B (V/V_B)^{-x} - D(V|V_B) \tag{3}
\]

where, $C$ is a dollar coupon for total debt, $P$ is a principal amount of total debt, $\tau$ is a corporate tax rate, $r$ 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 (3). The optimality
condition $\partial E / \partial V_B = 0$ obtains the following optimal default boundary:

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

(4)

Note that $V_B$ depends on $\alpha_2$, 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 $\alpha_2$ 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 $\alpha_1$ and $\alpha_2$ 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 $\sigma$, and the drift term $\mu$. 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 (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 $\delta$. The corporate tax rate $\tau$ and the bankruptcy cost $\alpha$ 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

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14This is guaranteed by the Clifford-Hammersley theorem. See Johannes and Polson (2003) for detailed explanations.
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 unknown parameters ($\sigma$, $\mu$) 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.

$$DD = \frac{\log(V/V_B) + (\mu - \delta - \sigma^2/2)}{\sigma} \tag{5}$$

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 $\sigma$, 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 (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.\(^{15}\)

### 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; 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

\(^{15}\)For more discussion about EDF and its estimation methodology, see Berndt et al. (2005) and Bharath and Shumway (2004).
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 following relationship for the reference rating score of a firm i at time t:

\[
Score_{it} = (\beta_1 + \beta_2 \cdot Regime_t) \cdot DD_{it} + \gamma' \cdot Z_i + u_{it} \equiv X \cdot B + u_{it} \tag{6}
\]

where, Regime\textsubscript{t} is a dummy variable with a value of 1 during a recession and 0 otherwise, DD\textsubscript{it} is the distance-to-default, Z\textsubscript{i} is a vector of issue or issuer-specific variables that do not have a time-variation, and \( u_{it} \mid X \sim N(0, 1) \). Next, I map the Score variable to the number-coded rating category Rating. Let \( \theta_k (\theta_1 > \theta_2 > \cdots > \theta_6) \) be the cut-off points between a \( k \) and \( k + 1 \) rating. For example, \( \theta_3 \) 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:

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

¹⁶Bongaerts et al. (2012) document that ratings may depend on how many rating agencies cover that specific issue.
Then for \( j = \{2, \ldots, 6\} \),

\[
Pr(Rating_{it} = j) = Pr(\theta_{j+1} \leq Score_{it} < \theta_j) = Pr(\theta_{j+1} \leq X \cdot B + u_{it} < \theta_j) = F(\theta_{j+1} - X \cdot B) - F(\theta_j - X \cdot B)
\]

where \( F(\cdot) \) is the standard normal CDF. The ordered probit model estimates the coefficient parameter, \( B \), and cut-off points, \( \theta \), 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 (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, \( \beta_1 \) should be negative in the distance-to-default. Moreover, a regime-dependent change of the slope is measured by the coefficient \( \beta_2 \) of the interaction term \((Regime_t \cdot DD_{it})\). Hence, \( \beta_2 \) teases out the rating policy variation over regimes. Specifically, the procyclicality of the rating standards predict that the \( \beta_2 \) in Equation (6) should be positive. This hypothesis is based on the following intuition: the positive \( \beta_2 \) 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.

5 Empirical Results and Discussion

5.1 Results of MCMC

I present results of the distance-to-default estimation from the procedure described in Section 4.1 in Table 2. The table shows that both mean and median of distance-to-default monotonically decrease as ratings become worse. This pattern indicates that the distance-to-default captures credit risk similar to the way credit ratings do. Figure C.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).

\[17\]The cases of \( j = 1 \) and 7 are omitted but they are straight forward.
5.2 Ordered Probit Regression

In this section, I report results of the rating policy estimation from the procedure explained in Section 4.2. The left four columns of Table 3 show the results of the regression in Equation (6). They confirm that the rating policy is procyclical: the coefficient $\beta_1$ is negative and the coefficient $\beta_2$ 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.\footnote{The results are qualitatively similar when Newey-West with reasonable lag (24 month) is used}

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 $\bar{R}$ is defined as $\text{Prob}(R \leq \bar{R}) = \sum_{r=1}^{\bar{R}} \text{Prob}(R = r)$, where $\text{Prob}(R = r)$ is the probability of being in rating category $r$. From the ordered probit regression specified in Equation (6), I predict those probabilities, $\text{Prob}(R = r)$, 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 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).\(^\text{19}\)

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.

