# Granularity of Corporate Debt*

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**Abstract**

We study to what extent firms spread out their debt maturity dates across time, which we call "granularity of corporate debt." In our model, firms are unable to roll over expiring debt in high-uncertainty states and are therefore forced to engage in inefficient liquidations. Since multiple small asset sales are less costly than a single large one, it can be advantageous to diversify debt rollovers across maturity dates. Using a large sample of corporate bond issuers during the 1991–2011 period, we find evidence that supports our model's predictions in cross-sectional and time-series tests. In the cross-section, corporate debt maturities are more dispersed for larger and more mature firms, for firms with better investment opportunities, with higher leverage ratios, and with lower levels of current cash flows. We find that during the recent financial crisis especially firms with valuable investment opportunities implemented more dispersed maturity structures. In the time-series, we document that firms manage rollover risk in that newly issued corporate bond maturities complement pre-existing bond maturity profiles.

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# 1 Introduction

It is not yet well understood to what extent firms manage the rollover dates of their bonds by spreading out maturities. Fixed cost components of bond issues and secondary market liquidity considerations should motivate firms to concentrate their debt in a single or few issues. However, even non-financial firms frequently have multiple bond issues outstanding, with different times to maturity. This suggests a potentially important but heretofore unrecognized dimension of debt structure requiring firms to trade off different frictions to determine an optimal debt maturity concentration.

Surprisingly, we lack both testable theoretical implications and empirical evidence. Even basic stylized facts are largely unavailable, so there is little guidance as to what one would expect to find. In practice, however, debt maturity decisions are affected by the incentive to mitigate rollover risk in that this is the most common motive in Servaes and Tufano's (2006) global survey of chief financial officers. This paper therefore provides a first step towards understanding firms' decisions to spread out bond maturity dates across time, which we call "granularity of corporate debt."

To gain an understanding of what factors might drive this dimension of debt structure and to generate a number of testable implications, we consider a simple, three-period model in which rollover risk has real effects and therefore influences debt maturity structure. The firm has an investment opportunity with decreasing returns to scale and payoffs at time three. The firm finances the project by issuing bonds with maturities less or equal to two. Thus, frictions, such as moral hazard or investor preferences, prevent the firm from issuing very long-term bonds that expire at time three, so that the firm must roll over the bonds issued at time zero at least once. In particular, we consider two maturity structures, a *concentrated* and a *dispersed* one. The firm with a *concentrated* maturity structure (or firm $C$) refinances its bonds at *one* point in time (i.e., date one or two), whereas the firm with a *dispersed* maturity structure (or firm $D$) refinances its bonds at *two* points in time.

Along some paths, the bonds can be rolled over and the final cash flows are eventually realized in full. Along other paths, however, the firm can temporarily lose its access to the bond market. The firm's inability to refinance its bonds may arise because markets freeze for exogenous reasons or it may arise endogenously since the firm can become temporarily exposed to a large risk. We show that, in such states, investors may not be able to roll over their bonds. As a consequence, the investment projects must be partially liquidated to repay the bondholders, and this is inefficient.[1]

[1]See, e.g., Acharya et al. (2011) for market freezes after a decline in collateral value. There are many reasons for

Firm $D$ only needs to liquidate a small fraction of its assets to repay its bonds. So it has the real option to keep the more profitable assets and liquidate those with a small or zero net present value (NPV). By contrast, if firm $C$ cannot roll over its bonds, then it must liquidate a larger fraction of its assets, including some with higher NPVs. Thus, in our model it is less costly being exposed to small rollover risks at two points in time rather than being exposed to large rollover risk at one point in time.[2] On the other hand, one larger bond issue has lower flotation costs (see Lee et al. (1996)) and liquidity costs (see Longstaff et al. (2005) and Mahanti et al. (2008)) than two smaller bond issues. Thus, there is a trade-off in that firm $D$ has a flexibility (or real option) advantage over firm $C$, whereas firm $C$ has a transaction cost advantage over firm $D$.

Based on the tension between costly project liquidations and transaction costs, we derive a number of testable implications. The difference in equity value between firm $C$ and firm $D$ implies that the benefits of dispersed corporate debt maturities increase with rollover risk and with the value of investment opportunities. Moreover, the solution of the model indicates that corporate debt should be more dispersed for larger and more mature firms due to their lower transaction costs, for firms with higher leverage ratios, and for firms with lower levels of current cash flows due to their lower ability to withstand inefficiencies induced by rollover risk.

We construct a large panel data set that contains information on maturity structures and firm characteristics by merging data on corporate bond issues from Mergent's Fixed Investment Securities Database (FISD) with the COMPUSTAT database. For the 1991–2011 period, we obtain an unbalanced panel with 17,396 (9,880) firm-year observations for firms with at least one bond (two bonds) outstanding. We use these firm-level data from FISD to measure how dispersed maturity structures are.[3] For each firm, we group bond maturities into the nearest integer years and compute

a state of increased uncertainty to adversely affect a firm's ability to access capital markets that can lead to a market freeze for that firm: negative supply shocks due to firm-specific or market-wide tightening of credit, large legal battles or liability risks (e.g., in the oil industry as documented by Cutler and Summers (1988) or in the pharmaceutical industry), recall risks of car manufacturers (e.g., Toyota's malfunctioning gas pedal), challenges or disputes of patents, regulatory risks of energy companies (e.g., whether or not to exit nuclear power production after disasters such as Fukushima) or hedge funds (e.g., after the financial crisis), and impending natural catastrophes, such as oil spills whose exact consequences for businesses such as tourism are unknown for some time (see, e.g., Massa and Zhang (2011)). One such example of a market freeze and rollover risk is the bankruptcy of General Growth Properties in April 2009.

[2] There may be additional motives why firms issue debt with different maturity dates. Matching maturities of firms' liabilities with those of their assets requires that asset maturities can be determined easily. In addition, firms usually consist of a large number of projects, so it is not feasible to issue a separate bond for each project. Also, asymmetric information problems are likely to be more severe at longer horizons compared to shorter horizons, which further limits firms' ability to match the maturities of liabilities with those of assets. Thus, the frictions that we consider in this paper remain relevant even in the presence of other motives for spreading debt maturity dates across time.

[3] In robustness tests, we also include information on the maturity structure of private debt from COMPUSTAT.

its fractions of the total amount of bonds outstanding each year. The first measure of maturity dispersion is the inverse of the maturity profile's Herfindahl index based on these fractions. The second measure is related to the distance of a firm's actual maturity profile from to the perfectly dispersed maturity profile, holding its average maturity constant.

After establishing a number of stylized facts, we document several novel results that are consistent with our tradeoff-based story. Specifically, we find that larger and more mature firms, firms with more valuable investment opportunities, and firms with more leverage exhibit more dispersed debt maturity structures. In contrast, granularity is negatively associated with profitability. Most of these firm characteristics remain economically and statistically important after controlling for industry or firm and year fixed effects, suggesting that firms condition on these variables in the management of their debt maturity profile. Our findings are robust to inclusion of private debt maturity profiles into our maturity dispersion measures, and also present in subsamples of firms with a high and a low proportion of private debt.[4] Moreover, during the 2008–2009 financial crisis when rollover risk was likely higher, we find that especially firms with valuable investment opportunities implemented more dispersed debt maturity structures. In addition, we establish that the dispersion of debt maturities moves over time towards target levels. In particular, speed-of-adjustment regressions reveal surprisingly high adjustment rates, ranging from 21% to 56% per year.[5]

To provide further evidence on active management of the dispersion of debt maturities, we also examine whether firms consider pre-existing maturity profiles when they issue new bonds. To do so, we investigate whether discrepancies between a firm's pre-existing maturity profile and a benchmark maturity profile (based on firm characteristics implied by our model) explain future debt issue behavior. We find that, if a firm has a large fraction of bonds outstanding in any given maturity bucket relative to its benchmark profile, then it is significantly less likely to issue bonds in those maturity buckets. For example, the probability of issuing additional nine- or ten-year maturity bonds drops by 0.18 of a percentage point for every percentage point that a firm's maturity profile exceeds the benchmark profile in this bucket. The results hold across all maturity buckets, are largely invariant to the definition of the benchmarks or buckets, and are also economically significant.

[4]Renegotiation is common for private debt, so realized maturity is much shorter than contracted maturity (see, e.g., Roberts and Sufi (2009)). Private debt's maturity is also easy to modify (see, e.g., Mian and Santos (2011)). Firms with a large proportion of private debt may therefore not need dispersed public debt rollover dates and yet we do not find evidence for such a substitution effect.

[5]These results also hold for the subsample of firms with at least two bonds outstanding and for the subsample of firms that have bonds without option features and sinking fund provisions.

Our paper is related to several models of debt maturity and rollover frictions.[6] By linking corporate bond credit risk and bond market liquidity risk, He and Xiong (2012) show that short-term debt exacerbates rollover risk. He and Milbradt (2012) endogenize the feedback between secondary market liquidity risk and rollover risk – reduced liquidity raises equity's rollover losses, leading to earlier endogenous default, which in turn worsens bond liquidity. Chen et al. (2012) study the link between systematic risk exposure and debt maturity. These papers focus on single-bond firms' debt maturity choice. Related to our setup is a recent paper by Diamond and He (2012). They show that maturing, risky short-term debt can lead to more debt overhang than non-maturing risky long-term debt, which is in accordance with our result that risky short-term debt leads to more instances of early project liquidations. However, none of these papers examines the trade-offs faced by firms when diversifying debt rollovers across dates to avoid maturity concentrations. In our setting, we show that neither the issuance of a single long-term nor that of a single short-term debt claim may be optimal. But a combination of debt with different rollover dates can reduce inefficiencies due to rollover risk.

Our paper is also related to recent empirical and survey research. Based on a comprehensive global survey of chief financial officers, Servaes and Tufano (2006) report that managers are concerned about losing access to debt markets and, in particular, that debt maturity choice is strongly driven by the objective of managing rollover risk by avoiding maturity concentrations. Almeida et al. (2011) document that firms with a greater fraction of long-term debt maturing at the onset of the 2007 financial crisis had a more pronounced investment decline than otherwise similar firms.[7] In the context of U.S. Treasury bonds, Greenwood et al. (2010) argue that firms vary their debt maturity to act as macro liquidity providers by absorbing supply shocks due to changes in the maturity of Treasuries. Using syndicated loan data for U.S. firms, Mian and Santos (2011) find that most credit worthy firms frequently manage (i.e. extend) loan maturities to reduce liquidity risk. Rauh and Sufi (2010) and Colla et al. (2012) establish that – relative to large, high credit quality firms – small, low rated firms have dispersed or multi-tiered debt structures, while small, unrated firms specialize in fewer types. Finally, Harford, Klasa, and Maxwell (2012), who document declining debt maturities for U.S. firms, find that firms with more refinancing risk increase their cash holdings and save more cash from their cash flows.[8] Unlike these studies, we focus on testing cross-sectional and time-series implications for the dispersion of corporate debt maturities.

[6]For earlier theories of maturity structure, see, e.g., Diamond (1991, 1993) and Flannery (1986, 1994).

[7]Similarly, Hu (2010) finds firms with more maturing long-term debt had larger increases in credit spreads.

[8]See Barclay and Smith (1995), Guedes and Opler (1996), and Johnson (2003) for empirical debt maturity studies.

The rest of the paper is organized as follows. Section 2 describes the model and its implications. Section 3 presents data sources, summary statistics, and stylized facts. Section 4 provides the empirical analysis of granularity and Section 5 reports the results for bond issuance. Section 6 concludes.

## 2 A Simple Model of Debt Granularity

In the presence of frictions due to rollover risk firms should respond by adjusting the distribution of debt maturity dates. To formalize this intuition and to better understand its implications for debt granularity, we study a three-period model of an initially all-equity financed firm. The firm has assets in place (or initial net worth), $A$, and a project that requires a capital outlay, $I$, at time $t_0$. In the absence of early project liquidations, the project generates a cash flow $I + H$ at time $t_3$. We assume that the net present value (NPV) of the project, $H$, is greater than $I/2$.

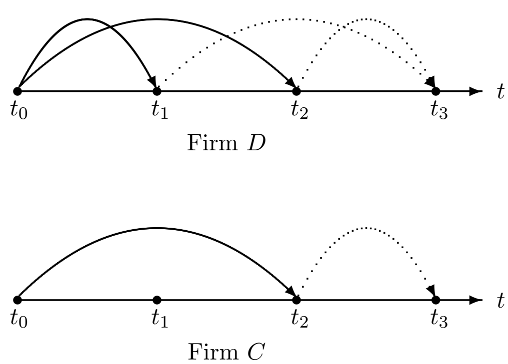
The firm issues straight one- or two-period bonds to raise the required capital of $I - A$. To keep the analysis focused, we do not consider three-period bonds or equity. In a more general model, short maturity debt is due to informational asymmetries (see, e.g., Diamond (1991), Diamond and He (2012), or Milbradt and Oehmke (2012)), and equity is also dominated as long as debt tax shields are sufficiently valuable. Thus, bonds issued at time $t_0$ must be rolled over. However, at times $t_1$ and $t_2$, the bond market may freeze with probability $\lambda$. In the Appendix, we consider an extension to endogenous market freezes, which generates the same implications for debt granularity.

If the firm is unable to refinance maturing bonds due to a market freeze, then assets from the project must be sold to generate the funds required to repay the bondholders. Such a partial liquidation reduces the final cash flow and generates an immediate cash flow. We consider two discrete levels of asset sales. A moderate asset sale generates liquidation proceeds of $I/2$ and reduces final cash flows by the same amount. Thus, at $t_1$ and $t_2$ cash flows of up to $I/2$ are costlessly transferable from time $t_3$ via an asset sale. By contrast, a large asset sale generates liquidation proceeds of $I$ but reduces the final cash flows by $I/2 + H$. Thus, a large asset sale is inefficient, since $H > I/2$. This is either because of illiquidity of the collateral assets to be sold or because of decreasing economies of scale, i.e. the first project units to be liquidated have zero NPV but as more units of the project must be liquidated, positive NPV is lost. We assume that any excess cash generated by the asset sale not needed to repay the maturing bonds is paid out to stockholders.[9]

[9] Thus, we assume that it is expensive to carry forward excess corporate cash balances from time $t_1$ to $t_2$. This is the case if free cash balances can be (partially) expropriated by management or used for empire building purposes.

We consider two initial maturity distributions, a *concentrated* and a *dispersed* one (see Figure 1). We refer to the former as firm $C$ and to the latter as firm $D$. Firm $C$ issues bonds at time $t_0$ with maturities at either time $t_1$ or time $t_2$, at which point they are rolled over to time $t_3$ whenever possible. Since it is straightforward to show that firm $C$ is indifferent between an initial maturity of time $t_1$ or time $t_2$, we only consider the concentrated maturity structure at time $t_2$. In contrast, firm $D$ issues two bonds at time $t_0$, one with maturity $t_1$ and one with maturity $t_2$. Thus, firm $D$ has a dispersed maturity structure. We assume that the bonds issued initially by firm $D$ have equal face value.

**Figure 1. Evolution of Rollover Decisions**




This figure plots the time line of rollover decisions for the dispersed maturity structure (or Firm $D$) with two smaller issues, which expire at time $t_1$ and $t_2$, and the concentrated maturity structure (or Firm $C$) with one larger issue, which expires at time $t_2$. An expiring bond issue needs to be rolled over to time $t_3$ to realize the project's cash flow.

In practice, bond issuances have a fixed cost component and also a minimum size requirement. To capture scale economies of larger issues, we assume that the firm pays a fixed cost per issue, $k$, at time $t_0$. As a result, firm $C$ has a transaction cost advantage, because it incurs issue costs of $k$, whereas firm $D$ incurs issue costs of $2\,k$. In addition, $k$ can be thought to reflect the fact that a single large bond issue may have a more liquid secondary market, thus leading to a lower illiquidity discount than two smaller bond issues. For evidence on a positive relation between issue size and direct issuance costs and secondary market liquidity, respectively, see Lee et al. (1996) and Longstaff et al. (2005) or Mahanti et al. (2008). Moreover, Altinkilic and Hansen (2000) provide evidence that bond spreads decline monotonically with issue size, which is consistent with an economies of scale interpretation. Finally, note that issue costs at each point in time would also favor firm $C$ because it has only two issuances, while firm $D$ has four issuances (see Figure 1).

A credit line from a bank cannot solve the refinancing problem either. As in Almeida et al. (2011), the bank cannot commit to not revoking the credit line precisely in the state when the firm needs to draw down the credit line. Sufi (2009) finds that if cash flows deteriorate, access to credit lines is restricted through loan covenants.

Notice that bonds are risk-free and hence the face value of the concentrated firm's bonds equals $B^C = I - A$. Therefore, if $B^C > I/2$, the concentrated firm faces costly rollover risk. If the bond market freezes at time $t_2$, then the firm must engage in a large asset sale, which reduces final cash flows by $I/2 + H$ to generate liquidation proceeds at time $t_2$ of $I$. On the other hand, the two bonds of the dispersed firm have a face value of $B_1^D = B_2^D = (I - A)/2$, which is less than $I/2$. In case of a market freeze, firm $D$ only needs to engage in a moderate asset sale, which reduces final cash flows by $I/2$ to generate liquidation proceeds at time $t_1$ and/or at time $t_2$ of $I/2$. Therefore, the dispersed firm does not face costly roll over risk. More generally, of course, both types of firms may find it costly to refinance their bonds and hence our framework corresponds to a relative statement in that a concentrated maturity structure will lead to larger inefficiencies than a dispersed one.