\(^\text{19}\)Figure C.3 in the Appendix shows the same pattern between cumulative probabilities under two regimes for other reference ratings.
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 \( \text{Score} \) in Equation (6) under the recession policy with \( V'_B \) yields the same level of \( \text{Score} \) as if it were under the benchmark policy. In other words, I offset the difference in the estimated \( \text{Score} \) under two different regimes in Equation (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 benchmark 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 7, respectively.
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.\textsuperscript{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 would be less forced to sell the securities, circumventing the spread spike.\textsuperscript{21} In 2011, insurance companies have adopted this concept, and called it Derivatives Risk Mitigation while calculating their risk-based capital

\textsuperscript{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 \(m \to 0\).

\textsuperscript{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.
requirements. 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:

$$ Effect_{it} = \beta_1 \cdot m_{it} + \beta_2 \cdot N_{i}^{CDS} + \beta_3 \cdot Corr_i + \lambda' \cdot X + e_{it} \tag{7} $$

where, $m$ is the fraction of debt to be rolled over, $N_{i}^{CDS}$ 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:

$$ \text{Rating Difference} = \text{actual rating} - \text{counter factual rating} $$

$$ \text{Pct. Difference in Default Boundary} = \frac{(V_B - V_B')}{V_B'} $$

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. Using these two variables has an implication for determining sources of cross-sectional variation. If 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

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23Rating 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.
across firms and that cross-sectional variation is not entirely due to the differential reaction to price.

[Insert Table 5 here.]

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.

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 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 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

24Since 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.

25Figure C.2 in the Appendix displays the relationship between these two measures of credit quality.
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 5 report results of the regression in Equation (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 $\beta_1$ and $\beta_2$ are positive and significant.\footnote{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.}

### 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 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
In the context of the model, this has implications for setting the default boundary $V_B$ shown in Equation (4) in Section 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 4, recall that $\alpha_1$ denotes creditors’ recovery rate, and $\alpha_2$ 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 $\alpha_1$ and $\alpha_2$ take two different values with respect to the regime. I denote a payoff to creditors by $\alpha_{1j}$ and a payoff to equity holders by $\alpha_{2j}$ in an expansion $(j = E)$ and a recession $(i = R)$. Chen (2010) provides evidence that the recovery rate ($\alpha_2$) is cyclical, i.e., the recovery rates for creditors in a recession is lower than in an expansion. These empirical findings imply that $\alpha_{1E} > \alpha_{1R}$. The equity holders’ rents, $\alpha_2$, 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 $\alpha_{2R} > \alpha_{2E}$ in the model framework. With the variation of $\alpha_1$ and $\alpha_2$ across regimes, the $V_B$ becomes regime-dependent. Equation (4) makes it clear that $V_B$ increases in $\alpha_2$ and decreases in $\alpha_1$. Therefore, with $\alpha_{1E} > \alpha_{1R}$ and $\alpha_{2R} > \alpha_{2E}$, it is easy to show that $V_{BE} > V_{BR}$, where $V_{BE}^{j=E,R}$ denotes $V_B$ in Equation (4) with $j = \{E,R\}$, 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 $\alpha_{1j}^{E,R}$. In the sample, the mean recovery rate during an expansion ($\alpha_{1E}^{E}$) is 0.44 and during a recession ($\alpha_{1R}^{E}$) is 0.41. This loss given default is almost identical to that of Altman and Kishore (1996). The ability

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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)
of equity holders to extract rent from credit event, $\alpha_2^{E,R}$, 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 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 $\alpha_2^E$ is 0.045 and $\alpha_2^R$ is 0.064. The variation in $\alpha_1$ and $\alpha_2$ gives an additional rise in the default boundary beyond what time-varying market and firm-specific parameters deliver. I repeat the analyses in Section 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.

### 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

\(^{28}\)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 C.2 in the Appendix.
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 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 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.]

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.

30In 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).
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. 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. 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. 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 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 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:

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

where $C$ is a dollar coupon of total debt, debt valuation $D(\cdot)$ is defined in Equation (2), default boundary $V_B$ can be found in Equation (4), and $r$ is a risk-free rate from yields of U.S. treasury securities. The difference between $\text{Spread}(V|V_B)$ and $\text{Spread}(V|V'_B)$ 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 (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 \( \text{Spread}(V|V_B) \) and \( \text{Spread}(V|V_B') \), 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 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 for alternative proxies of the risk-free rate such as OIS or Fed fund rate.

35These 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.
downgraded from AAA to AA. 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:

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

where, the equity valuation $E(\cdot)$ is defined as Equation (3) in Section 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

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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.
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 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.

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 (2013) 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 (2013) 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 (2013) 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.

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 have 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.
Figures and Tables

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 presents 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 $\frac{C}{D(V|V_p)}$, where $C$ is dollar coupon for total debt and $D(\cdot)$ is defined in Equation (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 (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.
### Panel A: Issue-Level Summary

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<th>Median</th>
<th>75th Pct.</th>
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<td>75,000</td>
<td>200,000</td>
<td>375,000</td>
<td>487,871</td>
</tr>
<tr>
<td>Bond Yield</td>
<td>0.06</td>
<td>0.04</td>
<td>0.04</td>
<td>0.06</td>
<td>0.07</td>
<td>176,372</td>
</tr>
<tr>
<td>Bond Age</td>
<td>5.47</td>
<td>4.58</td>
<td>2.08</td>
<td>4.50</td>
<td>7.67</td>
<td>487,871</td>
</tr>
<tr>
<td>Time to Maturity</td>
<td>8.53</td>
<td>9.64</td>
<td>2.67</td>
<td>5.58</td>
<td>9.83</td>
<td>484,176</td>
</tr>
<tr>
<td>Duration</td>
<td>6.09</td>
<td>4.36</td>
<td>3.15</td>
<td>5.17</td>
<td>7.58</td>
<td>176,031</td>
</tr>
</tbody>
</table>

### Panel B: Issuer-Level Summary

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

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, Callability, 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 Ratio 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.
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 4.1 and EDF is obtained from KMV Moody’s.