Given that firm $D$ encounters no inefficiencies, it is easy to verify that firm $D$'s equity is given by:

$$E^D \;=\; I + H - (I - A) - 2\,k \;. \tag{1}$$

Firm $C$ does not face a rollover problem with probability $1 - \lambda$ and repays the bonds at time $t_3$. However, if $B^C > I/2$, a large asset sale is required with probability $\lambda$ to generate a time $t_2$ cash flow of $I$ by reducing time $t_3$ cash flow by $I/2 + H$. The resulting inefficiency is given by $H - I/2$. Alternatively, if assets in place, $A$, are sufficiently high such that $B^C \leq I/2$, then even the firm with a concentrated maturity structure does not face costly rollover risk. Therefore, the value of firm $C$'s equity is given by:

$$E^C \;=\; \begin{cases} I + H - (I - A) - \lambda\,(H - I/2) - k & \text{if } B^C > I/2 \;, \\ I + H - (I - A) - k & \text{if } B^C \leq I/2 \;. \end{cases} \tag{2}$$

The potential benefits of a dispersed maturity structure are given by the difference in equity values, $\Delta E \equiv E^D - E^C$, in equations (1) and (2):

$$\Delta E \;=\; \begin{cases} \lambda\,(H - I/2) - k & \text{if } B^C > I/2 \;, \\ -k & \text{if } B^C \leq I/2 \;. \end{cases} \tag{3}$$

The comparison in equation (3) says that, for a sufficiently large amount of bonds (i.e. $B^C > I/2$), a dispersed maturity structure is preferred in the absence of transactions costs because of $H > I/2$. This result accords with practitioners' concern about maturity concentrations.

Our simple framework formalizes the intuition that firms may be unable to refinance expiring debt externally in some states of the world and are therefore forced to engage in inefficient liquidations. Since multiple small asset sales are less costly than a single large one, it can be advantageous (depending on firm characteristics) to diversify debt rollovers across maturity dates. The model leads to a number of testable implications. First, the potential benefits of a dispersed maturity structure increases with the probability of a market freeze, $\lambda$. Arguably, market freezes are more likely during economic downturns or financial crises. Second, dispersed debt maturities are increasingly valuable when the project's net present value, $H$, rises. Put differently, it is optimal for a firm with more profitable projects as measured, e.g., by a higher value of Tobin's $Q$, to have a more spread out maturity structure. Third, increasing transaction costs, $k$, works in favor of firm $C$, because it produces a downward shift of the difference in value given by equation (3). This implies that a firm with higher floatation and illiquidity costs will have a lower incentive to implement a more dispersed maturity structure. Since transaction costs are generally regarded to be inversely related to firm age and firm size, corporate bond maturities should be more dispersed for larger and more mature firms. Fourth, because a firm with a higher value of assets in place, $A$, needs less debt financing, the rollover problem in the $\lambda$ state vanishes for firm $C$ if $B^C \leq I/2$. Therefore, when leverage is sufficiently low, firm $C$ dominates firm $D$. In other words, bond maturity dates should be more dispersed for firms with higher leverage. Fifth, even though we do not model cash flows from assets in place, it is true that higher cash flows from assets in place correspond, in a present value sense, to a higher value of assets in place. Hence maturity profiles should be more dispersed for firms with lower cash flows from assets in place. Finally, notice that the above predictions should apply both to cross-sections of firms with different characteristics and to bond issuance decisions of a given firm through time.

# 3 Data Description

## 3.1 Data Sources

Corporate bond data are drawn from Mergent's Fixed Income Security Database (FISD), which includes fixed income securities that already have a CUSIP or are likely to have one in the near future. It also includes corporate bonds issued in private placements (e.g., Rule 144A securities). We obtain issue dates, bond maturities, initial and historical amounts outstanding, and other relevant information from FISD, which begins in the 1980s but becomes comprehensive in the early 1990s. Accounting data are drawn from the annual COMPUSTAT tapes. We exclude financial firms (SIC codes 6000-6999) and utilities (SIC codes 4900-4999), and winsorize the top and bottom 0.5% of variables to minimize the impact of data errors and outliers. The combined data set enables us to measure debt granularity and various firm characteristics for the 1991–2011 period.

### 3.2 Variable Construction

Using bond maturity data from FISD, we construct two different measures of granularity. The first one is based on a concentration index. For each firm, we group debt maturities into the nearest integer years, $i$, and multiply principal amounts in each year, $a_i$, by weights $x_i$ to get weighted principal amounts for each maturity. The weights, $x_i$, can capture the idea that firms are more concerned about rollover risk from shorter maturities (see, e.g., Harford et al. (2012)). For each debt maturity $i$, we then calculate the fraction of principal amounts outstanding, $w_i = (x_i\, a_i)/\sum_i (x_i\, a_i)$, to compute the Herfindahl index, $HERF = \sum_i w_i^2$.[10] We examine two different weighting schemes. The first scheme places more weight on the fractions of shorter debt maturities. Specifically, for maturities less than or equal to 25 years, we use $x_i = (\frac{1}{i})/(\sum_{i=1}^{25} \frac{1}{i})$ and, for maturities greater than 25 years, we use $x_i = 0$. The second scheme employs equal weights for all debt maturities of the same firm, i.e., $x_i = 1$. Since the empirical results are qualitatively similar, we report results in the subsequent sections only for the first scheme, which puts more weight on earlier rather than later maturities. The findings for the unadjusted fractions are available from the authors upon request.

The second measure is based on the distance of the observed maturity profile from the perfectly dispersed one. For each firm $j$ with average maturity $m$ in the sample, we envision a hypothetical firm that has a perfectly dispersed maturity profile with the same average maturity $m$ as firm $j$. Notice that the average maturity of a firm with a perfectly dispersed maturity profile (i.e. a constant fraction of debt expiring each period) is given by: $m = \frac{1}{n}\sum_i i$. Applying the summation formula and solving for $n$ yields that the perfectly dispersed firm would have $n = 2\,m - 1$ debt obligations (with different maturities) outstanding. This hypothetical firm would roll over a constant fraction $1/n$ of its total debt each period (i.e. replace debt issued $n$ periods ago by new debt with maturity $n$). We therefore calculate the mean squared deviation of firm $j$'s actual maturity profile from the perfectly dispersed one: $DIST = \frac{1}{t_j^{max}} \sum_{i=1}^{t_j^{max}} \left(w_i - \frac{1}{2\,m-1}\right)^2$ where $w_i$ is the (unadjusted) fraction of principal amounts outstanding with equal weights (i.e. $x_i = 1$) and $t_j^{max}$ is the longest debt maturity of firm $j$.[11] Intuitively, this measure captures the average distance from a perfectly

[10] For examining corporate bonds' influence on role of credit default swaps, Oehmke and Zawadowski (2012) also use a Herfindahl index as a proxy for the fragmentation of a firms total bonds outstanding.

[11] In an earlier version of the paper, we also proxy maturity dispersion based on an inequality index (Atkinson (1970)). The results (available from the authors upon request) are qualitatively identical.

dispersed maturity profile.

To capture maturity dispersion rather than concentration or distance, we define the following measures of debt granularity: the inverse of the Herfindahl index, $GRAN1 \equiv 1/HERF$, and the negative value of the natural logarithm of the squared distance from perfect dispersion, $GRAN2 \equiv -\log(DIST)$.[12] We use the maturity structure of corporate bonds from FISD rather than the maturity structure of total debt, which includes bank loans, because rollover frictions are more relevant for bonds than for loans. The results are similar when we extend the analysis to the maturity structure of total debt (see Section 4.5 for details).

To investigate the empirical predictions from Section 2, we include a number of explanatory and control variables in our regression specifications. The main variables are defined as follows. Firm size ($Size$) is the log of total assets: COMPUSTAT's $AT$. Firm age ($Age$) is measured as the number of years in the COMPUSTAT database prior to each observation. Profitability ($Prof$) is operating income before depreciation scaled by total assets: $OIBDP/AT$, which measures cash flow from assets in place. Leverage ($Lev$) is book debt over market assets: $(DLTT + DLC)/(AT + PRCC \cdot CSHO - CEQ - TXDB)$. We use the market-to-book ratio ($Q$) as a proxy of the firm's investment opportunities: $(AT + PRCC \cdot CSHO - CDQ - TXDB)/AT$. Asset tangibility ($Tan$) is measured as plant, property, and equipment scaled by total assets: $PPENT/AT$. Cash flow volatility ($ProfVol$) is the standard deviation of operating income before depreciation divided by total assets (OIBDP/AT) using the past five years. Average maturity of bonds ($BondMat$) is the average of firms' bond maturities weighted by amounts.

### 3.3 Summary Statistics and Stylized Facts

Table 3 contains the summary statistics for our sample of 2,477 firms over the 1991–2011 period, for which we have 17,396 firm-year observations. The sample consists of large firms with significant leverage, because firms are required to have corporate bonds outstanding to enter the sample. For example, the average (median) book assets are \$7.65 (\$1.69) billion, and the average (median) leverage ratio is 0.28 (0.24). In addition, in the sample, bonds account for the majority of debt financing. On average, 65% of debt consists of corporate bonds (see $BondPct$). The distribution of principal amounts, $BondAmt$, is informative about the plausibility of fixed costs associated with bond issuance and the plausibility of the principle to match maturities of a firm's liabilities with

[12] Similar to Lemmon et al. (2008), we add 0.001 to $DIST$ to prevent $GRAN2$ from being negative infinity.

those of its assets (i.e. the matching principle). Typical issue sizes of bonds are quite large with a median of \$150 million and an average of \$208.8 million. Observe also that the interquartile range of *BondAmt* starts at \$87.5 million and ends at \$250 million. The fact that 75% of the bonds in our sample have a face value greater than \$87.5 million is consistent with the presence of a fixed cost element associated with bond issuance (see also footnote 23). Furthermore, since most firms are likely to have many projects that are smaller than the average or median issue size, implementing the matching principle seems challenging in practice. While this by itself may not be sufficient to rule out the matching principle as the main motive for debt granularity, we report several other facts in Section 4 that also provide little support for this explanation.

Table 4 documents statistics on key variables for tercile groups defined by the empirical distributions of granularity, bond percentage, and debt maturity. The table reveals that there is observed heterogeneity in debt granularity across tercile groups. In the $GRAN1$ tercile groups, for example, the lowest granularity firms have on average 1.17 bonds outstanding (see $NBond$) and the Herfindahl-based granularity measure ($GRAN1$) equals 1.00. In contrast, the highest granularity firms have on average 13.76 bonds outstanding with $GRAN1$ value of 3.77. If one assumes equal principal amounts outstanding for the first fourteen years, then the perfectly granular firm would have $GRAN1 \approx 6.7$. So the Herfindahl-based granularity measure of 3.77 suggests that debt structures are not perfectly granular even for the firms with the largest number of bonds outstanding.[13] Observe also that in the top tercile $GRAN1$ is almost twice as large as the corresponding value in the mid tercile. For the $GRAN2$ tercile groups, the lowest granularity firms have $GRAN2 = 2.18$, which translates to an average standard deviation from perfect granularity of 33.5%, whereas the highest granularity firms corresponding standard deviation from the perfect granularity is only 9.15%. The sample properties are similar when we use $GRAN2$ to stratify the data in columns 4–6 of Table 4.

[Insert Table 4 here]

These subsamples reveal that there is substantial variation in debt granularity and, at the same time, that firms do not appear to completely spread out their debt maturities dates. In particular, we highlight that a large number of firms have very concentrated maturity structures. In the tercile group based on $GRAN1$, for example, 8,415 out of 17,253 firm-year observations have perfectly

[13]The interpretation of the unadjusted $GRAN1$ measure (not reported) is more straightforward in that a perfectly granular firm with $n$ bonds outstanding would have $GRAN1$ equal to $n$ because then $GRAN1$ is the inverse of the Herfindahl index. If the firm has a more concentrated debt structure, e.g., $n$ bonds with different face values, $GRAN1$ will be less than $n$ but cannot be less than one. For this reason, $GRAN1$ tends to be positively skewed.

concentrated debt structure, because one is a lower bound for $GRAN1$. These firm-year observations are not all composed of single-bond firms, as seen from the average number of bonds, which is 1.17. In addition, we document that these firms issue large bonds relative to their assets. In the low tercile group based on $GRAN1$, the average bond amount with respect to assets is 0.28, whereas that for the high tercile is only 0.04. In addition, these firms are relatively younger (average age 17 years) and smaller, but are similar to higher tercile firms in other dimensions. If firms matched the maturities of their liabilities to their assets for all projects (according to the matching principle), then we should observe a large number of bonds and a high level of granularity for all tercile groups, because firms tend to have many projects that begin (and end) at different points in time. However, the evidence in this table does not support this view.

This substantial variation in debt maturity profiles does not seem to be explained by bank loans. For the tercile groups based on corporate bonds' percentages of total debt outstanding in colums 7–9 of Table 4, we observe the high $BondPct$ group has a bond percentage of 97%, meaning that almost all of their debt financing is through bonds. In this group firms have, on average, 4.7 bonds outstanding but a $GRAN1$ value of only 1.85, which clearly suggests that their bond maturity structures are still relatively concentrated. Moreover, we also observe from the granularity-based tercile groups that the variation in e.g. $GRAN1$ is not much different for $GRAN1L$, which includes COMPUSTAT's maturity variables to reflect private debt granularity.[14] That is, for both granularity-based tercile groups, higher bond maturity dispersion is associated with higher debt maturity dispersion.

Finally, the last three columns of Table 4 consider tercile groups based on debt maturity. Two observations can be made. First, perhaps not surprisingly, firms with longer debt maturities tend to have more granular debt structures, possibly because they have a wider range of issuance choices. Second, asset maturity ($AssetMat$) is neither clearly increasing with nor reliably related to debt maturity. For the low, mid, and high terciles, average maturity is 3.91, 7.60, and 15.90, respectively, whereas average asset maturity is similar across the terciles, 4.15, 6.09, and 5.87. Despite the limitations of interpreting these statistics, it seems unlikely that the intuitive idea behind the maturity matching principle strongly influences firms' behavior in the data.

Figure 4 plots time-series averages of debt maturity dispersion for issuing and non-issuing firms. For issuing firms, maturity dispersion is countercyclical, i.e. firms issue bonds to make maturity structures more dispersed during recessions. Increased rollover risk during recessions appears to

[14]See Section 4.5 for the construction of $GRAN1L$ and $GRAN2L$.

push firms towards more dispersed debt structures, even though costs of issuance are typically higher in these periods. Thus, firms clearly manage debt maturity dispersion over the business cycle. This pattern over the business cycles is also consistent with our rollover risk model, because in recessions the probability of a market freeze, $\lambda$, is likely to be higher.

[Insert Figure 4 here]

Summarizing, we have established several stylized facts. First, there is a lot of variation in granularity across firms. This variation is largely insensitive to the fraction of the firm's private debt. Second, many firms have relatively concentrated maturity profiles, although they could have chosen more dispersed ones, which suggests that they evaluate costs and benefits of debt granularity. Third, average granularity also varies considerably over time (e.g., with macroeconomic conditions). Finally, matching debt maturities with asset maturities does not seem to explain observed debt granularity. In the subsequent sections, we analyze debt granularity and bond issuance across firms and across time in more detail.

# 4 Empirical Analysis of Debt Granularity

We have argued in Section 2 that firms might face trade-offs when they manage their debt maturity structures over time. This implies that different firms will follow different strategies depending on their characteristics, which is broadly confirmed by the heterogeneity of debt granularity observed in Section 3. In this section, we examine whether firm characteristics that proxy for different incentives for granularity management are reliably related to observed variation in the dispersion of firms' debt maturity structures.

## 4.1 Baseline Regressions

We begin by estimating the following baseline regression:

$$GRAN_{i,t+1} = \beta X_{i,t} + \alpha_i + y_t + \epsilon_{i,t+1} \tag{4}$$

where $X_{i,t}$ is a vector of explanatory and control variables, $\alpha_i$ is an industry- or firm-level fixed effect, $y_t$ is a year fixed effect. As the explanatory variable, we consider proxies that capture the forces described in our model. Specifically, we include market-to-book ($Q$), leverage ($Lev$), firm size ($Size$), firm age ($Age$), and profitability ($Prof$) as explanatory variables, given that these variables are related to debt granularity according to our framework in Section 2. In an extended baseline specification, we add the following control variables. We use tangibility ($Tan$) to control for the effect of pledgeable assets on maturity dispersion. We include average maturity ($BondMat$), because we want to study the incremental effect of firm characteristics on maturity dispersion. Finally, cash flow volatility ($ProfVol$) might affect a firm's ability to rollover its debt, so we include it too.[15]

Debt granularity may be affected by unobservable firm or industry characteristics and also vary within firms over time (e.g., due to granularity management through recapitalization). We therefore include either industry or firm level fixed effects to examine the extent to which unmeasured characteristics (or proxies) affect across- or within-firm variation in granularity.[16] Recall that Figure 4 suggests that bond issuance decisions could depend on macroeconomic variables, so we allow for year fixed effects too. Note that a term structure measure (see, e.g., Johnson (2003)) or an aggregate supply measure of Treasury bonds (see, e.g., Greenwood et al. (2010)) is absorbed by year fixed effects, so our tests control for these considerations. We allow for clustering of standard errors at the firm level.[17]

Table 5 gives the estimation results of equation (4) for the measures $GRAN1$ (in the left panel) and $GRAN2$ (in the right panel). Overall, the estimated coefficients are mostly statistically significant, and their explanatory power is large. For example, in the first columns of the table for both granularity measures, all the variables are significant at the 1% level. Also, the $R^2$ is quite high, i.e. 0.369 and 0.488 for $GRAN1$ and $GRAN2$, respectively. The economic significance is also significant. Consider, for instance, the coefficient estimate of 0.20 on the market-to-book ratio ($Q$) in the first column of Table 5. It implies that a one standard deviation change (0.99) in the market-to-book ratio changes $GRAN1$ by 0.2, which corresponds to a 10.5% change relative to the sample average of $GRAN1$ (1.90) in Table 3.

[Insert Table 5 here]

Furthermore, the relation between the explanatory variables and debt maturity dispersion is consistent with our arguments in Section 2. The market-to-book ratio is reliably positively associated with maturity dispersion across all specifications for both of the granularity measures and

[15] In an earlier version, we control for other variables, such as cash holdings and credit ratings, which can be potentially related to rollover risk and hence debt granularity. The baseline results are qualitatively similar.

[16] We employ the Fama-French 49 industry classification. The results are robust to other industry specification, for example, two-digit SIC codes.