<table>
<thead>
<tr>
<th></th>
<th>Distance-to-Default</th>
<th>EDF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
</tr>
<tr>
<td>AAA</td>
<td>8.95</td>
<td>9.10</td>
</tr>
<tr>
<td>AA</td>
<td>7.60</td>
<td>7.30</td>
</tr>
<tr>
<td>A</td>
<td>6.99</td>
<td>6.90</td>
</tr>
<tr>
<td>BBB</td>
<td>5.48</td>
<td>5.14</td>
</tr>
<tr>
<td>BB</td>
<td>3.93</td>
<td>3.72</td>
</tr>
<tr>
<td>B</td>
<td>2.96</td>
<td>2.59</td>
</tr>
<tr>
<td>CCC</td>
<td>1.74</td>
<td>1.18</td>
</tr>
<tr>
<td>Distance-to-Default EDF</td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>------------------------</td>
<td>-----</td>
<td>-----</td>
</tr>
<tr>
<td>Metric</td>
<td>-0.24***</td>
<td>-0.26***</td>
</tr>
<tr>
<td></td>
<td>(-47.31)</td>
<td>(-40.51)</td>
</tr>
<tr>
<td>Metric-Regime</td>
<td>0.01***</td>
<td>0.01***</td>
</tr>
<tr>
<td></td>
<td>(6.28)</td>
<td>(5.73)</td>
</tr>
<tr>
<td>Issuer Industry</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Nbr of CRA</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Seniority</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>Credit Enhance</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>Preferred</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>Callability</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>Puttability</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>Covenant</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>Coupon Type</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>Cut-offs</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>θ₁</td>
<td>-3.20***</td>
<td>-3.11***</td>
</tr>
<tr>
<td></td>
<td>(-76.95)</td>
<td>(-45.30)</td>
</tr>
<tr>
<td>θ₂</td>
<td>-2.83***</td>
<td>-2.63***</td>
</tr>
<tr>
<td></td>
<td>(-76.74)</td>
<td>(-41.52)</td>
</tr>
<tr>
<td>θ₃</td>
<td>-1.99***</td>
<td>-1.60***</td>
</tr>
<tr>
<td></td>
<td>(-64.54)</td>
<td>(-27.14)</td>
</tr>
<tr>
<td>θ₄</td>
<td>-1.14***</td>
<td>-0.57***</td>
</tr>
<tr>
<td></td>
<td>(-42.51)</td>
<td>(-10.34)</td>
</tr>
<tr>
<td>θ₅</td>
<td>-0.65***</td>
<td>-0.02</td>
</tr>
<tr>
<td></td>
<td>(-25.78)</td>
<td>(-0.33)</td>
</tr>
<tr>
<td>θ₆</td>
<td>0.43***</td>
<td>1.17***</td>
</tr>
<tr>
<td></td>
<td>(16.91)</td>
<td>(19.71)</td>
</tr>
<tr>
<td>N</td>
<td>486850</td>
<td>486850</td>
</tr>
<tr>
<td>Pseudo R2</td>
<td>0.092</td>
<td>0.172</td>
</tr>
</tbody>
</table>

Table 3: **Result of Ordered Probit Regression**: This table presents the result of ordered probit regression specified in Equation (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. Callability 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(*).
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.

<table>
<thead>
<tr>
<th></th>
<th>Prob(R = AAA)</th>
<th>Prob(R ≥ AA)</th>
<th>Prob(R ≥ A)</th>
<th>Prob(R ≥ BBB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diff. at Most Likely DD</td>
<td>6.61%</td>
<td>5.88%</td>
<td>4.31%</td>
<td>2.46%</td>
</tr>
<tr>
<td>Range of Most Likely DD</td>
<td>18-19</td>
<td>13-14</td>
<td>10-11</td>
<td>6-7</td>
</tr>
<tr>
<td>Max.Diff.</td>
<td>7.32%</td>
<td>6.38%</td>
<td>4.77%</td>
<td>3.29%</td>
</tr>
<tr>
<td>Range of DD for Max Diff.</td>
<td>14-15</td>
<td>14-15</td>
<td>9-10</td>
<td>7-8</td>
</tr>
</tbody>
</table>
Table 5: Cross-Sectional Analysis: This table presents a regression result for the cross-sectional analysis specified in Equation (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 $V_B - V_B'$, 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 is industry specific variable, hence it is omitted when industry fixed effect is used.
### 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.

<table>
<thead>
<tr>
<th></th>
<th>Expansion</th>
<th>Expansion (excl. def. in rec.)</th>
<th>Recession</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Def. Fraction</td>
<td>Total N. Bonds</td>
<td>Def. Fraction</td>
</tr>
<tr>
<td>AAA</td>
<td>0.00%</td>
<td>432</td>
<td>0.00%</td>
</tr>
<tr>
<td>AA</td>
<td>0.00%</td>
<td>80</td>
<td>0.00%</td>
</tr>
<tr>
<td>A</td>
<td>0.00%</td>
<td>522</td>
<td>0.00%</td>
</tr>
<tr>
<td>BBB</td>
<td>0.09%</td>
<td>1077</td>
<td>0.14%</td>
</tr>
<tr>
<td>BB</td>
<td>0.44%</td>
<td>900</td>
<td>0.54%</td>
</tr>
<tr>
<td>B</td>
<td>1.02%</td>
<td>1767</td>
<td>1.09%</td>
</tr>
<tr>
<td>CCC</td>
<td>5.56%</td>
<td>701</td>
<td>8.44%</td>
</tr>
</tbody>
</table>
Appendix

A  Proofs

A.1 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:

\[
E_g[\theta|p \leq \theta \leq q] = \int_p^q u \cdot h_g(u) \, du
\]
\[
= \left[ -u \cdot (1 - H_g(u)) \right]_p^q + \int_p^q (1 - H_g(u)) \, du
\]
\[
= (q \cdot H_g(q) - p \cdot H_g(p)) - (q - p) + \int_p^q (1 - H_g(u)) \, du
\]

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,

\[
E_f[\theta|p \leq \theta \leq q] = (q \cdot H_f(q) - p \cdot H_f(p)) - (q - p) + \int_p^q (1 - H_f(u)) \, du
\]

Then,

\[
E_g[\theta|p \leq \theta \leq q] - E_f[\theta|p \leq \theta \leq q] = p \cdot (H_f(p) - H_g(p))
\]
\[
- q \cdot (H_f(q) - H_g(q)) + \int_p^q (H_f(u) - H_g(u)) \, du \quad (A.1)
\]

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:
\[ q \cdot (H_f(q) - H_g(q)) < \int_{q-\epsilon}^{q} q \cdot (H_f(v) - H_g(v)) \, dv \]
\[ < \int_{p}^{q} q \cdot (H_f(v) - H_g(v)) \, dv \]

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

\[-q \cdot (H_f(q) - H_g(q)) + \int_{p}^{q} (H_f(u) - H_g(u)) \, du = -q \cdot (H_f(q) - H_g(q)) + \frac{1}{q} \int_{p}^{q} q \cdot (H_f(u) - H_g(u)) \, du \]
\[ > \frac{1}{q} \int_{p}^{q} q \cdot (H_f(u) - H_g(u)) \, du - \int_{p}^{q} q \cdot (H_f(v) - H_g(v)) \, dv \]
\[ \geq 0 \]

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

**A.2 Corollary**

Contraposition of Proposition 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 \( p_f < p_g \) 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 \( \Box \)

**A.3 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 (1), I can re-write the process \( V \) as follows:

\[ \ln(V_t/V_0) = (r - \delta - \sigma^2/2)t + \sigma W_t^Q \quad \text{(A.2)} \]

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

\[ M(t) = e^{(-rt+x(r-\delta-\sigma^2/2)t+x\sigma W_t^Q)} \quad \text{(A.3)} \]
Applying Ito’s rule to Equation (A.3) yields:

$$\frac{dM(t)}{M(t)} = \left(-r + x(r - \delta - \frac{\sigma^2}{2}) + \frac{1}{2}x^2\sigma^2\right)dt + x\sigma dW^Q_t$$  \hspace{1cm} (A.4)$$

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

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

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

$$E_0^Q[M(\tau_B)] = E_0^Q[M(\tau_B)]$$
$$= E_0^Q[e^{(-r\tau_B + x\ln(V_B/V_0))}]$$
$$= E_0^Q[e^{-r\tau_B}] \cdot e^{x\ln(V_B/V_0)}$$
$$= M(0) = 1$$

Therefore, I obtain:

$$E_0^Q[e^{-r\tau_B}] = e^{-x\ln(V_B/V_0)} = (V_0/V_B)^{-x}$$  \hspace{1cm} (A.6)$$