[17] The results are robust to using industry-level clustering of standard errors.

with or without various fixed effects. This evidence supports the implication of our model that firms with more valuable growth opportunities have a higher incentive to spread out their bonds' maturity dates across time to protect their valuable projects from inefficient liquidation.[18]

The coefficient estimates on firm size ($Size$), as measured by log of total book assets, are reliably positive across all specifications in Table 5. Economically, firm size is highly significant. Observe that, given a one standard deviation change in log of total assets (1.63), the dependent variable is predicted to change by about 0.8 according to the first columns for each granularity measure. Firm age ($Age$) is also positively related to maturity dispersion, although its effect becomes weaker and statistically insignificant when we include firm fixed effects. Overall, these findings are consistent with the prediction that small, young firms are plagued by high transaction costs, and are therefore not able to spread out their bonds' maturity dates across time.[19]

Leverage ($Lev$) is also positively associated with granularity across all the models considered. Although consistent with our prediction, this result can be partly due to endogeneity between maturity dispersion and leverage. A more dispersed debt structure can enhance debt capacity and may therefore lead the firm to select higher leverage. Also, firms might consider amounts of bond issuance and bond maturity simultaneously when making financing decisions. We address this endogeneity issue later in Section 4.3, using instrumental variable regressions.

Cash flow ($Prof$) is reliably related to granularity. Consistent with the trade-off derived in Section 2, it is negatively associated with maturity dispersion. Intuitively, firms with lower cash flows want to avoid having to repay large amounts of debt at one point in time. We note that the negative coefficient estimate on cash flow is also consistent with signaling in the sense that "good types" want to separate from "bad types" by exposing themselves to rollover risk, because they are in a better position to handle rollover problems. This interpretation of the relation between cash flow and granularity is in line with Diamond's (1991) argument that links liquidity risk to debt maturity.

Moving to the extended baseline specification indicates that tangibility, maturity, and cash flow volatility are positively associated with granularity. However, these control variables do not reduce the explanatory power of the firm characteristics suggested by the model in Section 2. For example,

[18]Note that this evidence is probably also inconsistent with the matching principle. If firms simply match the maturities of their liabilities to their assets irrespective of the quality of their assets or investment opportunities, then we should not observe a reliable relation between granularity and $Q$.

[19]To validate our assumption that size and age proxy for issuance costs, we perform in untabulated results an analysis of gross spreads, the commissions paid to underwriters. Given issue amounts, we find a statistically significant, negative relation between firm size (or firm age) and gross spreads.

the reliably positive coefficient for $BondMat$ confirms that a firm's average bond maturity imposes a restriction on its granularity (i.e. a firm that cannot issue longer maturities cannot spread out its maturities over as many dates as an otherwise identical firm that can). While this effect is statistically significant, it by no means explains the relation between granularity and the main explanatory variables. This underscores the robustness of our baseline results.

In sum, the evidence in Table 5 establishes that firm characteristics, such as $Q$, $Size$, $Age$, $Lev$, and $Prof$, are strongly related to debt maturity dispersion in a way consistent with our model. These variables' statistical significance is mostly unaffected by inclusion of different combinations of fixed effects. This shows that our variables measure granularity variation even after controlling for unobservable cross-sectional and time-series heterogeneity. Their economic significance is also sizable. The remainder of this section studies several alternative specifications and robustness tests for these baseline results.

### 4.2 Number and Type of Bonds

While our main variables are strongly associated with debt granularity, this does not rule out the possibility that firms do not consider debt granularity when making bond issuance decisions. Accordingly, one might be tempted to argue that larger, more mature firms with higher leverage simply have more bonds outstanding. In addition, firms with better investment opportunities could have issued more bonds because of higher financing needs. Firms with many bonds outstanding probably have granular debt structures, because they are more likely to (or just randomly) issue bonds with different maturity dates, which would explain our baseline findings. This would be especially true if firms adhered to the matching principle. According to this interpretation, the firm characteristics we consider are associated with granularity through the number of bonds outstanding. If this is true, then the granularity measures would only pick up the effect of the number of bonds outstanding. Thus, controlling for the number of bonds outstanding should significantly weaken our baseline results.

[Insert Table 6 here]

Similar to Table 5, the left panel of Table 6 is for $GRAN1$ and the right panel is for $GRAN2$. In the first columns of the two panels, we examine whether our main explanatory variables are still reliably related to our granularity measures after including the number of bonds ($NBond$). The columns show that the results are largely the same. The coefficients do not change much after controlling for the number of bonds. In the second columns of each panel in Table 6, we use as a dependent variable the residuals from the regression of granularity on the number of bonds to further control for the potential influence of variation in the number of bonds on debt granularity. The results are again very similar to the baseline results in Table 5. Overall, these robustness checks indicate that our main explanatory variables are significantly associated with debt granularity management even after controlling for the number of bonds outstanding.

Since there is a significant number of firms with only one bond outstanding, it is possible that the baseline results in Table 5 are mainly driven by these firms. If single-bond firms are not able to issue multiple bonds with different maturities for reasons not captured by the control variables, then having too many single-bond firms in the sample can be problematic. Moving to the columns labeled "$N >= 2$" in Table 6 reveals that the results for firms with at least two bonds outstanding are similar to ones for the full sample. In fact, the economic significance of the main explanatory variables, such as market-to-book, size, leverage, and profitability, tends to be higher for this subsample of firms. Thus, the results in Table 5 are not driven by firm-year observations for which only one bond is outstanding.

Finally, in the center columns of the two panels in Table 6, we exclude firms that have more than 80% of their total bond amounts in bonds with option features and sinking fun provisions. Since effective maturities for bonds with options and sinking funds are likely to be much shorter than for straight bonds, re-estimating equation (4) for the subsample that is composed mostly of straight bonds is potentially more informative. Indeed, the columns "Straight" report stronger or similar relations between the granularity measures and the explanatory variables, i.e., the economic and statistical significance levels are larger in this subsample compared to the full sample.

### 4.3 Instrumental Variable Regressions

In the prior analysis, we find that leverage is positively and reliably related to granularity. These regressions treat leverage as an exogenous variable and granularity as an endogenous variable. In reality, however, these variables are likely to be determined jointly and subject to the longest available maturity. That is, firms are likely to make corporate financing decisions by considering the level of leverage along with the first two moments of maturity (i.e. average maturity and dispersion of maturity) simultaneously. Notice that higher granularity will lower firms' rollover risk, which in turn can increase debt capacity and thereby increase leverage (and even increase average maturity).

In this subsection, we address these concerns by performing two-stage least-squares (2SLS) regressions. Specifically, we instrument leverage and maturity by including exogenous variables in addition to the other explanatory variables and controls. The additional exogenous variables need to affect granularity indirectly through leverage and maturity (but not directly). Previous studies guide us in selecting potential instruments. The first instrument we consider is industry leverage. For example, Frank and Goyal (2009) document that industry leverage is an important factor for explaining firm leverage. Industry leverage is likely to affect an individual firm's granularity only through its leverage. The second instrument is industry asset maturity. Asset maturity influences granularity mostly through average debt maturity but is unlikely to have a direct effect on granularity. We employ industry asset maturity to reduce the noise in measuring firm-level asset maturities following previous studies (see, e.g., Saretto and Tookes (2012) for the use of these two instruments in a related setting). The third instrument is credit rating. Rating agencies consider mainly debt coverage and cash flows to rate firms. Granularity is likely to be of little or no importance in determining credit ratings. This observation implies that rating is associated with granularity primarily through leverage and maturity. In our implementation of the 2SLS estimations, we employ all of these three instruments.

Columns $IV$ of Table 6 report the results from the 2SLS regressions using industry leverage, asset maturity, and credit rating as instruments. We report the results based on firm fixed effects. The results show that instrumenting leverage and maturity sharpens the coefficient estimates on the key variables compared to the baseline results. For example, the effect of $Q$ and $Prof$ almost doubles in the left panel for $GRAN1$. All the explanatory variables are statistically significant at the same levels as in Table 5 with the exception of $Age$ in case of $GRAN1$, where $Age$ is still significant at the 10% level. Taken together, these results provide further evidence on the trade-off in Section 2 that motivates firms' incentives to manage the granularity of their debt.

### 4.4 Industry Granularity

The analysis in the previous subsection suggests that it might be important to control for industry granularity, if asset maturity distributions are roughly constant across firms within an industry but different across industries. In addition, it seems plausible that industry granularity should diminish the importance of some of the explanatory variables especially if firms use the matching principle. We therefore consider in the last columns of Table 6 the possibility that industry granularity might explain our baseline results. It turns out that $IndGRAN$ is economically and statistically significant, when we add it to the regression specifications for $GRAN1$ and $GRAN2$. However, it does not strongly influence the relations between granularity and firm characteristics, which we report in Table 5. In fact, the estimation results in the last columns of Table 6 suggest that firm characteristics, such as market-to-book or leverage, are independently important. We conclude that some but by no means all within-industry variation in granularity is driven by industry granularity and that these findings lend little support to the matching principle in our sample.

### 4.5 Including Private Debt in Granularity Measures

Our empirical analysis largely focuses on bond maturity profiles, because rollover frictions are likely to be smaller for private debt, such as bank loans. Recall that private debt is commonly and frequently renegotiated (see, e.g., Roberts and Sufi (2009)) and that the maturity of private debt is more easily manageable (see, e.g., Mian and Santos (2011)). In addition, bank loans are available in relatively small increments, meaning that our arguments do not apply very well to private debt. On the other hand, corporate bonds, which are mostly public debt and characterized by a dispersed, anonymous ownership structure, are difficult to renegotiate once issued, are associated with sizable issue costs, and have large minimum issue sizes.[20] As a result, private debt maturity dispersion is less precisely measured and also less relevant for the arguments developed in Section 2.

Nonetheless, we examine whether our results are robust to inclusion of private debt maturity profiles, so that our granularity measures are based on total instead of public debt maturity profiles. To this end, we augment the corporate bond maturity structures from FISD by debt maturity variables from COMPUSTAT. Given that most bank loans have stated maturities of less than five years, we use COMPUSTAT's $DD1$ to $DD5$ variables for maturities of one to five years instead of the data from FISD, and continue to use FISD's variables for maturities greater than five years.[21] Note that these COMPUSTAT variables include public debt expiring in less than or equal to five years.

To begin, notice that the descriptive statistics in Table 4 show that bond granularity (i.e. $GRAN1$ or $GRAN2$) is largely unaffected by incorporating maturity profiles from COMPUSTAT to compute total debt granularity (i.e. $GRAN1L$ or $GRAN2L$). More importantly, we re-estimate

[20]Blackwell and Kidwell (1988) and Krishnaswami et al. (1999) find that issuance costs are larger for public debt than for private debt, which includes bank loans. In addition, Carey et al. (1993) find that public debt is cost-effective only above $100 million, while bank debt and non-bank private debt are cost-effective even for smaller issues.

[21]To validate this approach, we examined maturities of bank loans for the limited sample (2002 onwards) using Standard & Poor's Capital IQ data. We find that more than 85% of bank loans have maturities shorter than 5 years.

equation (4) using the granularity measures that include private debt as dependent variables. The regression results based on these measures are gathered in the fifth columns of Table 6. As seen in the "Loans" columns, most of the explanatory variables are statistically significant and their signs are consistent with the ones predicted by the model in Section 2. Overall, these results indicate that the firm characteristics we consider are also associated with total granularity.

### 4.6 Proportion of Private Debt

In addition to the results provided in Table 6 for including private debt maturity profiles into our granularity measures, we further examine the impact of private debt on public debt granularity. Recall that debt renegotiation is very common for private debt, so realized maturity is much shorter than contracted maturity (see, e.g., Roberts and Sufi (2009)). As a result, firms with a large proportion of bank loans may not need to spread out the maturity dates of their corporate bonds. Put differently, since private debt is easier to adjust and renegotiate than public debt, firms might effectively maintain a high degree of total debt maturity dispersion by managing bank debt dispersion, but leaving bond maturity structures less dispersed. In addition, some components of private debt, such as credit lines, might even be used to manage rollover risk.

To examine this substitution hypothesis, we estimate the model in equation (4) for low and high bank debt subsamples. That is, we investigate in Table 7 whether a larger fraction of bank debt affects firms' granularity decisions. Firms are categorized as low bank loan firms if corporate bonds in FISD account for more than 50% of their total debt (long-term debt plus debt in current liabilities in COMPUSTAT), and they are categorized as high bank loan firms otherwise. Notably, the estimation results for both subsamples are qualitatively similar to the full sample results. Thus, the baseline results in Table 5 are robust to variation in the proportion of private debt. Consistent with the finding in Section 4.5, this suggests that granularity is mainly relevant for public debt, which supports our assumptions in Section 2.

[Insert Table 7 here]

### 4.7 Granularity during the Financial Crisis

During the recent financial crisis, most firms probably faced substantially increased rollover risk. Almeida et al. (2012), for example, document that firms with long-term debt maturing during the financial crisis had to decrease investments. We therefore examine whether firms' incentives to implement a more dispersed maturity structure are stronger during the 2008–2009 financial crisis.

Table 8 reports estimation results of equation (4) for the 2008–2009 crisis period and for the non-crisis period (i.e. 1991 to 2007 and 2010 to 2011). Compared to the non-crisis period, the effect of $Q$ is more precisely measured in the crisis subsample for both granularity measures (i.e. the $t$-statistics are similar but there is a substantial differences in the number of observations between the two subsamples). In addition, the economic effect of investment opportunities on granularity rises considerably during the crisis. For example, the coefficient estimate on $Q$ in the fourth column of $GRAN1$ with firm fixed effects is 0.54, compared to 0.22 for the non-crisis period. In untabulated results, the differences in coefficients between the two subsamples are in most cases statistically significant at the 1% level. These estimation results suggest that given the higher likelihood of investment inefficiencies due to rollover risk during the crisis, especially firms with valuable investment opportunities (as measured by a higher $Q$) selected reliably higher maturity dispersions.

[Insert Table 8 here]

### 4.8 Partial Adjustment and Target Granularity

The regression specification (4) assumes implicitly that observed maturity dispersion is also firms' target dispersion. In a world without adjustment costs, this would be plausible. With adjustment costs, however, realized dispersion is likely to deviate from its target level, and firms will typically make partial adjustments towards their targets. If firms manage granularity, then it will revert to target levels rapidly. In contrast, if there is no target granularity, or if adjustment costs are too high, then firms are passive and adjustment speeds should be slow.

In this section, we account for the time-varying nature of target maturity dispersion and partial adjustments by estimating the following speed-of-adjustment (SOA) regression of debt granularity:

$$\Delta GRAN_{i,t+1} = \gamma(\beta X_{i,t} - GRAN_{i,t}) + \nu_{i,t+1}, \tag{5}$$

where $X_{i,t}$ is a vector of explanatory variables, such as $Q$, $Size$, $Age$, $Lev$, and $Prof$. So, $\beta X_{i,t}$ denotes target maturity dispersion and $-\gamma$ is the speed of adjustment towards target dispersion. In other words, firms narrow the gap between target dispersion and actual dispersion by a fraction of $\gamma$ each year. Rearranging terms, the above regression model is equivalent to:

$$GRAN_{i,t+1} = (\gamma\beta)X_{i,t} + (1-\gamma)GRAN_{i,t} + \nu_{i,t+1}. \tag{6}$$

Equation (6) says that, in a world of partial adjustments, next year's granularity, $GRAN_{i,t+1}$, is a linear combination of target granularity ($\beta X_{i,t}$) and actual granularity ($GRAN_{i,t}$) this year.

Table 9 displays again results separately for $GRAN1$ and $GRAN2$. The first columns for $GRAN1$ and $GRAN2$ present the OLS estimation results with industry fixed and year effects. The estimated SOA coefficients are 0.21 and 0.30 for $GRAN1$ and $GRAN2$, respectively. Economically, these estimates on lagged granularity imply that the half lives of excess granularity are between 2.94 to 1.94 years. Moreover, the estimated SOA coefficients are statistically highly significant, which indicates that firms have target granularity levels and are involved in the management of granularity.

[Insert Table 9 here]

These relatively low adjustment speeds can be due to unobservable firm-specific heterogeneity in target granularity. As pointed out by Flannery and Rangan (2006), the lack of fixed effects potentially biases the SOA coefficients towards zero. Therefore, we include firm and year fixed effects in Table 9. With fixed effects, the SOA estimates increase dramatically and are also highly significant. In the second column for $GRAN1$, for example, the coefficient on lagged $GRAN1$ equals 0.41. At this high rate of adjustment, firms close the dispersion gap approximately by 65% within two years. In untabulated results, an F-test for the joint significance of the fixed effects rejects the hypothesis that these terms are all equal, supporting heterogeneity in granularity targets.

The rapid adjustment speeds with fixed effect estimations require careful interpretation, because equation (6) is a dynamic panel model. It is well-known that coefficient estimates are inconsistent with fixed effects in a dynamic panel. To address this issue, we employ a panel GMM estimation using lags of maturity dispersion as instruments as in Arellano and Bond (1991) in the fifth and sixth columns in Table 9. With this approach, the estimated speeds of adjustment are quite similar to the results with fixed effects. In the last column for $GRAN1$, for example, the estimated SOA coefficient is 0.54, which indicates that a typical firm adjusts approximately 79% of maturity dispersion towards its target dispersion within two years. These results based on instrumental variables strongly suggest that firms manage debt granularity even when allowing for non-zero adjustment costs.

In addition to the SOA estimates in the first line, Table 9 also provides coefficient estimates for $(\gamma\beta)X_{i,t}$, which allow us to deduce maturity dispersion targets as a function of firm characteristics. Note that the estimated dispersion targets also confirm the predictions from our theory. Tobin's $Q$, firm size, and leverage are reliably positively related to target dispersion across all the models considered. The other variables (i.e. firm age, tangibility, and profitability) also tend to be associated with target dispersion in a way that is consistent with our hypotheses.