The price of state-dependent asset that pays $1 \cdot e^{mt}$ when $V \downarrow V_B$ can be similarly written as $E_0[e^{-r\tau_B} \cdot e^{-m\tau_B} \cdot 1]$. Through a similar step this price can be expressed as:

$$E_0^Q[e^{-(r+m)\tau_B}] = (V_0/V_B)^{-y}$$  \hspace{1cm} (A.7)$$

where

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

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

$$d(0) = \frac{c + mp}{r + m} \cdot (1 - (V_0/V_B)^{-y}) + m\alpha_1 V_B (V_0/V_B)^{-y}$$  \hspace{1cm} (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 contin-
uum of individual debt $d$ with different time to maturity. Integrating over time to maturity, I obtain Equation (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 $V$:

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

From the accounting identity $v = E + D$, the equity value, $E$, can be calculated from $v - D$ which yields Equation (3) \hspace{1cm} \square
B Estimation procedure for Leland (1994b) model

B.1 Set-up

I use MCMC methodology, following Korteweg and Polson (2010) to estimate the model parameters. Recall that Proposition 2 provides valuation equation for equity and debt as follows:

\[ D_t = \left( \frac{C + mP}{r + m} \right) \left( 1 - (V_t / V_B)^{-y} \right) + \alpha_1 V_B (V_t / V_B)^{-y} \]  
\[ E_t = V_t + \left( \frac{\tau C}{r} \right) \left( 1 - (V_t / V_B)^{-x} \right) - (\alpha_1 - \alpha_2) V_B (V_t / V_B)^{-x} - D_t \]

where,

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

For each firm, I estimate the following system:

\[ Y_t \equiv \ln(f_{E}^{-1}(E_t, \Theta)) = X_t + \epsilon_t, \quad \epsilon_t \sim N(0, \nu^2) \]  
\[ X_t = X_{t-1} + (\mu - \delta - \sigma^2/2) + \sigma \eta_t, \quad \eta_t \sim N(0,1) \]

The Equation (B.3) 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 (3), the evolution of \( X \) is characterized in Equation (B.4).
B.2 Objectives

I need to estimate \( \{V_t\} \) and \( \Theta \) in Equation (B.3) and (B.4) and \( \nu \). Among the parameter set \( \Theta \), I can easily observe \( \{\delta, r, C, F, m\} \). \( \delta \) 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 \( \tau \), I use 35 percent as suggested by Korteweg and Polson (2010). For \( \alpha^j_1 = \{E, R\} \), 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, \( \alpha^j_2 = \{E, R\} \), 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 \( p(\{X_t\}, \mu, \sigma, \nu^2|\{E_t\}) \). For calculation convenience, I modify Equation (B.4) to \( X_t = X_{t-1} + (\mu^* - \delta) + \sigma \eta_t \), where I define \( \mu^* = \mu - \sigma^2/2 \).

B.3 Estimation procedure

The estimation steps in big picture are as follows:

1. \( X_{(g+1)} \sim p(X|\sigma^2_{(g)}, \mu^*_{(g)}, \nu^2_{(g)}, E) \sim FFBS \)
2. \( \sigma^2_{(g+1)} \sim p(\sigma^2|X_{(g+1)}, \mu^*_{(g)}, \nu^2_{(g)}, E) \sim IG \)
3. \( \mu^*_{(g+1)} \sim p(\mu^*|X_{(g+1)}, \sigma^2_{(g+1)}, \nu^2_{(g)}, E) \sim N \)
4. \( \nu^2_{(g+1)} \sim p(\nu^2|X_{(g+1)}, \sigma^2_{(g+1)}, \mu^*_{(g+1)}, E) \sim IG \)

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 \( DD_t = (log(V/V_B) + (\mu^* - \delta))/\sigma \) and compute the mean of the distribution. This measure provides proxy for the credit quality of the firm in monthly frequency.
### B.4 Asset value $X = \ln(V)$

I implement Filter Forward Backward Sampling algorithm.