Overall, the SOA test results lead us to conclude that firms manage debt maturity dispersion. The speed with which firms make adjustments towards granularity targets is fairly high, implying that firms regard maturity dispersion management as important. Furthermore, granularity targets are explained by firm characteristics in ways that are in line with the predictions of our theory and that are also consistent with the cross-sectional test results in Section 5.1.

# 5 Granularity Management through Bond Issuance

In this section, we provide further evidence on the management of the dispersion of debt maturities. Specifically, we ask the following question: how important is maturity dispersion when firms determine the maturity of newly-issued bonds?

To address this question, we investigate whether discrepancies between a firm's pre-existing maturity profile and a benchmark maturity profile (based on firm characteristics implied by our model) explain future debt issue behavior. In other words, we conduct time-series tests, which are informative about whether newly-issued bonds' maturities are consistent with debt maturity dispersion management. For this purpose, we run a series of binomial choice regressions ($j = 1, 2, ..., 7$):

$$Prob(I_i^{K_j}) = a_1 m_i^{K_1} + a_2 m_i^{K_2} + a_3 m_i^{K_3} + a_4 m_i^{K_4} + a_5 m_i^{K_5} + a_6 m_i^{K_6} + a_7 m_i^{K_7} + \alpha_n + y_t \ , \qquad (7)$$

where $K_j$ represent maturity buckets, $I_i^{K_j}$ is an issuance dummy which takes on the value of one if the newly issued bond's maturity falls into bucket $K_j$, and $m_i^{K_j}$ are deviations of the issuing firm's maturity profile from its benchmark. The maturity buckets $K_j$ are defined as follows. For maturity shorter than 10 years, there are five two-year buckets. In other words, for $1 \leq j \leq 5$, $K_j$ is from $2j-1$ to $2j$ years. For maturities longer than 10 years, there are two maturity buckets $K_6$ and $K_7$. $K_6$ corresponds to years from 11 to 20 and $K_7$ to years from 21 or longer. $\alpha_n$ is an industry fixed effect for the issuing firm $n$ and $y_t$ denotes a year fixed effect.[22]

The independent variable $m_i^{K_j}$ (the deviation of maturity profiles from the benchmark) is defined in the following way. Each firm's maturity profiles are first calculated as fractions of pre-existing

[22]We have obtained remarkably similar results for a probit model instead of a linear probability model. As the linear model is easier to interpret (i.e. coefficients correspond to probabilities), we tabulate these results.

bond amounts in each maturity bucket $K_j$. To obtain the benchmark maturity profile, firms are sorted into high (top 50%) and low (bottom 50%) groups based on the firm characteristics ($Q$, market leverage, age, size, profitability, and average maturity). This procedure yields 64 maturity profile groups. The benchmark profile of each group is then obtained by averaging maturity profiles in that group. The deviations from the benchmark profiles are obtained by subtracting average maturity profiles of the group that the issuing firm belongs to.

For the new issue to be sufficiently important, we apply different relative issuance size cut-offs.[23] We note that this time-series analysis is conditional in that it estimates a maturity choice problem given the firm issues a bond.

If firms manage their debt maturity dispersion relative to benchmarks, then the probability of issuing a bond in the $K_j$ maturity bucket will be negatively related to the deviation of bond fractions in that bucket, $m_i^{K_j}$. The coefficient $a_j$ will be negative and smaller than coefficients on other maturity buckets, $a_i$, where $i \neq j$. To examine these predictions, linear probability models are estimated for each maturity bucket $K_j$. We have experimented with other probability models, such as panel logit models, and the results are qualitatively identical. Industry and year fixed effects are included in the estimation. Any economy-wide supply side effects on firms' issuance are absorbed by year fixed effect. Standard errors are clustered at the Fama-French 48 industry level.

Results in Panel A of Table 10 confirm the model's key insights. Panel A1 provides the results for the sample of bonds with issue sizes greater than 3% of firms' total pre-existing bond amounts. Except for the shortest maturity bucket ($K_1$), all diagonal coefficients are negative and statistically significant at 1% or 5% level, suggesting that firms engage in maturity dispersion management by avoiding maturity towers. For the five to six year maturity bucket, for example, the coefficient on $K_3$ is -0.36. That is, the probability of issuing additional five- or six-year maturity bonds drops by 0.36 of a percentage point for every percentage point that a firm's maturity profile exceeds the benchmark maturity profile in the bucket $K_3$. Perhaps because bank loans and other private debt are confounding our analysis for shorter maturities, the weakest result is found at the shortest maturity bucket ($K_1$), which is still negative but not statistically significant. Non-diagonal coefficients are in many cases positive and not significant. The results in Panel A2 for the sample with the issue cutoff at 10% are even stronger, further confirming firms' motives to maintain dispersed bond

[23] We do not count bond exchanges due to Rule 144A securities as new issues. Many firms issue Rule 144A bonds in private placements, which are exchanged later with near identical public bonds.

maturity structures when the relative size of the new issue is larger.

[Insert Table 10 here]

In addition, we examine in Table 10 if the diagonal coefficients are, on average, smaller than the other six coefficients in the same binomial choice regression (i.e. column). For this purpose, we test the null hypothesis, $H_0\colon\ a_i - \frac{1}{6}\sum_{n\neq i} a_n = 0$, in the last rows of Table 10. The results reveal that the diagonal coefficients are always smaller than the average of non-diagonal coefficients. The difference $(a_i - \frac{1}{6}\sum_{n\neq i} a_n)$ is negative across all maturity buckets, ranging from -0.05 to -0.30 in Panel A1. Furthermore, they are all statistically significant at the 5% level. When the 10% issue cutoff is used in Panel A2, the results are stronger with the hypothesis rejected in all cases at the 1% level.

In Panels B1 and B2 of Table 10, we perform the same tests after excluding all option-embedded bonds, such as callable, convertible, and putable bonds, and bonds with sinking fund provisions, as a robustness check. This exercise is important and informative because effective maturities could be shorter with these option-embedded bonds. Compared to the results in Panels A1 and A2, the results for the sample of straight bonds are slightly weaker but qualitatively very similar.

To summarize, firms manage maturity dispersion in that newly issued corporate bonds complement pre-existing bond maturity profiles. The findings in this subsection reinforce the results from the previous subsection. That is, they also support the view that firms manage debt maturity dispersion, especially when they issue new bonds.

# 6 Conclusion

This paper studies firms' debt maturity profiles. It deviates from the existing literature by focusing on the dispersion of each firm's debt maturities instead of its average debt maturity. Maturity structure matters due to rollover risk, i.e. the risk that the firm may not be able to refinance an expiring bond externally and thus may be forced to engage in inefficient asset sales to repay the bondholders. A firm with a dispersed maturity structure faces multiple small rollover risks, whereas a firm with a concentrated maturity structure faces a single large rollover risk. Since multiple small asset sales are less inefficient than an equivalent single large asset sale, dispersed maturity structures are advantageous in the absence of transactions costs or illiquidity costs. The model predicts that corporate debt maturities should be more dispersed when access to external debt markets is more uncertain, for firms with more profitable investment projects, for larger and more mature firms, with more tangible assets, with higher leverage ratios, with lower values of assets in place, and with lower levels of current cash flows.

In a large panel of corporate bond issuers during the 1991–2009 period, we find evidence that supports our model's predictions in cross-sectional and time-series tests. In the cross-section, corporate debt maturities are more dispersed and, in the time series, maturity dispersion adjusts faster for larger and more mature firms, for firms with better investment opportunities, with more tangible assets, with higher leverage ratios, with lower values of assets in place, and with lower levels of current cash flows. Moreover, during the recent financial crisis when access to primary capital markets was difficult, we find that especially firms with valuable investment opportunities implemented more dispersed debt maturity structures. In the time-series, we also document that firms actively manage dispersion of debt maturity in that newly issued corporate bond maturities complement pre-existing bond maturity profiles.

Taken together, the model predictions and test results suggest several novel insights for the joint choice of capital structure and debt structure. In essence, we establish that there is heterogeneity in how firms spread out their bonds' maturity dates across time and that recognition of this heterogeneity has important implications for the determinants of capital structure across firms and over time. More generally, we believe that our understanding of corporate financial decision making can be improved by recognizing the costs and benefits associated with firms' decisions on how many different types, sources, and maturities of debt to use.

# Appendix A. Model Extension to Endogenous Market Freezes

In this Appendix, we provide an extension of the simple model of debt granularity to endogenous market freezes. We again study a three-period model of an initially all-equity financed firm. The firm has assets in place (or initial net worth), $A$, and two projects, $H$ and $L$. Each project requires a capital outlay, $I$, at time $t_0$ and, in the absence of early project liquidations, generates a cash flow at time $t_2$ of $2\,R_i$, where $i \in H, L$ and $R_H > R_L = I$ implies decreasing returns to scale. At time $t_3$ the firm realizes a continuation value of $V > 2\,I$. Similar to, e.g., Hart and Moore (1995), cash flows are observable but non-verifiable, while continuation values are also verifiable.

The firm issues straight one- or two-period bonds to raise the required capital of $2\,I - A$. Thus, bonds issued at time $t_0$ must be rolled over. If the firm is unable to refinance maturing bonds, assets from one or both projects must be sold to generate the funds required to repay the debtholders. Such a partial liquidation reduces the final cash flow by $R_i$ and generates an immediate cash flow of $I$, which is inefficient. Partial liquidations can be interpreted broadly. For example, the firm may have to sell part of a project's capital stock, such as land or buildings, or reduce marketing campaigns or capital maintenance programs, lowering the project's profitability in the long run. As long as the maturing bonds' face value does not exceed $I$, only one project needs to be partially liquidated. In this case, the firm sells assets from the low-profitability project $L$, thereby giving up future cash flows of $R_L$. By contrast, the firm has to liquidate assets from both projects if the maturing bonds' face value exceeds $I$, thereby giving up future cash flows of $R_H + R_L$.

The firm may be unable to roll over its debt, which leads to partial liquidations, when it becomes vulnerable to a technology shock at time $t_1^-$ and at time $t_2^-$. Specifically, at each of these points in time, there is a probability $\lambda$ with which the firm becomes vulnerable to such a potential technology shock. We refer to this state as the *high-uncertainty state.* With probability $\pi$ the technology shock then actually takes place, the firm seizes to exist, each project only produces a final, non-contractible cash flow of $I$, and each project's collateral value drops from $I$ to zero.[24] With probability $1-\pi$ the technology shock does not follow the high-uncertainty state, however, and the firm continues its projects as a going concern, just as in the *low-uncertainty state* that arises with probability $1-\lambda$.

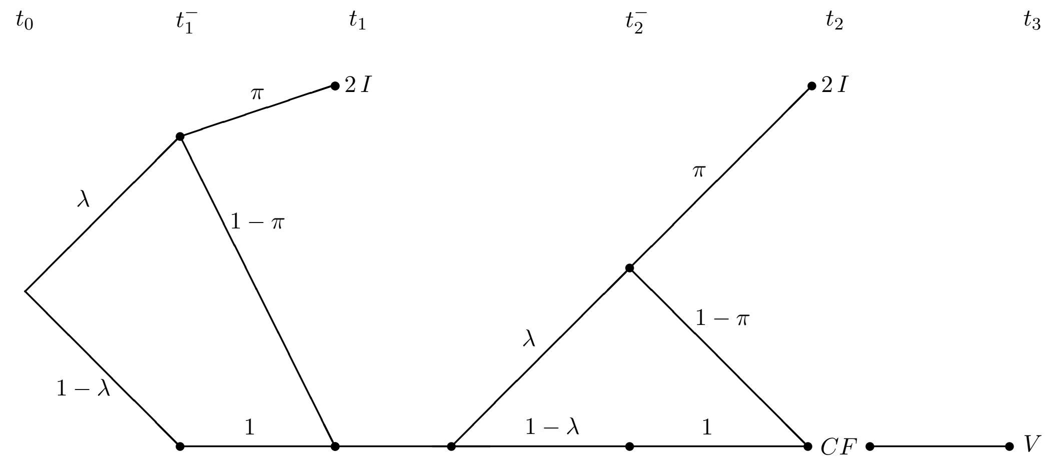
To rule out trivial solutions, we impose the following condition:

$$\frac{2\,I - A}{1 - \lambda\,\pi} \;<\; V \;<\; \frac{I - \frac{1}{2}A}{(1-\pi)\,(1-\lambda\,\pi)}\;. \tag{A.1}$$

[24] The final, non-contractible cash flow of $I$ ensures equityholders never have an incentive to liquidate a project early.

Essentially, the left-hand side of condition (A.1) implies that a bond can be rolled over in the low-uncertainty state, whereas the right-hand side states that this is not feasible in the high-uncertainty state. Furthermore, we require that $0 < A < 2\,I$ so the firm cannot fully fund the projects using its initial net worth, $A$. Figure 2 depicts the cash flows of a project through time.

**Figure 2. Evolution of Cash Flows, Risks, and Shocks**




This figure plots the time line of cash flows, risks, and shocks. In each of the two periods, there is a probability $\lambda$ with which firms become vulnerable to a technology shock, which will then occur with probability $\pi$. If the technology shock takes place, each project's collateral value drops from $I$ or zero and each project only pays off a final, non-contractible cash flow of $I$. In the absence of a technology shock, the time $t_2$ cash flow generated by the two projects is $CF = R_H(2 - l_H) + R_L(2 - l_L)$ where $l_H$ and $l_L$ represent the number of partial liquidations of projects $H$ and $L$ respectively. In the absence of any technology shocks, the firm realizes a contractible continuation value of $V$ at time $t_3$.

We also let $2\,I > (2\,I - A)/(1 - \lambda\,\pi)$, which will ensure that there is enough collateral to satisfy bondholders in full when the bond expires and cannot be rolled over. For simplicity, all investors are assumed to be risk-neutral and the risk-free interest rate is normalized to zero.

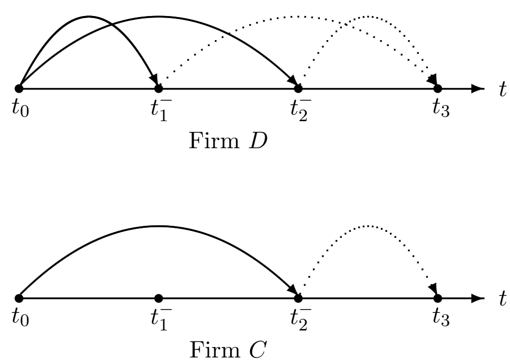
We consider two initial maturity distributions, a *concentrated* and a *dispersed* one. We refer to the former as firm $C$ and to the latter as firm $D$. Firm $C$ issues bonds at time $t_0$ with maturity concentrated at time $t_2^-$, where they are rolled over to time $t_3$ whenever possible.[25] In contrast, firm $D$ issues bonds at time $t_0$ with maturities dispersed across time $t_1^-$ and time $t_2^-$, such that each of the two issues raises $I - \frac{1}{2}A$. Figure 3 provides the evolution of rollover decisions over time.

In practice, bond issuances have a fixed cost component and also a minimum size requirement. To capture scale economies of larger issues, we assume that the firm pays a fixed cost per issue,

[25] An alternative strategy for firm $C$ would be to select time $t_1^-$ as maturity date and, if possible, roll the bonds over to $t_3$. We have also investigated this alternative, but it is weakly dominated by issuing bonds that expires at time $t_2^-$. Intuitively, this is so, because issuing initially long-term rather than a short-term bonds shields time $t_1$ cash flows (efficiency gain) and inefficiencies arise only at time $t_2$.

$k$, at time $t_0$. As a result, firm $C$ has a transaction cost advantage, because it incurs issue cost of $k$, whereas firm $D$ incurs issue costs of $2\,k$. In addition, $k$ can be thought to reflect the fact that a single large bond issue may have a more liquid secondary market, thus leading to a lower illiquidity discount than two smaller bond issues. For evidence on a positive relation between issue size and direct issuance costs and secondary market liquidity, respectively, see Lee et al. (1996) and Longstaff et al. (2005) or Mahanti et al. (2008). Moreover, Altinkilic and Hansen (2000) provide evidence that bond spreads decline monotonically with issue size, which is consistent with an economies of scale interpretation. Finally, note that issue costs at each point in time would also favor firm $C$ because it has only two issuances, while firm $D$ has four issuances (see Figure 3).

**Figure 3. Evolution of Rollover Decisions**




This figure plots the time line of rollover decisions for the dispersed maturity structure (or Firm $D$) with two smaller issues, which expire at time $t_1^-$ and $t_2^-$, and the concentrated maturity structure (or Firm $C$) with one larger issue, which expires at time $t_2^-$. An expiring issue needs to be rolled over to time $t_3$ to obtain the firm's continuation value.

We first derive the early partial liquidations for firms $C$ and $D$, respectively. Condition (A.1) implies that firm $C$ cannot roll over its bond and thus must liquidate assets from both projects in the high-uncertainty state at time $t_2^-$. In this state project cash flows $R_L + R_H$ are lost and instead the projects' collateral values, $2\,I$, are realized, of which $(2\,I - A)/(1 - \lambda\,\pi)$ must be used to repay the face value of the bond. Note that bondholders receive zero if the technology shock takes place at $t_1$. No other project liquidations are required for firm $C$ since no bonds expire at time $t_1^-$.

Firm $D$ faces rollover risk at both times $t_1^-$ and $t_2^-$. Condition (A.1) implies that the expiring bonds cannot be rolled over in the high-uncertainty states. In each of these states the firm optimally liquidates assets from project $L$ and thus gives up time $t_2$ cash flows of $R_L$. Instead, collateral value of $I$ is realized, of which $I - \frac{1}{2}A$ (at time $t_1^-$) and $(I - \frac{1}{2}A)/(1 - \lambda\,\pi)$ (at time $t_2^-$), is used to repay bondholders. Note that only the bond which matures at time $t_2^-$ is risky, because bondholders receive zero if the technology shock takes place at $t_1$, and therefore requires a higher face value.

Figure 2 reveals that there are seven possible paths along which each of the two types of firms can evolve. Consider first path (i) for the firm with a concentrated maturity structure (or firm $C$) in Table 1, where it becomes vulnerable to a technology shock at time $t_1^-$. Since firm $C$ does not have any bonds outstanding that expire at $t_1^-$, no early project liquidation is enforced. Along this path the technology shock actually takes place at time $t_1$. Therefore, each project generates a non-contractible, final cash flow of $I$ to equityholders, bondholders receive nothing, and the firm seizes to exist. The probability of this path is $\lambda\,\pi$.

**Table 1. Paths, Probabilities, and Cash Flows for Firm $C$**

| Paths | Probabilities | Cash Flows to Equity |
|---|---|---|
| (i) | $\lambda\,\pi$ | $2\,I$ |
| (ii) | $\lambda\,(1-\pi)\,\lambda\,\pi$ | $2\,I - P_C(t_0, t_2^-)$ |
| (iii) | $\lambda\,(1-\pi)\,\lambda\,(1-\pi)$ | $R_H + R_L + 2\,I - P_C(t_0, t_2^-) + V$ |
| (iv) | $\lambda\,(1-\pi)\,(1-\lambda)$ | $2\,(R_L + R_H) - P_C(t_2^-, t_3) + V$ |
| (v) | $(1-\lambda)\,\lambda\,\pi$ | $2\,I - P_C(t_0, t_2^-)$ |
| (vi) | $(1-\lambda)\,\lambda\,(1-\pi)$ | $R_H + R_L + 2\,I - P_C(t_0, t_2^-) + V$ |
| (vii) | $(1-\lambda)\,(1-\lambda)$ | $2\,(R_L + R_H) - P_C(t_2^-, t_3) + V$ |

Next consider path (ii) for firm $C$, where it also reaches the high-uncertainty state at time $t_1^-$. Again, since no bonds expire at this point, no early project liquidation is required. Along this path, the technology shock subsequently does not take place at time $t_1$, and thus the projects continue as a going concern. At time $t_2^-$ the firm again ends up in the high-uncertainty state. The firm's bonds expire at this time, but condition (A.1) implies that investors would not be willing to roll over the bond. Therefore, the firm must sell assets from both projects to repay the principal amount of the expiring debt, $P_C(t_0, t_2^-)$. This generates cash flows to equity of $2\,I - P_C(t_0, t_2^-)$. Then the technology shock takes place at time $t_2$. Since the project's assets have already been sold, no more cash flows are generated, and the firm seizes to exist. The probability of this path is $\lambda\,(1-\lambda)\,\lambda\,\pi$.

Along path (iii), firm $C$ also reaches the high-uncertainty state at time $t_1^-$. Since no bonds expire at this point, no early project liquidation is required. The technology shock subsequently does not take place at time $t_1$ and hence the projects continue as a going concern. At time $t_2^-$ the firm again ends up in the high-uncertainty state. The firm's bonds expire at this time, but condition (A.1) implies that investors would not be willing to roll over the bond. Therefore, the firm must sell assets from both projects to repay the principal amount of the expiring debt, $P_C(t_0, t_2^-)$. This generates cash flows to equity of $2\,I - P_C(t_0, t_2^-)$. Along this path, the technology shock does subsequently not take place, and thus the firm continues its operations. That is, the projects generate cash flows of $R_H + R_L$ (recall that no project assets had to be sold at time $t_1^-$) and the continuation value of $V$ is realized. This path occurs with probability $\lambda\,(1-\pi)\,\lambda\,(1-\pi)$.

Along path (iv), firm $C$ reaches the high-uncertainty state at time $t_1^-$, but no bonds need to be rolled over, so no early project liquidation is required. The technology shock does not occur at time $t_1$. At time $t_2^-$, the firm is in the low-uncertainty state. By condition (A.1) the expiring bonds can be refinanced by issuing new bonds with the same face value, $P_C(t_2^-, t_3) = P_C(t_0, t_2^-)$. The firm can continue as a going concern and does not need to sell any assets. Therefore, the cash flows to equity are $2\,(R_H + R_L) - P_C(t_2^-, t_3) + V$. This path occurs with probability $\lambda\,(1-\pi)\,(1-\lambda)$.

It is straightforward to verify that the cash flows to equity from path (v) are identical to those along path (ii) and that path (vii) leads to the same cash flows to equity as path (iv). Finally, the high-uncertainty state never arises along path (vii). Hence bonds can be rolled over, and asset sales are not necessary. Cash flows to equity are $2\,(R_H + R_L) - P_C(t_2^-, t_3) + V$.

We now turn to the firm with a dispersed maturity structure (or firm $D$). Consider first path (i) in Table 2, where the firm becomes vulnerable to a technology shock at time $t_1^-$. Since some of firm $D$'s bonds expire at $t_1^-$, assets from project $L$ must be sold, because condition (A.1) implies that the expiring bonds cannot be refinanced externally. This generates cash flows to equity of $I - P_D(t_0, t_1^-)$. Then the technology shock actually takes place at time $t_1$. Therefore, the second project only produces a final, non-contractible cash flow of $I$ to equityholders, bondholders of $P_D(t_0, t_2^-)$ receive nothing, and the firm seizes to exist. The probability of this path is $\lambda\,\pi$.

Next consider path (ii) for firm $D$, where it also reaches the high-uncertainty state at time $t_1^-$. Again, some of firm $D$'s bonds expire at $t_1^-$, and thus assets from project $L$ are sold. This generates cash flows of $I - P_D(t_0, t_1^-)$ to equity. Then the technology shock does not take place at time $t_1$, so the firm continues its projects as a going concern. At time $t_2^-$ the firm again ends up in the high-uncertainty state. The firm's other time $t_0$ issue expires at this point in time, but condition (A.1) implies that investors would not be willing to refinance it. Therefore, the firm must sell assets from one project to repay the principal amount of $P_D(t_0, t_2^-)$. This generates cash flows to equity of $I - P_D(t_0, t_2^-)$. Along this path, the technology shock actually takes place at time $t_2$. This means that the not-yet liquidated second project also produces a final, non-contractible cash flow of $I$ to equity, bondholders of $P_D(t_1, t_3)$ receive nothing, and the firm seizes to exist. The probability of this path is $\lambda\,(1-\pi)\,\lambda\,\pi$.

**Table 2. Paths, Probabilities, and Cash Flows for Firm $D$**

| Paths | Probabilities | Cash Flows to Equity |
|---|---|---|
| (i) | $\lambda\,\pi$ | $I - P_D(t_0, t_1^-) + I$ |
| (ii) | $\lambda\,(1-\pi)\,\lambda\,\pi$ | $I - P_D(t_0, t_1^-) + I - P_D(t_0, t_2^-) + I$ |
| (iii) | $\lambda\,(1-\pi)\,\lambda\,(1-\pi)$ | $I - P_D(t_0, t_1^-) + I - P_D(t_0, t_2^-) + 2\,R_H + V$ |
| (iv) | $\lambda\,(1-\pi)\,(1-\lambda)$ | $I - P_D(t_0, t_1^-) - P_D(t_2^-, t_3) + 2\,R_H + R_L + V$ |
| (v) | $(1-\lambda)\,\lambda\,\pi$ | $I - P_D(t_0, t_2^-) + I$ |
| (vi) | $(1-\lambda)\,\lambda\,(1-\pi)$ | $I - P_D(t_0, t_2^-) - P_D(t_1^-, t_3) + 2\,R_H + R_L + V$ |
| (vii) | $(1-\lambda)\,(1-\lambda)$ | $2\,(R_L + R_H) - P_D(t_1^-, t_3) - P_D(t_2^-, t_3) + V$ |

Along path (iii), firm $D$ also reaches the high-uncertainty state at time $t_1^-$. Again, some of firm $D$'s bonds expires at $t_1^-$, and thus assets from project $L$ are sold, since condition (A.1) implies that the expiring bonds cannot be rolled over. This generates cash flows to equity of $I - P_D(t_0, t_1^-)$. Then the technology shock subsequently does not take place at time $t_1$ and hence continues its projects as a going concern. At time $t_2^-$ the firm again ends up in the high-uncertainty state. The firm's second bond issue expires at this point, and condition (A.1) implies that investors would not be willing to refinance the bond. Therefore, the firm must sell assets from project $L$ again to repay the principal amount of the expiring debt, $P_D(t_0, t_2^-)$. This generates cash flows to equity of $I - P_D(t_0, t_2^-)$. Subsequently, there is no technology shock on this path, and thus the firm continues its operations. This implies that the projects pay off $2\,R_H$ (recall that assets of project $L$ had to be sold at time $t_1^-$ and at time $t_2^-$ so that project $L$ does not produce any time $t_2$ cash flows), and the continuation value of $V$ is realized. This path occurs with probability $\lambda(1-\pi)\lambda(1-\pi)$.

Observe that path (iv) is identical to path (iii) until time $t_2^-$. At this point, however, the low-uncertainty state occurs. The expiring bonds with face value $P_D(t_0, t_2^-)$ can be rolled over by issuing new bonds with face value $P_D(t_2^-, t_3) = P_D(t_0, t_2^-)$. Therefore, the firm continues as a going concern and does not need to sell assets. The cash flows to equity are $I - P_D(t_0, t_2^-) - P_D(t_2^-, t_3) + 2\,R_H + R_L + V$ (note that assets of project $L$ had to be sold at time $t_1^-$). This path occurs with probability $\lambda(1-\pi)(1-\lambda)$.

Along path (v) the firm is in the low-uncertainty state at time $t_1^-$ and can therefore refinance the expiring bond by issuing a new bond with maturity $t_3$ and face value $P_D(t_1^-, t_3) = (I - \frac{1}{2}A)/(1-\lambda\,\pi)$, since the new bondholders face the risk of receiving zero if the technology shock occurs at time $t_2$. The high-uncertainty state at time $t_2^-$ is reached along path (v), and therefore the expiring bond cannot be rolled over. Project $L$ must be sold, and the resulting cash flows to equity are $I - P_D(t_0, t_2^-)$. Subsequently, the technology shock takes place and project $H$ only generates a final, non-contractible cash flow of $I$ to equity, bondholders of $P_D(t_1^-, t_3)$ receive nothing, and the firm seizes to exist. This path occurs with probability $(1-\lambda)\,\lambda\,\pi$.

Path (vi) differs from (v) only since the technology shock does not take place at time $t_2$. So the cash flows are as above, but the firm continues as a going concern. The cash flows to equity are $I - P_D(t_0, t_2^-)$ as along path (v) from selling assets of project $L$ at time $t_2^-$ plus the cash flows from continuation of $2\,R_H + R_L - P_D(t_1^-, t_3) + V$. This path occurs with probability $(1-\lambda)\,\lambda\,(1-\pi)$.

Finally, the bonds can always be rolled over along path (vii), and asset sales are not necessary. The resulting cash flows to equity are therefore $2\,(R_H + R_L) - P_D(t_1^-, t_3) - P_D(t_2^-, t_3) + V$.

Substituting the principal amounts $P_C(t_0, t_2^-) = P_C(t_2^-, t_3) = (2\,I - A)/(1-\lambda\,\pi)$, $P_D(t_0, t_1^-) = I - \frac{1}{2}A$ and $P_D(t_0, t_2^-) = P_D(t_1^-, t_3) = P_D(t_1, t_3) = P_D(t_2^-, t_3) = (I - \frac{1}{2}A)/(1-\lambda\,\pi)$ into the cash flows to equity for each of the paths in Tables 1 and 2, multiplying by the respective probabilities, adding up, and recalling that each initial bond issue is associated with a fixed transaction cost, $k$, to capture floatation and illiquidity costs, we find the following equity values:

$$E_C \;=\; A + (1-\lambda\,\pi)[(2-\lambda\,(1+\pi))\,R_H + (1-\lambda\,\pi)\,V + \lambda\,(1-\pi)\,I] - k\;, \tag{A.2}$$

and

$$E_D \;=\; A + (1-\lambda\,\pi)^2(2\,R_H + V) + \lambda^2(1-\pi)\,\pi\,I - 2\,k\;. \tag{A.3}$$

The expressions for the equity values of firms $C$ and $D$ reveal several intuitive properties, such as equity values are decreasing in $\lambda$ and $\pi$ and increasing in the high project payoff, $R_H$. However, we are mainly interested in the determinants of the difference in value between firm $C$ and firm $D$ to see under what circumstances dispersed corporate debt maturities are more or less useful.

The difference in equity values, $\Delta E \equiv E^D - E^C$, in equations (A.2) and (A.3) is given by:

$$\Delta E \; = \; \lambda\,(1-\pi)\,[(1-\lambda\,\pi)(R_H - I) + \lambda\,\pi\,I] - k \;, \tag{A.4}$$

which says that, in the absence of transactions costs, a dispersed maturity structure is preferred, since $R_H > I$. This result accords with practitioners' concern about debt maturity concentrations. If a large amount of debt needs to be rolled over at a single point in time and the firm is in a high-uncertainty state, then external funds for refinancing may be unavailable and the firm may need to liquidate assets, even those of profitable projects. As can be seen in equation (A.4), the benefits from a dispersed maturity profile decrease with transaction costs $k$.

Differentiating equation (A.4) with respect to $R_H$, it can be seen that the benefits of dispersed debt maturities increase with the payoff from the better project. Higher $R_H$ makes asset sales more costly and this cost can be mitigated by diversifying the rollover dates across time.

Differentiating equation (A.4) with respect to $\lambda$ shows that the benefit of a dispersed maturity structure generally increases with the probability of the high-uncertainty state. A sufficient condition for this to be the case is that $R_H$ does not exceed $3\,I$, i.e. three times the initial investment. This is a weak condition, since in the absence of early liquidation, project $H$ produces cash flows of $2\,R_H$ plus a continuation value. An alternative sufficient condition for the comparative static for $\lambda$ to be positive is that $(1-2\,\lambda\,\pi) \geq 0$. If this condition holds, then the positive sign of the comparative static is obtained, even if $R_H > 3\,I$. If $\lambda$ is zero, then there are no benefits to a dispersed maturity structure. Bonds can always be rolled over, and a fully concentrated maturity structure poses no risk.

Furthermore, ignoring transactions costs, the benefit due to dispersed debt maturities also becomes zero as the probability of the technology shock in the high-uncertainty state, $\pi$, goes to one, because inefficiency due to early liquidation becomes zero in this special case. In the limit, if $\pi = 1$, liquidating a project early in the high-uncertainty state or continuing the project generate an identical cash flow of $I$ (although the former liquidating cash flow is contractible and the latter is not). Thus, in the limit when the technology shock always follows the high-uncertainty state, the flexibility advantage generated by dispersed debt maturities vanishes.

These observations lead to the same testable implications as we discuss for the simple model in the last paragraph of Section 2. We therefore do not restate them here.

# References


Acharya, V., D. Gale, and T. Yorulmazer, 2011. Rollover Risk and Market Freezes. Journal of Finance 66, 1177–1209.

Almeida, H., M. Campello, and D. Hackbarth, 2011. Liquidity Mergers. Journal of Financial Economics 102, 526–558.

Almeida, H., M. Campello, B. Laranjeira, and S. Weisbenner, 2012. Corporate Debt Maturity and the Real Effects of the 2007 Credit Crisis. Critical Finance Review 1, 3–58.

Altinkilic, O. and R. Hansen, 2000. Are There Economies of Scale in Underwriting Fees? Evidence of Rising External Financing Costs. Review of Financial Studies 13, 191–218.

Arellano, M., and S. Bond, 1991. Another Look at the Instrumental Variable Estimation of Error-Components Models. Journal of Econometrics 68, 29–51.

Barclay, M., and C. Smith, 1995. The Maturity Structure of Corporate Debt. Journal of Finance 50, 609–631.

Berglöf, E., and E. von Thadden, 1994. Short-Term versus Long-Term Interests: Capital Structure with Multiple Investors. Quarterly Journal Economics 109, 1055–1084.

Blackwell, D., and D. Kidwell, 1988. An Investigation of Cost Differences between Public Sales and Private Placements of Debt. Journal of Financial Economics 22, 253–278.

Carey, M., S. Prowse, J. Rhea, J., and G. Udell, 1993. The economics of the private placement markets: A new look. Financial Markets, Institutions, and Instrument 2, 1–66.

Chen, H., X. Yu, and J. Yang, 2012. Systematic Risk, Debt Maturity, and the Term Structure of Credit Spreads, Working Paper, MIT.

Colla, P., and F. Ippolito, and K. Li, 2012. Debt Specialization. Journal of Finance, Forthcoming.

Cutler, D., and L. Summers, 1988. The Costs of Conflict Resolution and Financial Distress: Evidence from the Texaco-Pennzoil Litigation. RAND Journal of Economics 19, 157–172.

Diamond, D., 1991. Debt Maturity Structure and Liquidity Risk. Quarterly Journal of Economics 106, 709–737.

Diamond, D., 1993. Seniority and Maturity of Debt Contracts. Journal of Financial Economics 33, 341–368.

Diamond, D., and Z. He, 2012. A Theory of Debt Maturity: The Long and Short of Debt Overhang. Working Paper, University of Chicago.

Flannery, M., 1986. Asymmetric Information and Risky Debt Maturity Choice. Journal of Finance 41, 19–37.

Flannery, M., 1994. Debt Maturity and the Deadweight Cost of Leverage: Optimally Financing Banking Firms. American Economic Review 84, 320–331.

Flannery, M., and K. Rangan, 2006. Partial Adjustment toward Target Capital Structures. Journal of Financial Economics 41, 41–73.

Frank, M., and V. Goyal, 2009. Capital Structure Decisions: Which Factors Are Reliably Important?, Financial Management 38, 1–37.

Greenwood, R., S. Hanson, and J. Stein, 2008. A Gap-Filling Theory of Corporate Debt Maturity Choice. Journal of Finance 65, 993–1028.

Guedes, J., and T. Opler, 1996. The Determinants of the Maturity of Corporate Debt Issues. Journal of Finance 51, 1809–1833.

Harford, J., S. Klasa, and W. Maxwell, 2012. Refinancing Risk and Cash Holdings. Working Paper, University of Washington.

Hart, O., and J. Moore, 1995. Debt and Seniority: An Analysis of the Role of Hard Claims in Constraining Management. American Economic Review 85, 567–585.