#### B.4.1 Filter Forward (FF)

Initialize the Equation (B.3):

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

The Equation (B.4) gives the forecasting of $X_1$:

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

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

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

where the updated mean $M$ and updated variance $V$ are:

$$M = Y_0 + (\mu^* - \delta) + \frac{\nu^2 + \sigma^2}{\sigma^2 + 2\nu^2} \cdot [Y_1 - (Y_0 + (\mu^* - \delta))]$$

$$V = (\nu^2 + \sigma^2) - \frac{(\nu^2 + \sigma^2)^2}{\sigma^2 + 2\nu^2}$$

Now I can formulate for the $t$:

$$\mathbb{E}[X_t|Y^t] = \mathbb{E}[X_t|Y^{t-1}] + \frac{\text{Var}[X_t|Y^{t-1}]}{\text{Var}[X_t|Y^{t-1}] + \nu^2} \cdot (Y_t - \mathbb{E}[X_t|Y^t])$$

$$\text{Var}[X_t|Y^t] = \text{Var}[X_t|Y^{t-1}] - \frac{\text{Var}[X_t|Y^{t-1}]^2}{\text{Var}[X_t|Y^{t-1}] + \nu^2}$$

#### B.4.2 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
\[
\begin{pmatrix}
X_t \\
X_{t+1}
\end{pmatrix} | Y^t \sim N \left( \begin{pmatrix}
\mathbb{E}[X_t|Y^t] \\
\mathbb{E}[X_{t+1}|Y^t]
\end{pmatrix}, \begin{pmatrix}
\text{Var}[X_t|Y^t] & \text{Cov}[X_t, X_{t+1}|Y^t] \\
\text{Cov}[X_t, X_{t+1}|Y^t] & \text{Var}[X_{t+1}|Y^t]
\end{pmatrix} \right)
\]

Therefore the conditional distribution is:

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

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

\[
\begin{align*}
X_{T-1} & \sim p(X_{T-1}|X_T, Y^{T-1}) \\
X_{T-2} & \sim p(X_{T-2}|X_{T-1}, Y^{T-2}) \\
& \vdots \\
X_1 & \sim p(X_1|X_2, Y^1)
\end{align*}
\]

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.

### B.5 Asset volatility \( \sigma^2 \)

From Bayes rule, I obtain the following equality:

\[
p(\sigma^2|X, \mu^*, \nu^2, E) \cdot p(X, \mu, \nu^2, E) = p(E|\sigma^2, X, \mu, \nu^2) \cdot p(\sigma^2|X, \mu, \nu^2) \cdot p(X, \mu, \nu^2)
\]

The third term in the RHS of the above equation is independent of \( \sigma^2 \). So I can rewrite:

\[
p(\sigma^2|X, \mu^*, \nu^2, E) \propto p(E|\sigma^2, X, \mu^*, \nu^2) \cdot p(\sigma^2|X, \mu^*, \nu^2)
\]

where, \( p(\sigma^2|X, \mu^*, \nu^2) \sim IG \left( a + \frac{T}{2}, b + \frac{1}{2} \sum_{t=2}^{T-1} (X_{t+1}^{(g+1)} - X_t^{(g+1)} - \mu^{(g)})^2 \right) \) with prior of \( a = 2.1 \) and \( b = 300 \). Since distribution in Equation (B.5) is not a standard one, I use independent Metropolis-Hastings algorithm such that:

1. Draw \( \sigma_{(s)}^2 \sim IG \left( a + \frac{T}{2}, b + \frac{1}{2} \sum_{t=2}^{T-1} (X_{t+1}^{(g+1)} - X_t^{(g+1)} - \mu^{(g)})^2 \right) \)
(2) Generate \( u \sim U[0, 1] \)

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

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

Note that \( p(E|\sigma^2_{(g)}, X_{(g+1)}, \mu^*_g, \nu^2_{(g)}) \) and \( p(E|\sigma^2_{(g)}, X_{(g+1)}, \mu^*_g, \nu^2_{(g)}) \) are easy to calculate by

\[
\Pi_{t=1}^T p \left( \ln(f^{-1}_E(E_t, \sigma^2_{(g)}, \mu^*_g, \nu^2_{(g)})) \right) \quad \text{and} \quad \Pi_{t=1}^T p \left( \ln(f^{-1}_E(E_t, \sigma^2_{(g)}, \mu^*_g, \nu^2_{(g)})) \right), \text{respectively.}
\]