He, Z., and K. Milbradt, 2012. Endogenous Liquidity and Defaultable Bonds. Working Paper, MIT.

He, Z., and W. Xiong, 2012. Rollover Risk and Credit Risk. Journal of Finance 67, 391–430.

Hu, X., 2010. Rollover Risk and Credit Spreads in the Financial Crisis of 2008. Working Paper, Princeton University.

Johnson, S., 2003. Debt Maturity and the Effects of Growth Opportunities and Liquidity Risk on Leverage. Review of Financial Studies 16, 209–236.

Krishnaswami, S., P. Spindt, and V. Subramaniam, 1999. Information Asymmetry, Monitoring, and the Placement Structure of Corporate Debt. Journal of Financial Economics 51, 407–434.

Lee, I., S. Lochhead, J. Ritter, and Q. Zhao, 1996. The Cost of Raising Capital. Journal of Financial Research 19, 59–74

Lemmon, M., M. Roberts, and J. Zender, 2008. Back to the Beginning: Persistence and the Cross-Section of Corporate Capital Structure. Journal of Finance 63, 1575–1608.

Longstaff, F., S. Mithal, and E. Neis, 2005. Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit-Default Swap Market. Journal of Finance 60, 2213–2253.

Mahanti, S., A. Nashikkar, M. Subrahmanyam, G. Chacko, and G. Mallik, 2008. Latent liquidity: A New Measure of Liquidity, with an Application to Corporate Bonds. Journal of Financial Economics 88, 272–298.

Massa, M., and L. Zhang, 2011. The Spillover Effects of Hurricane Katrina on Corporate Bonds and the Choice between Bank and Bond Financing. Working Paper, INSEAD.

Mian, A., and J. Santos, 2011. Liquidity Risk And Maturity Management Over The Credit Cycle. Working Paper, Princeton University.

Milbradt, K., and M. Oehmke, 2012. Maturity Rationing. Working Paper, Columbia University.

Oehmke, M. and A. Zawadowski, 2012. The Anatomy of the CDS Market. Working Paper, Boston University.

Rauh, J., and A. Sufi, 2010. Capital Structure and Debt Structure. Review of Financial Studies 23, 4242–4280.

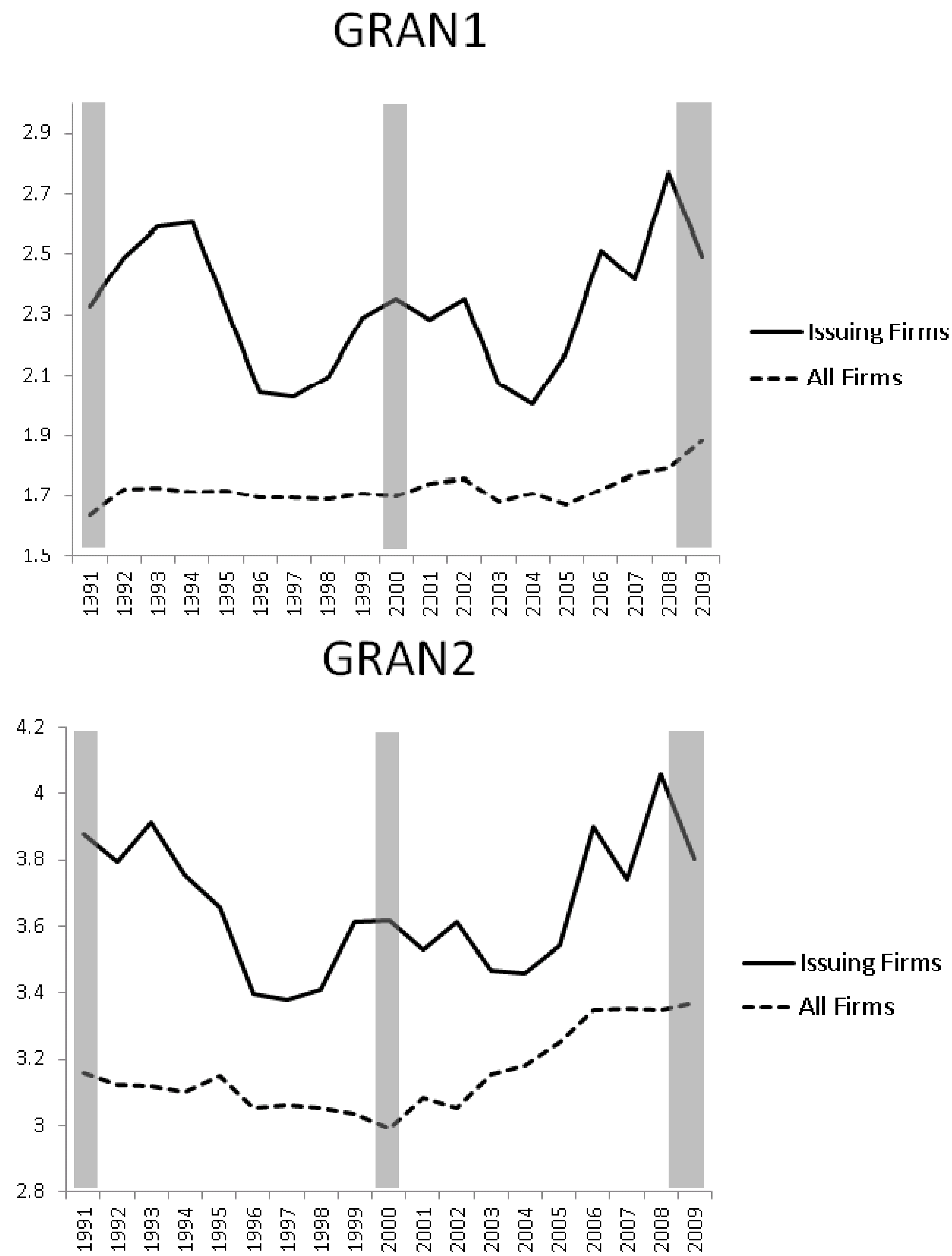
Roberts, M., and A. Sufi, 2009. Renegotiation of Financial Contracts: Evidence from Private Credit Agreements. Journal of Financial Economics 93, 159–184.

Saretto, A., and H. Tookes, 2012, Corporate Leverage, Debt Maturity and Credit Default Swaps: The Role of Credit Supply. Review of Financial Studies, Forthcoming.

Servaes, H., and P. Tufano, 2006. The Theory and Practice of Corporate Debt Structure. Global Survey of Corporate Financial Policies and Practices, Deutsche Bank.

Sufi, A., 2009. Bank Lines of Credit in Corporate Finance: An Empirical Analysis. Review of Financial Studies 22, 1057–1088.

**Figure 4. Time Series of Debt Maturity Dispersion**




This figure plots the time series of aggregate debt granularity measures, $GRAN1$ and $GRAN2$, for bond issuing firms only and for all firms. $GRAN1$ is the inverse of the weighted Herfindahl index of bond maturity fractions. $GRAN2$ is the negative value of the natural logarithm of the average, squared distance from the perfect maturity dispersion. To obtain bond maturity fractions, we group bond maturities into the nearest integer years and compute their fractions out of the total amount of bonds outstanding. To be included in the bond issuing sample, firms are required to have at least one bond issued greater than 1% of existing bond amounts. Aggregate debt dispersion is the cross-sectional average of individual firm-level granularity measures, $GRAN1$ and $GRAN2$. Shaded areas are NBER recessions.

## Table 3. Sample Descriptive Statistics

The sample is drawn from Mergent's Fixed Income Security Database (FISD) and the annual COMPUSTAT files, excluding financial and utility firms, for the period from 1991 to 2011. Panel A reports means, standard deviations, 25%, median, and 75% of main variables. $GRAN1$ is the inverse of the weighted Herfindahl index of bond maturity fractions. $GRAN2$ is the negative of the log distance from the perfect maturity dispersion. *Asset* is the total assets in million dollars. *Age* is the number of years in the COMPUSTAT file prior to observations. $Q$ is the market-to-book ratio and *Lev* is the market value of leverage. $Prof$ and $Tan$ are the profitability (operating income divided by assets) and tangibility (property, plant, and equipments divided by assets), respectively. $ProfVol$ is standard deviation of earnings divided by total assets using the past five years. $BondMat$ is the average of firms' bond maturities weighted by amounts. $NBond$ is the number of bonds outstanding for each firm. *BondPct* is the ratio of total book value of bonds available in the FISD to total book debt in COMPUSTAT for each firm. *BondAmt* is the average amounts of bond issues outstanding for each firm. *BondAmt/Asset* is *BondAmt* divided by total assets.

| | Mean | Stdev | 25% | Median | 75% |
|---|---|---|---|---|---|
| $GRAN1$ | 1.90 | 1.33 | 1.00 | 1.09 | 2.30 |
| $GRAN2$ | 3.15 | 1.25 | 2.06 | 2.92 | 4.02 |
| *Asset* | 7651.4 | 28272.0 | 593.4 | 1685.4 | 5070.8 |
| *Age* | 21.7 | 13.5 | 9.0 | 19.0 | 33.0 |
| $Q$ | 1.68 | 0.99 | 1.10 | 1.38 | 1.88 |
| *Lev* | 0.28 | 0.18 | 0.14 | 0.24 | 0.39 |
| $Prof$ | 0.11 | 0.11 | 0.08 | 0.12 | 0.17 |
| $Tan$ | 0.33 | 0.24 | 0.14 | 0.28 | 0.50 |
| $ProfVol$ | 0.06 | 0.08 | 0.03 | 0.04 | 0.07 |
| $BondMat$ | 9.14 | 5.89 | 5.06 | 7.53 | 11.84 |
| $NBond$ | 4.97 | 9.72 | 1.00 | 2.00 | 4.00 |
| *BondPct* | 0.65 | 0.30 | 0.41 | 0.68 | 0.95 |
| *BondAmt* | 208.8 | 300.3 | 87.5 | 150.0 | 250.0 |
| *BondAmt/Asset* | 0.18 | 0.87 | 0.03 | 0.09 | 0.20 |

## Table 4. Sample Descriptive Statistics Across Tercile Groups

The table reports sample statistics for tercile groups based on two granularity measures ($GRAN1$ and $GRAN2$), bond percentage ($BondPct$), and bond maturity ($BondMat$). We report mean and median (in parentheses). $GRAN1$ is the inverse of the weighted Herfindahl index of bond maturity fractions and $GRAN2$ is the negative of the log distance of bond maturity profiles from the perfect maturity dispersion. $GRAN1L$ and $GRAN2L$ are defined similar to $GRAN1$ and $GRAN2$, respectively, but use COMPUSTAT's $DD1$ to $DD5$ variables for maturities of one to five years and bond amounts in FISD for maturities greater than five years. $Asset$ is the total assets in million dollars. $Age$ is the number of years in the COMPUSTAT file prior to observations. $Q$ is the market-to-book ratio and $Lev$ is the market value of leverage. $Prof$ and $Tan$ are the profitability (operating income divided by assets) and tangibility (property, plant, and equipments divided by assets), respectively. $ProfVol$ is standard deviation of earnings divided by total assets using the past five years. $BondMat$ is the average of firms' bond maturities weighted by amounts. $AssetMat$ is the (book) value-weighted average of the maturities of current assets and net property, plant and equipment, where the maturity of current assets is current assets divided by the cost of goods sold, and the maturity of net property, plant, and equipment is that amount divided by annual depreciation expense. $NBond$ is the number of bonds outstanding for each firm. $BondPct$ is the ratio of total book value of bonds available in the FISD to total book debt in COMPUSTAT for each firm. $BondAmt$ is the average amounts of bond issues outstanding for each firm.

| | $GRAN1$ | | | $GRAN2$ | | | $BondPct$ | | | $BondMat$ | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low | Mid | High | Low | Mid | High | Low | Mid | High | Low | Mid | High |
| $GRAN1$ | 1.00 | 1.73 | 3.77 | 1.01 | 1.55 | 3.16 | 1.69 | 2.14 | 1.85 | 1.52 | 1.87 | 2.33 |
| | (1.00) | (1.81) | (3.39) | (1.00) | (1.53) | (2.90) | (1.00) | (1.73) | (1.00) | (1.00) | (1.11) | (1.81) |
| $GRAN1L$ | 2.03 | 2.68 | 4.02 | 1.99 | 2.59 | 3.60 | 2.93 | 3.01 | 2.17 | 2.19 | 2.88 | 3.08 |
| | (1.68) | (2.42) | (3.84) | (1.66) | (2.36) | (3.45) | (2.78) | (2.78) | (1.75) | (1.95) | (2.64) | (2.87) |
| $GRAN2$ | 2.18 | 3.37 | 4.67 | 1.88 | 2.91 | 4.66 | 2.98 | 3.38 | 3.07 | 2.34 | 2.99 | 4.08 |
| | (2.06) | (3.14) | (4.71) | (1.93) | (2.92) | (4.57) | (2.68) | (3.11) | (2.92) | (1.93) | (2.47) | (3.98) |
| $GRAN2L$ | 2.81 | 3.74 | 4.77 | 2.56 | 3.38 | 4.78 | 3.73 | 3.75 | 3.23 | 2.89 | 3.43 | 4.37 |
| | (2.72) | (3.64) | (4.81) | (2.35) | (3.34) | (4.74) | (3.74) | (3.63) | (3.01) | (2.78) | (3.34) | (4.42) |
| $Asset$ | 2052.1 | 8082.6 | 17979.2 | 2009.7 | 4503.3 | 16691.0 | 12170.7 | 6144.4 | 4639.1 | 6276.3 | 5208.9 | 11583.9 |
| | (716.59) | (2201.65) | (7461.30) | (687.47) | (1247.93) | (6446.24) | (2328.63) | (1829.20) | (1019.45) | (1148.51) | (1428.71) | (3187.80) |
| $Age$ | 17.3 | 22.9 | 28.8 | 16.3 | 19.7 | 29.1 | 22.3 | 22.6 | 20.1 | 20.4 | 19.4 | 25.3 |
| | (13.0) | (22.0) | (32.0) | (12.0) | (17.0) | (32.0) | (23.0) | (22.0) | (16.0) | (16.0) | (15.0) | (29.0) |
| $Q$ | 1.71 | 1.68 | 1.59 | 1.70 | 1.69 | 1.63 | 1.53 | 1.60 | 1.90 | 1.75 | 1.59 | 1.69 |
| | (1.37) | (1.40) | (1.36) | (1.36) | (1.38) | (1.39) | (1.29) | (1.37) | (1.51) | (1.41) | (1.33) | (1.41) |
| $Lev$ | 0.28 | 0.28 | 0.27 | 0.30 | 0.29 | 0.25 | 0.32 | 0.29 | 0.23 | 0.28 | 0.32 | 0.23 |
| | (0.24) | (0.24) | (0.24) | (0.26) | (0.25) | (0.22) | (0.29) | (0.25) | (0.18) | (0.24) | (0.29) | (0.20) |
| $Prof$ | 0.10 | 0.12 | 0.13 | 0.09 | 0.11 | 0.13 | 0.13 | 0.12 | 0.09 | 0.09 | 0.12 | 0.12 |
| | (0.11) | (0.12) | (0.13) | (0.11) | (0.12) | (0.13) | (0.12) | (0.13) | (0.11) | (0.11) | (0.12) | (0.13) |
| $Tan$ | 0.31 | 0.34 | 0.38 | 0.31 | 0.32 | 0.37 | 0.36 | 0.37 | 0.27 | 0.30 | 0.35 | 0.35 |
| | (0.23) | (0.29) | (0.34) | (0.23) | (0.26) | (0.33) | (0.32) | (0.32) | (0.19) | (0.23) | (0.31) | (0.30) |
| $ProfVol$ | 0.08 | 0.06 | 0.04 | 0.08 | 0.07 | 0.04 | 0.05 | 0.05 | 0.09 | 0.08 | 0.06 | 0.05 |
| | (0.05) | (0.04) | (0.03) | (0.05) | (0.04) | (0.03) | (0.03) | (0.04) | (0.05) | (0.05) | (0.04) | (0.04) |
| $BondMat$ | 7.90 | 8.74 | 10.14 | 5.30 | 10.49 | 12.01 | 9.04 | 9.32 | 9.04 | 3.91 | 7.60 | 15.90 |
| | (6.59) | (7.43) | (8.97) | (5.37) | (9.05) | (11.20) | (7.50) | (7.80) | (7.16) | (4.19) | (7.53) | (15.14) |
| $AssetMat$ | 5.21 | 5.83 | 6.67 | 5.23 | 5.57 | 6.38 | 6.18 | 5.87 | 5.07 | 5.15 | 6.09 | 5.87 |
| | (3.68) | (4.51) | (5.47) | (3.69) | (4.15) | (5.19) | (4.94) | (4.55) | (3.55) | (3.72) | (4.72) | (4.53) |
| $NBond$ | 1.17 | 3.87 | 13.76 | 1.13 | 2.16 | 11.85 | 4.23 | 5.97 | 4.70 | 2.89 | 3.93 | 8.15 |
| | (1.00) | (2.00) | (8.00) | (1.00) | (2.00) | (6.00) | (1.00) | (2.00) | (2.00) | (1.00) | (2.00) | (3.00) |
| $BondPct$ | 0.63 | 0.66 | 0.68 | 0.63 | 0.65 | 0.67 | 0.29 | 0.68 | 0.97 | 0.65 | 0.64 | 0.66 |
| | (0.66) | (0.70) | (0.71) | (0.65) | (0.69) | (0.70) | (0.31) | (0.68) | (1.00) | (0.72) | (0.65) | (0.70) |
| $BondAmt$ | 165.2 | 252.9 | 249.4 | 163.6 | 208.4 | 262.2 | 163.8 | 204.1 | 258.6 | 203.4 | 207.5 | 219.5 |
| | (125.0) | (165.0) | (195.0) | (125.0) | (150.0) | (187.5) | (125.0) | (150.4) | (171.3) | (137.5) | (150.0) | (150.0) |
| $BondAmt/Asset$ | 0.28 | 0.13 | 0.04 | 0.28 | 0.20 | 0.05 | 0.08 | 0.14 | 0.32 | 0.24 | 0.18 | 0.12 |
| | (0.17) | (0.08) | (0.03) | (0.19) | (0.12) | (0.03) | (0.05) | (0.09) | (0.17) | (0.12) | (0.11) | (0.05) |
| *Obs.* | 8,415 | 4,419 | 4,419 | 5,873 | 5,773 | 5,822 | 5,938 | 5,938 | 5,938 | 5,902 | 5,902 | 5,901 |

## Table 5. Cross-Sectional Analysis

The sample includes firms with corporate bond and accounting information available in the FISD and COMPUSTAT Annual databases for the period from 1991 to 2011. Financial and utility firms are excluded. We run the following panel regression:

$$GRAN_{i,t+1} = \alpha_i + y_t + \beta X_{i,t} + \epsilon_{i,t+1},$$

where $X_{i,t}$ is a vector of explanatory variables, $\alpha_i$ is a firm or industry level fixed effect, and $y_t$ is a year fixed effect. $GRAN1$ is the inverse of the Herfindahl index of bond maturity fractions. $GRAN2$ is the negative of the log distance from the perfect maturity dispersion. $Size$ is the log of total assets. $Age$ is the number of years in the COMPUSTAT file prior to observations. $Q$ is the market-to-book ratio and $Lev$ is the market value of leverage. $Prof$ and $Tan$ are the profitability (operating income divided by assets) and tangibility (property, plant, and equipments divided by assets), respectively. $BondMat$ is the average of firms' bond maturities and $ProfVol$ is the standard deviation of earnings divided by assets using the past five years. Numbers in parentheses are $t$-statistics for which standard errors are clustered at the firm level.

| | $GRAN1$ | | | | | | $GRAN2$ | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $Q$ | 0.20 | 0.22 | 0.23 | 0.23 | 0.25 | 0.24 | 0.15 | 0.20 | 0.16 | 0.20 | 0.18 | 0.17 |
| | (4.27) | (4.88) | (5.29) | (5.29) | (4.56) | (4.45) | (3.52) | (5.55) | (3.64) | (5.37) | (4.17) | (4.24) |
| $Size$ | 0.49 | 0.47 | 0.47 | 0.46 | 0.47 | 0.46 | 0.50 | 0.44 | 0.49 | 0.43 | 0.42 | 0.38 |
| | (24.85) | (24.44) | (24.78) | (24.23) | (11.93) | (11.64) | (31.61) | (33.01) | (29.95) | (31.78) | (14.62) | (15.23) |
| $Age$ | 0.01 | 0.01 | 0.02 | 0.02 | 0.14 | 0.05 | 0.02 | 0.02 | 0.02 | 0.02 | 0.18 | 0.08 |
| | (8.71) | (8.83) | (9.08) | (8.95) | (0.78) | (0.35) | (11.82) | (13.01) | (11.92) | (12.33) | (2.01) | (0.78) |
| $Lev$ | 1.39 | 1.29 | 1.17 | 1.12 | 1.24 | 1.26 | 0.79 | 1.01 | 0.65 | 0.90 | 1.02 | 1.06 |
| | (11.96) | (11.03) | (9.86) | (9.58) | (8.78) | (8.81) | (7.53) | (11.15) | (5.94) | (9.66) | (9.23) | (10.42) |
| $Prof$ | -0.86 | -1.03 | -0.98 | -1.06 | -0.59 | -0.57 | -0.46 | -0.67 | -0.53 | -0.74 | -0.35 | -0.44 |
| | (-7.10) | (-8.55) | (-7.65) | (-8.56) | (-4.64) | (-4.62) | (-3.65) | (-6.80) | (-4.10) | (-7.36) | (-2.97) | (-4.40) |
| $Tan$ | | 0.48 | | 0.47 | | -0.12 | | 0.34 | | 0.33 | | -0.24 |
| | | (4.75) | | (3.74) | | (-0.61) | | (5.20) | | (3.93) | | (-1.83) |
| $BondMat$ | | 0.01 | | 0.01 | | 0.00 | | 0.08 | | 0.08 | | 0.07 |
| | | (3.15) | | (3.15) | | (0.75) | | (32.26) | | (33.01) | | (22.49) |
| $ProfVol$ | | 0.03 | | 0.03 | | 0.08 | | 0.02 | | 0.02 | | 0.05 |
| | | (1.03) | | (1.10) | | (0.81) | | (0.75) | | (0.69) | | (0.48) |
| *Obs.* | 17,179 | 17,125 | 17,179 | 17,125 | 17,179 | 17,125 | 17,396 | 17,342 | 17,396 | 17,342 | 17,396 | 17,342 |
| $R^2$ | 0.369 | 0.378 | 0.386 | 0.391 | 0.654 | 0.655 | 0.488 | 0.632 | 0.502 | 0.640 | 0.786 | 0.831 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | No | No | Yes | Yes | No | No | No | No | Yes | Yes | No | No |
| Firm FE | No | No | No | No | Yes | Yes | No | No | No | No | Yes | Yes |

# Table 6. Cross-Sectional Analysis: Robustness Checks

The sample includes firms with corporate bond and accounting information available in the FISD and COMPUSTAT Annual databases for the period from 1991 to 2011. Financial and utility firms are excluded. We run the following panel regression:

$$GRAN_{i,t+1} = \alpha_i + y_t + \beta X_{i,t} + \epsilon_{i,t+1},$$

where $X_{i,t}$ is a vector of explanatory variables, $\alpha_i$ is a firm or industry level fixed effect, and $y_t$ is a year fixed effect. $GRAN1$ is the inverse of the Herfindahl index of bond maturity fractions. $GRAN2$ is the negative of the log distance from the perfect maturity dispersion. $Size$ is the log of total assets. $Age$ is the number of years in the COMPUSTAT file prior to observations. $Q$ is the market-to-book ratio and $Lev$ is the market value of leverage. $Prof$ and $Tan$ are the profitability (operating income divided by assets) and tangibility (property, plant, and equipments divided by assets), respectively. $BondMat$ is the average of firms' bond maturities and $ProfVol$ is the standard deviation of earnings divided by assets using the past five years. $IndGRAN$ is the industry level granularity, measured as median granularity. In column $NBond$, we control for the number of bonds. In column $Resid$, granularity measures are first regressed on the number of bonds and we use the residuals from the first-stage regression as the dependent variable in the panel regression. In column $N >= 2$, we include firms with more than or equal to two bonds outstanding in the regressions. The column *Straight* reports results for the sample of firms with more than 80% of total bond amounts in bonds without option features or sinking fund provisions. In column $IV$, we run two-stage least squares using industry leverage, industry asset maturity and issuer-level credit ratings for the firm's leverage and maturity. Column *IndGran* reports the regression results with industry level granularity controls. In column *Loans*, the dependent variables are $GRAN1L$ and $GRAN2L$, which use COMPUSTAT's $DD1$ to $DD5$ variables for maturities of one to five years and bond amounts in FISD for maturities greater than five years. Numbers in parentheses are $t$-statistics for which standard errors are clustered at the firm level.

| | $GRAN1$ | | | | | | | $GRAN2$ | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $NBond$ | $Resid$ | $N >= 2$ | Straight | IV | $IndGRAN$ | $Loans$ | $NBond$ | $Resid$ | $N >= 2$ | Straight | IV | $IndGRAN$ | $Loans$ |
| $Q$ | 0.20 | 0.19 | 0.36 | 0.23 | 0.42 | 0.23 | 0.23 | 0.14 | 0.12 | 0.14 | 0.19 | 0.27 | 0.17 | 0.12 |
| | (4.09) | (3.71) | (3.59) | (4.61) | (3.91) | (4.23) | (3.83) | (3.98) | (3.20) | (2.48) | (4.64) | (3.20) | (4.45) | (3.23) |
| $Size$ | 0.36 | 0.32 | 0.64 | 0.38 | 0.50 | 0.45 | 0.44 | 0.32 | 0.25 | 0.41 | 0.35 | 0.39 | 0.38 | 0.36 |
| | (9.63) | (9.40) | (9.94) | (9.33) | (12.50) | (11.29) | (11.18) | (13.31) | (11.63) | (12.24) | (12.52) | (15.41) | (15.13) | (16.10) |
| $Age$ | -0.07 | -0.11 | 0.27 | -0.12 | 0.01 | 0.06 | -0.13 | 0.01 | -0.06 | 0.15 | -0.10 | 0.02 | 0.08 | -0.05 |
| | (-0.53) | (-0.91) | (0.81) | (-1.02) | (1.76) | (0.41) | (-0.72) | (0.11) | (-0.63) | (0.94) | (-0.89) | (5.15) | (0.78) | (-0.46) |
| $Lev$ | 0.98 | 0.87 | 1.58 | 0.93 | 2.04 | 1.27 | 1.66 | 0.89 | 0.72 | 0.89 | 0.88 | 1.48 | 1.06 | 1.12 |
| | (7.55) | (6.72) | (5.92) | (6.95) | (4.12) | (9.08) | (9.55) | (9.50) | (7.46) | (5.89) | (8.43) | (3.91) | (10.52) | (10.90) |
| $Prof$ | -0.43 | -0.38 | -0.73 | -0.61 | -0.57 | -0.56 | -0.10 | -0.36 | -0.28 | -0.49 | -0.46 | -0.46 | -0.46 | -0.24 |
| | (-3.64) | (-3.08) | (-2.98) | (-5.38) | (-3.01) | (-4.56) | (-0.66) | (-3.78) | (-2.86) | (-2.75) | (-4.27) | (-3.17) | (-4.56) | (-2.55) |
| $Tan$ | 0.05 | 0.11 | 0.08 | -0.24 | -0.16 | -0.14 | 0.36 | -0.13 | -0.01 | 0.02 | -0.18 | -0.30 | -0.26 | 0.13 |
| | (0.25) | (0.60) | (0.25) | (-1.48) | (-0.74) | (-0.72) | (1.73) | (-1.00) | (-0.07) | (0.12) | (-1.29) | (-1.98) | (-2.00) | (1.10) |
| $BondMat$ | 0.00 | 0.00 | -0.01 | 0.00 | 0.00 | 0.00 | 0.02 | 0.07 | 0.07 | 0.06 | 0.07 | 0.07 | 0.07 | 0.06 |
| | (0.31) | (0.10) | (-1.13) | (-0.16) | (0.62) | (0.76) | (4.19) | (23.86) | (23.45) | (15.36) | (18.05) | (22.70) | (22.27) | (23.05) |
| $ProfVol$ | 0.09 | 0.10 | 0.31 | 0.14 | 0.27 | 0.04 | -0.01 | 0.06 | 0.07 | 0.39 | 0.11 | 0.23 | 0.05 | -0.11 |
| | (1.10) | (1.17) | (0.91) | (1.55) | (0.71) | (0.48) | (-0.10) | (0.63) | (0.78) | (1.33) | (1.26) | (0.68) | (0.45) | (-1.16) |
| $Nbond$ | 0.06 | | | | | | | 0.04 | | | | | | |
| | (7.14) | | | | | | | (6.88) | | | | | | |
| $IndGRAN$ | | | | | | 0.27 | | | | | | | 0.17 | |
| | | | | | | (6.95) | | | | | | | (6.59) | |
| $Obs.$ | 17,125 | 17,125 | 9,880 | 11,170 | 17,125 | 14,412 | 17,125 | 17,342 | 17,342 | 9,962 | 11,354 | 17,342 | 14,764 | 17,342 |
| $R^2$ | 0.701 | 0.453 | 0.576 | 0.723 | 0.537 | 0.638 | 0.66 | 0.850 | 0.734 | 0.818 | 0.817 | 0.790 | 0.775 | 0.833 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | No | No | No | No | No | No | No | No | No | No | No | No | No | No |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

## Table 7. Cross-Sectional Analysis: Low and High Bank Loan Subsamples

The sample includes firms with corporate bond and accounting information available in the FISD and COMPUSTAT Annual databases for the period from 1991 to 2009. Financial and utility firms are excluded. The table provides results for the following panel regression equation:

$$GRAN_{i,t+1} = \alpha_i + y_t + \beta X_{i,t} + \epsilon_{i,t+1}$$

for the low and the high bank loan subsamples. Firms are categorized as low bank loan firms if corporate bonds in FISD are more than 50% of their total debt (long-term debt plus debt in current liabilities in COMPUSTAT), and they are categorized as high bank loan firms otherwise. $X_{i,t}$ is a vector of explanatory variables, $\alpha_i$ is a firm or industry level fixed effect, and $y_t$ is a year fixed effect. $GRAN1$ is the inverse of the Herfindahl index of bond maturity fractions. $GRAN2$ is the negative of the log distance from the perfect maturity dispersion. $Size$ is the log of total assets. $Age$ is the number of years in the COMPUSTAT file prior to observations. $Q$ is the market-to-book ratio and $Lev$ is the market value of leverage. $Prof$ and $Tan$ are the profitability (operating income divided by assets) and tangibility (property, plant, and equipments divided by assets), respectively. $BondMat$ is the average of firms' bond maturities and $ProfVol$ is the standard deviation of earnings divided by assets using the past five years. Numbers in parentheses are $t$-statistics for which standard errors are clustered at the firm level.

| | $GRAN1$ | | | | $GRAN2$ | | | |
|---|---|---|---|---|---|---|---|---|
| | Low | High | Low | High | Low | High | Low | High |
| $Q$ | 0.21 | 0.22 | 0.28 | 0.22 | 0.17 | 0.18 | 0.19 | 0.04 |
| | (4.39) | (2.49) | (4.58) | (1.58) | (4.54) | (1.97) | (4.45) | (0.36) |
| $Size$ | 0.58 | 0.28 | 0.54 | 0.40 | 0.53 | 0.31 | 0.42 | 0.34 |
| | (24.96) | (11.25) | (10.13) | (3.86) | (36.47) | (14.11) | (13.69) | (4.32) |
| $Age$ | 0.01 | 0.01 | -0.06 | 0.55 | 0.02 | 0.02 | -0.01 | 0.34 |
| | (6.76) | (5.32) | (-0.24) | (1.83) | (10.20) | (6.14) | (-0.10) | (1.27) |
| $Lev$ | 1.97 | 0.97 | 1.87 | 1.34 | 1.55 | 0.94 | 1.54 | 0.90 |
| | (12.80) | (4.96) | (9.19) | (3.13) | (14.44) | (5.37) | (11.41) | (3.21) |
| $Prof$ | -1.11 | -0.97 | -0.32 | -0.83 | -0.70 | -0.68 | -0.22 | -0.37 |
| | (-8.23) | (-2.86) | (-2.25) | (-1.83) | (-6.42) | (-2.20) | (-1.95) | (-0.95) |
| $Tan$ | 0.54 | -0.01 | -0.01 | -0.43 | 0.28 | 0.01 | -0.07 | -0.39 |
| | (3.82) | (-0.08) | (-0.06) | (-0.94) | (3.04) | (0.06) | (-0.46) | (-1.14) |
| $BondMat$ | 0.00 | 0.02 | -0.01 | 0.00 | 0.08 | 0.09 | 0.07 | 0.08 |
| | (-0.26) | (3.89) | (-0.89) | (0.32) | (27.00) | (16.53) | (16.10) | (8.36) |
| $ProfVol$ | 0.08 | 0.01 | -0.20 | -0.01 | 0.07 | 0.00 | -0.15 | 0.09 |
| | (2.28) | (0.93) | (-0.90) | (-0.07) | (2.37) | (-0.04) | (-0.72) | (1.10) |
| *Obs.* | 8,355 | 2,651 | 8,355 | 2,651 | 8,439 | 2,667 | 8,439 | 2,667 |
| $R^2$ | 0.524 | 0.326 | 0.763 | 0.634 | 0.737 | 0.627 | 0.899 | 0.850 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | No | No | Yes | Yes | No | No |
| Firm FE | No | No | Yes | Yes | No | No | Yes | Yes |

## Table 8. Cross-Sectional Analysis: Non-Crisis and Crisis Subsamples

The sample includes firms with corporate bond and accounting information available in the FISD and COMPUSTAT Annual databases for the period from 1991 to 2011. Financial and utility firms are excluded. The table provides results for the following panel regression equation:

$$GRAN_{i,t+1} = \alpha_i + y_t + \beta X_{i,t} + \epsilon_{i,t+1}$$

for the non-crisis (1991–2007 and 2010–2011) and the crisis (2008–2009) periods. $X_{i,t}$ is a vector of explanatory variables, $\alpha_i$ is a firm or industry level fixed effect, and $y_t$ is a year fixed effect. $GRAN1$ is the inverse of the Herfindahl index of bond maturity fractions. $GRAN2$ is the negative of the log distance from the perfect maturity dispersion. $Size$ is the log of total assets. $Age$ is the number of years in the COMPUSTAT file prior to observations. $Q$ is the market-to-book ratio and $Lev$ is market leverage. $Prof$ and $Tan$ are the profitability (operating income divided by assets) and tangibility (property, plant, and equipments divided by assets), respectively. $BondMat$ is the average of firms' bond maturities and $ProfVol$ is the standard deviation of earnings divided by assets using the past five years. Numbers in parentheses are $t$-statistics for which standard errors are clustered at the firm level.