### B.6 Drift of log asset value \( \mu^* \)

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 \((\mu^*|\sigma^2) \sim N(A, \sigma^2/B) \) with \( A = 0.15 \) and \( B = 5 \), the posterior distribution is

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

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

### B.7 Pricing error \( \nu^2 \)

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

\[
p(\nu^2_{(g+1)}|X_{(g+1)}, \mu^*_{(g+1)}, E) \sim IG \left( a + \frac{T}{2}, b + \frac{1}{2} \sum_{t=2}^{T-1} (\ln(f^{-1}_E(E_t, |\mu^*_{(g+1)}, \sigma^2_{(g+1)})) - X_t^{(g+1)})^2 \right)
\]
### C. Additional Tables and Figures

#### C.1 Distribution of Expected Default Frequency and Distance-to-Default

<table>
<thead>
<tr>
<th>Rating</th>
<th>Mean</th>
<th>Median</th>
<th>Mean</th>
<th>Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>AA+</td>
<td>0.9%</td>
<td>0.5%</td>
<td>0.4%</td>
<td>0.1%</td>
</tr>
<tr>
<td>A</td>
<td>1.3%</td>
<td>0.8%</td>
<td>0.8%</td>
<td>0.4%</td>
</tr>
<tr>
<td>BBB</td>
<td>3.1%</td>
<td>2.0%</td>
<td>1.6%</td>
<td>0.8%</td>
</tr>
<tr>
<td>BB</td>
<td>9.4%</td>
<td>6.6%</td>
<td>3.9%</td>
<td>1.9%</td>
</tr>
<tr>
<td>B</td>
<td>16.4%</td>
<td>9.6%</td>
<td>7.9%</td>
<td>2.6%</td>
</tr>
<tr>
<td>CCC</td>
<td>28.5%</td>
<td>24.5%</td>
<td>21.7%</td>
<td>11.7%</td>
</tr>
</tbody>
</table>

**Table C.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.
### C.2 Results of Ordered Probit Regression with Borrowers’ Strategic Behavior

<table>
<thead>
<tr>
<th>Metric</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distance-to-Default</td>
<td>-0.25***</td>
<td>-0.27***</td>
<td>-0.27***</td>
<td>-0.27***</td>
</tr>
<tr>
<td></td>
<td>(-49.16)</td>
<td>(-41.70)</td>
<td>(-42.59)</td>
<td>(-42.28)</td>
</tr>
<tr>
<td>Metric Regime</td>
<td>0.01***</td>
<td>0.01***</td>
<td>0.01***</td>
<td>0.01***</td>
</tr>
<tr>
<td></td>
<td>(5.22)</td>
<td>(4.43)</td>
<td>(4.51)</td>
<td>(3.57)</td>
</tr>
<tr>
<td>Issuer Industry</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Nbr of CRA</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Seniority</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Credit Enhance</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Preferred</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Callability</td>
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<td>N</td>
<td>Y</td>
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<tr>
<td>Puttability</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Covenant</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Coupon Type</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
</tbody>
</table>

| 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 C.2: **Result of Ordered Probit Regression with Borrowers’ Strategic Behavior**: This table presents the result of ordered probit regression specified in Equation (6). I present four specifications when distance-to-default in each column (1) to (4). In this case, borrowers’ strategic behaviors described in Section 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. Callability 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(*)
C.3 Distance-to-Default and Expected Default Frequencies

Figure C.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 its 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 C.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).
C.4 Predicted Cumulative Probability

Figure C.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.
References


Huang, J.-z., Huang, M., 2003. How Much of the Corporate-Treasury Yield Spread is Due to Credit Risk?