| | $GRAN1$ | | | | $GRAN2$ | | | |
|---|---|---|---|---|---|---|---|---|
| | Non-Crisis | Crisis | Non-Crisis | Crisis | Non-Crisis | Crisis | Non-Crisis | Crisis |
| $Q$ | 0.21 | 0.40 | 0.22 | 0.54 | 0.18 | 0.37 | 0.15 | 0.24 |
| | (4.66) | (4.50) | (3.91) | (3.07) | (4.73) | (5.10) | (3.81) | (2.03) |
| $Size$ | 0.46 | 0.48 | 0.46 | 0.45 | 0.42 | 0.48 | 0.37 | 0.44 |
| | (23.69) | (15.81) | (11.39) | (1.86) | (31.09) | (21.19) | (14.87) | (2.92) |
| $Age$ | 0.02 | 0.02 | 0.04 | 0.14 | 0.02 | 0.02 | 0.07 | 0.08 |
| | (8.78) | (5.69) | (0.29) | (3.30) | (12.05) | (7.88) | (0.71) | (2.72) |
| $Lev$ | 1.11 | 1.22 | 1.28 | 1.02 | 0.88 | 0.98 | 1.07 | 0.67 |
| | (9.40) | (5.40) | (8.41) | (2.04) | (9.50) | (5.33) | (9.88) | (1.78) |
| $Prof$ | -1.02 | -1.25 | -0.54 | -0.13 | -0.72 | -0.91 | -0.45 | -0.19 |
| | (-7.83) | (-5.07) | (-4.17) | (-0.26) | (-7.10) | (-4.29) | (-4.24) | (-0.53) |
| $Tan$ | 0.48 | 0.36 | -0.05 | -0.83 | 0.37 | -0.01 | -0.20 | -0.64 |
| | (3.83) | (1.68) | (-0.27) | (-0.86) | (4.32) | (-0.07) | (-1.46) | (-1.03) |
| $BondMat$ | 0.01 | 0.00 | 0.00 | 0.00 | 0.08 | 0.08 | 0.07 | 0.04 |
| | (3.20) | (0.62) | (0.81) | (-0.13) | (32.33) | (17.18) | (22.38) | (1.88) |
| $ProfVol$ | 0.04 | 0.02 | 0.08 | 0.63 | 0.03 | 0.01 | 0.05 | 0.59 |
| | (1.17) | (1.40) | (0.72) | (1.19) | (0.86) | (0.51) | (0.42) | (1.34) |
| *Obs.* | 15,478 | 1,647 | 15,478 | 1,647 | 15,678 | 1,664 | 15,678 | 1,664 |
| $R^2$ | 0.391 | 0.412 | 0.651 | 0.877 | 0.643 | 0.628 | 0.831 | 0.953 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | No | No | Yes | Yes | No | No |
| Firm FE | No | No | Yes | Yes | No | No | Yes | Yes |

## Table 9. Speed-Of-Adjustment Analysis

This table provides results for the following panel regression equation:

$$\Delta GRAN_{i,t+1} = -\gamma GRAN_{i,t} + (\gamma\beta)X_{i,t} + \nu_{i,t+1},$$

where $X_{i,t}$ is a vector of explanatory variables. $GRAN2$ is the negative of the log distance from the perfect maturity dispersion. $Size$ is the log of total assets. $Age$ is the number of years in the COMPUSTAT file prior to observations. $Q$ is the market-to-book ratio and $Lev$ is the market value of leverage. $Prof$ and $Tan$ are the profitability (operating income divided by assets) and tangibility (property, plant, and equipments divided by assets), respectively. $BondMat$ is the average of firms' bond maturities and $ProfVol$ is the standard deviation of earnings divided by assets using the past five years. In columns *Industry FE* and *Firm FE*, we report the estimation results by including industry-year fixed effects and firm-year fixed effects, respectively. In column *Arellano-Bond*, we report the estimation results employing a panel GMM estimation using lags of maturity dispersion as instruments as in Arellano and Bond (1991). $GRAN1$ is the inverse of the Herfindahl index of bond maturity fractions. Numbers in parentheses are $t$-statistics for which standard errors are clustered at the firm level. The sample period is from 1991 to 2011.

| | $GRAN1$ | | | $GRAN2$ | | |
|---|---|---|---|---|---|---|
| | Industry FE | Firm FE | Arellano-Bond | Industry FE | Firm FE | Arellano-Bond |
| $GRAN1_{t-1}$ | 0.21 | 0.41 | 0.54 | 0.30 | 0.56 | 0.43 |
| | (24.72) | (28.72) | (12.98) | (23.33) | (33.70) | (11.42) |
| $Q$ | 0.10 | 0.18 | 0.19 | 0.11 | 0.14 | 0.19 |
| | (7.02) | (4.86) | (4.65) | (6.16) | (4.36) | (6.81) |
| $Size$ | 0.12 | 0.26 | 0.37 | 0.16 | 0.26 | 0.33 |
| | (16.95) | (10.66) | (9.64) | (18.79) | (14.14) | (13.93) |
| $Age$ | 0.00 | 0.17 | -0.02 | 0.00 | 0.47 | 0.00 |
| | (2.63) | (0.49) | (-3.89) | (5.92) | (1.66) | (-0.76) |
| $Lev$ | 0.39 | 0.81 | 0.78 | 0.44 | 0.79 | 0.66 |
| | (9.55) | (8.29) | (6.80) | (9.96) | (10.28) | (8.81) |
| $Prof$ | -0.29 | -0.34 | -0.33 | -0.28 | -0.34 | -0.32 |
| | (-6.21) | (-3.47) | (-3.12) | (-5.61) | (-3.94) | (-3.99) |
| $Tan$ | 0.08 | -0.16 | -0.18 | 0.09 | -0.21 | -0.36 |
| | (2.16) | (-1.19) | (-1.16) | (2.34) | (-2.07) | (-3.75) |
| $BondMat$ | 0.01 | 0.01 | 0.04 | 0.04 | 0.05 | 0.07 |
| | (7.78) | (4.48) | (8.15) | (20.81) | (18.97) | (20.05) |
| $ProfVol$ | 0.00 | -0.03 | -0.18 | 0.00 | 0.04 | -0.18 |
| | (0.52) | (-0.31) | (-1.73) | (0.10) | (0.37) | (-1.31) |
| *Obs.* | 15,282 | 15,282 | 12,426 | 15,576 | 15,576 | 12,516 |
| $R^2$ | 0.114 | 0.136 | | 0.228 | 0.399 | |
| Year FE | Yes | Yes | | Yes | Yes | |
| Industry FE | Yes | No | | Yes | No | |
| Firm FE | No | Yes | | No | Yes | |

## Table 10. Time-Series Analysis

Linear probability models are estimated for each maturity bucket ($j = 1, 2, ..., 7$):

$$Prob(I_i^{K_j}) = a_1 m_i^{K_1} + a_2 m_i^{K_2} + a_3 m_i^{K_3} + a_4 m_i^{K_4} + a_5 m_i^{K_5} + a_6 m_i^{K_6} + a_7 m_i^{K_7} + \alpha_n + y_t,$$

where $K_j$ is five two-year maturity buckets defined as $2j-1$ to $2j$ years for maturities shorter than 10 years ($j \leq 5$), and two maturity buckets (11 to 20 years and 11 years or longer) for maturities longer than 10 ($j = 6$ or $j = 7$). The variable $m_i^{K_j}$ is obtained by subtracting a benchmark from each firm's maturity profile where the maturity profile is defined as fractions of pre-existing bond amounts in each maturity bucket $K_j$. After firms are sorted into 64 (=$2^6$) groups based on seven variables (market-to-book, market leverage, age, size, profitability, and average maturity), the benchmark is obtained by averaging maturity profiles in each group. Issuance dummy $I_i^{K_j}$ is one if the bond $i$'s maturity falls in $K_j$, and is zero if the bond has a different maturity than $K_j$. $\alpha_n$ is an Fama-French 49 industry effect for the issuing firm $n$ and $y_t$ denotes a year fixed effect. Panel A1 is for a sample with bond issues greater than 3% of firms' pre-existing bonds, and Panel A2 is for bond issues greater than 5%. Panel B1 and B2 exclude all bonds with option features (callability, convertibility, putability and sinking fund provisions) from the sample. The hypothesis test ($H_0$: $a_i - \frac{1}{6}\sum_{n \neq i} a_n = 0$) is also reported. Numbers in parenthesis are $t$-statistics for which standard errors are clustered at the industry level. The sample period is from 1991 to 2011.

| Panel A1: Issue Cutoff at 3%, All Bonds | | | | | | | |
|---|---|---|---|---|---|---|---|
| | $K_1$: 1-2 Yr | $K_2$: 3-4 Yr | $K_3$: 5-6 Yr | $K_4$: 7-8 Yr | $K_5$: 9-10 Yr | $K_6$: 11-20 Yr | $K_7$ 21- Yr |
| $m^{K_1}$ | **-0.04** | -0.09 | -0.29 | -0.07 | -0.05 | 0.09 | 0.17 |
| | **(-1.42)** | (-1.96) | (-4.30) | (-1.01) | (-0.64) | (1.07) | (2.37) |
| $m^{K_2}$ | 0.05 | **-0.09** | -0.28 | -0.06 | -0.05 | 0.16 | 0.18 |
| | (3.03) | **(-3.19)** | (-6.85) | (-1.30) | (-1.12) | (2.98) | (4.16) |
| $m^{K_3}$ | -0.02 | -0.01 | **-0.36** | -0.03 | -0.05 | 0.12 | 0.06 |
| | (-1.40) | (-0.42) | **(-9.99)** | (-0.88) | (-1.22) | (2.55) | (1.68) |
| $m^{K_4}$ | 0.01 | 0.00 | -0.09 | **-0.17** | -0.06 | 0.06 | -0.01 |
| | (0.93) | (0.17) | (-2.48) | **(-4.82)** | (-1.71) | (1.28) | (-0.29) |
| $m^{K_5}$ | 0.00 | 0.02 | 0.02 | -0.12 | **-0.18** | 0.15 | -0.06 |
| | (-0.12) | (1.16) | (0.66) | (-3.60) | **(-5.21)** | (3.58) | (-1.75) |
| $m^{K_6}$ | 0.01 | 0.05 | 0.04 | 0.02 | -0.14 | **-0.12** | -0.20 |
| | (0.46) | (1.96) | (1.10) | (0.62) | (-3.62) | **(-2.70)** | (-5.18) |
| $m^{K_7}$ | 0.07 | 0.09 | 0.16 | 0.08 | -0.26 | -0.26 | **-0.27** |
| | (3.87) | (3.38) | (3.67) | (1.76) | (-5.74) | (-4.82) | **(-6.11)** |
| *Obs.* | 6,985 | 6,985 | 6,985 | 6,985 | 6,985 | 6,985 | 6,985 |
| $H_0$ | -0.05 | -0.09 | -0.30 | -0.15 | -0.09 | -0.17 | -0.29 |
| | (-2.25) | (-3.43) | (-7.87) | (-3.91) | (-2.54) | (-3.51) | (-6.18) |

| Panel A2: Issue Cutoff at 10%, All Bonds | | | | | | | |
|---|---|---|---|---|---|---|---|
| | $K_1$: 1-2 Yr | $K_2$: 3-4 Yr | $K_3$: 5-6 Yr | $K_4$: 7-8 Yr | $K_5$: 9-10 Yr | $K_6$: 11-20 Yr | $K_7$ 21- Yr |
| $m^{K_1}$ | **-0.07** | -0.20 | -0.39 | 0.02 | 0.03 | 0.23 | 0.12 |
| | **(-2.79)** | (-4.75) | (-5.14) | (0.21) | (0.30) | (2.37) | (1.57) |
| $m^{K_2}$ | -0.01 | **-0.14** | -0.31 | -0.04 | -0.03 | 0.18 | 0.17 |
| | (-0.90) | **(-5.78)** | (-6.98) | (-0.94) | (-0.62) | (3.18) | (3.89) |
| $m^{K_3}$ | -0.02 | -0.02 | **-0.37** | -0.01 | -0.01 | 0.12 | 0.05 |
| | (-1.85) | (-0.94) | **(-9.78)** | (-0.29) | (-0.33) | (2.41) | (1.32) |
| $m^{K_4}$ | 0.00 | -0.01 | -0.10 | **-0.16** | -0.07 | 0.05 | -0.01 |
| | (0.24) | (-0.45) | (-2.64) | **(-4.08)** | (-1.65) | (0.99) | (-0.15) |
| $m^{K_5}$ | -0.01 | 0.02 | 0.00 | -0.12 | **-0.19** | 0.17 | -0.04 |
| | (-0.46) | (0.84) | (-0.08) | (-3.29) | **(-5.15)** | (3.86) | (-1.18) |
| $m^{K_6}$ | 0.02 | 0.04 | 0.13 | 0.08 | -0.09 | **-0.23** | -0.28 |
| | (1.29) | (1.60) | (3.35) | (1.86) | (-1.99) | **(-4.46)** | (-7.20) |
| $m^{K_7}$ | 0.07 | 0.11 | 0.26 | 0.19 | -0.20 | -0.36 | **-0.60** |
| | (4.70) | (4.15) | (5.32) | (3.59) | (-3.65) | (-5.92) | **(-12.63)** |
| *Obs.* | 5,755 | 5,755 | 5,755 | 5,755 | 5,755 | 5,755 | 5,755 |
| $H_0$ | -0.08 | -0.13 | -0.31 | -0.17 | -0.14 | -0.28 | -0.60 |
| | (-3.06) | (-5.16) | (-7.83) | (-4.22) | (-3.48) | (-5.26) | (-11.92) |

| Panel B1: Issue Cutoff at 3%, Straight Bonds Only | | | | | | | |
|---|---|---|---|---|---|---|---|
| | $K_1$: 1-2 Yr | $K_2$: 3-4 Yr | $K_3$: 5-6 Yr | $K_4$: 7-8 Yr | $K_5$: 9-10 Yr | $K_6$: 11-20 Yr | $K_7$ 21- Yr |
| $m^{K_1}$ | **-0.09** | -0.10 | -0.37 | -0.02 | -0.01 | 0.02 | 0.13 |
| | **(-1.32)** | (-1.04) | (-2.96) | (-0.18) | (-0.05) | (0.17) | (1.12) |
| $m^{K_2}$ | 0.11 | **-0.12** | -0.34 | 0.05 | -0.09 | 0.20 | 0.11 |
| | (2.61) | **(-1.88)** | (-4.45) | (0.77) | (-1.40) | (2.44) | (1.59) |
| $m^{K_3}$ | -0.04 | -0.03 | **-0.45** | -0.01 | 0.02 | 0.18 | 0.07 |
| | (-1.18) | (-0.46) | **(-6.51)** | (-0.14) | (0.35) | (2.48) | (1.11) |
| $m^{K_4}$ | 0.05 | 0.05 | -0.05 | **-0.15** | -0.05 | 0.06 | -0.16 |
| | (1.43) | (0.86) | (-0.69) | **(-2.47)** | (-0.82) | (0.85) | (-2.58) |
| $m^{K_5}$ | -0.02 | -0.02 | -0.02 | -0.03 | **-0.17** | 0.17 | -0.12 |
| | (-0.72) | (-0.33) | (-0.33) | (-0.47) | **(-3.21)** | (2.57) | (-2.00) |
| $m^{K_6}$ | 0.01 | 0.05 | -0.10 | -0.10 | -0.18 | **0.12** | -0.10 |
| | (0.30) | (0.92) | (-1.51) | (-1.70) | (-3.28) | **(1.85)** | (-1.77) |
| $m^{K_7}$ | 0.07 | 0.06 | 0.01 | -0.01 | -0.19 | -0.20 | **-0.21** |
| | (1.83) | (0.97) | (0.12) | (-0.09) | (-3.08) | (-2.57) | **(-3.21)** |
| *Obs.* | 2,525 | 2,525 | 2,525 | 2,525 | 2,525 | 2,525 | 2,525 |
| $H_0$ | -0.11 | -0.12 | -0.33 | -0.13 | -0.10 | 0.06 | -0.21 |
| | (-1.66) | (-1.82) | (-4.54) | (-2.11) | (-1.86) | (0.46) | (-2.96) |

| Panel B2: Issue Cutoff at 10%, Straight Bonds Only | | | | | | | |
|---|---|---|---|---|---|---|---|
| | $K_1$: 1-2 Yr | $K_2$: 3-4 Yr | $K_3$: 5-6 Yr | $K_4$: 7-8 Yr | $K_5$: 9-10 Yr | $K_6$: 11-20 Yr | $K_7$ 21- Yr |
| $m^{K_1}$ | **-0.14** | -0.28 | -0.38 | 0.19 | 0.01 | 0.09 | 0.20 |
| | **(-2.06)** | (-2.63) | (-2.50) | (1.33) | (0.06) | (0.59) | (1.50) |
| $m^{K_2}$ | 0.00 | **-0.16** | -0.37 | 0.12 | -0.04 | 0.23 | 0.12 |
| | (-0.03) | **(-2.52)** | (-4.18) | (1.42) | (-0.50) | (2.53) | (1.56) |
| $m^{K_3}$ | -0.04 | -0.06 | **-0.47** | 0.00 | 0.05 | 0.15 | 0.11 |
| | (-1.09) | (-0.96) | **(-5.83)** | (0.00) | (0.76) | (1.81) | (1.57) |
| $m^{K_4}$ | 0.05 | -0.01 | -0.04 | **-0.12** | -0.04 | 0.04 | -0.14 |
| | (1.31) | (-0.16) | (-0.47) | **(-1.67)** | (-0.57) | (0.45) | (-2.05) |
| $m^{K_5}$ | -0.03 | -0.03 | -0.01 | -0.01 | **-0.20** | 0.21 | -0.11 |
| | (-0.96) | (-0.53) | (-0.11) | (-0.15) | **(-3.06)** | (2.90) | (-1.67) |
| $m^{K_6}$ | 0.03 | 0.03 | 0.07 | -0.05 | -0.14 | **0.02** | -0.23 |
| | (0.81) | (0.52) | (0.88) | (-0.68) | (-2.11) | **(0.26)** | (-3.40) |
| $m^{K_7}$ | 0.09 | 0.08 | 0.17 | 0.02 | -0.18 | -0.23 | **-0.34** |
| | (2.22) | (1.24) | (1.88) | (0.21) | (-2.28) | (-2.63) | **(-4.33)** |
| *Obs.* | 1,822 | 1,822 | 1,822 | 1,822 | 1,822 | 1,822 | 1,822 |
| $H_0$ | -0.15 | -0.12 | -0.39 | -0.16 | -0.15 | -0.05 | -0.33 |
| | (-2.31) | (-1.83) | (-4.56) | (-2.06) | (-2.23) | (-0.59) | (-4.07) |