Granularity of Corporate Debt*

Jaewon Choi† Dirk Hackbarth‡ Josef Zechner§

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Abstract

We study the dispersion of debt maturities across time, which we call "granularity of corporate debt," using a model in which a firm's inability to roll over expiring debt causes inefficiencies, such as costly asset sales or underinvestment. Since multiple small asset sales are less costly than a single large one, firms diversify debt rollovers across maturity dates. We construct granularity measures using data on corporate bond issuers for the 1991–2012 period and establish a number of novel findings. First, there is substantial variation in granularity in that we observe both very concentrated and highly dispersed maturity structures. Second, observed variation in granularity supports the model's predictions, i.e., 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. Third, firms manage granularity actively and adjust toward target levels. Finally, newly issued bond maturities complement pre-existing bond maturity profiles.

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†University of Illinois, 515 E. Gregory Dr., Champaign, IL 61820, USA. Email: jaewchoi@illinois.edu.

‡Boston University School of Management, 595 Commonwealth Avenue, Boston, MA 02215, USA. Email: dhackbar@bu.edu.

§Vienna University of Economics and Business, Heiligenstaedter Str. 46, 1190 Vienna, Austria. Email: josef.zechner@wu.ac.at.

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, which is the most commonly mentioned determinant in Servaes and Tufano's (2006) survey of chief financial officers. Our 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 drives 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 than 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.[1] We show

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

that, in such states, investors may not be able to roll over their bonds. As a result, the firm must pass up or partially liquidate investment projects to repay the bondholders, and this is inefficient.

Firm D only needs to liquidate a small fraction of its assets to repay its bonds. 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 large fraction of its assets (including some with higher NPVs) or forgo new positive NPV projects. Thus, in our model it is less costly to be 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, Mithal, and Neis (2005) and Mahanti et al. (2008)) than two smaller bond issues. Thus, there is a trade-off in that firm D faces lower expected costs due to rollover risk than firm C, whereas firm C has a transaction cost advantage over firm D.

Based on the tension between costly asset sales or underinvestment on the one hand and transaction costs on the other hand, we derive a number of testable implications. Our model implies that the benefits of dispersed corporate debt maturities increase with rollover risk and with the value of investment opportunities. Moreover, 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 episodes of limited access to external funding without costly investment reductions or project liquidations.

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 1991–2012 period, we obtain an unbalanced panel with 19,262 (11,051) firm-year observations for 2,537 firms with at least one bond (two bonds) outstanding. We use these firm-level data from FISD to measure debt maturity dispersion.[3] For each firm, we group bond maturities into the nearest integer years and compute the

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 case 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.

fractions of bond amounts 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 based on the average squared distance between a firm's actual maturity profile and its perfectly dispersed maturity profile, i.e. one that has an equal fraction of debt maturing in each maturity bucket.

We begin by documenting stylized facts about debt granularity. Although a large number of firms have highly dispersed maturity structures, we find at the same time that many firms have very concentrated maturity structures. These concentrated firms are typically young and small and finance a significant portion of their assets through a single, small bond issue, which suggests that spreading out maturities using smaller bonds might be too costly for them. We also find that firms issue bonds to become more granular during economic downturns when rollover risk is supposedly high, which supports the view that firms consider trade-offs in determining maturity structure.

We next report results about observed variation in granularity that support the model's predictions. We find that larger and more mature firms, firms with more valuable investment projects, and firms with more leverage exhibit more dispersed maturity profiles. In contrast, granularity is negatively associated with profitability. Most of these firm characteristics remain economically and statistically significant after controlling for industry or firm and year fixed effects, suggesting that firms condition on these variables when managing their debt maturity profiles.[4] These findings are robust to, e.g., including the number of bonds as an explanatory variable, to including private debt maturity profiles into our granularity measures, to instrumenting leverage and maturity, and to stratifying the sample into firms with high and low proportions of private debt.

In addition, we perform tests that show firms manage debt maturity dispersion. First, to isolate the active granularity change from the observed one, we define passive granularity change as the change in granularity when expiring bonds are replaced by otherwise identical new bonds. We then estimate a partial adjustment model for both components and find that the active component explains most of the change in granularity. We also establish that the dispersion of debt maturities moves over time towards target levels. In particular, speed-of-adjustment regressions reveal fairly high and statistically significant adjustment rates, ranging from 14% to 52% per year.

Second, we examine whether firms consider pre-existing maturity profiles when they issue bonds. We investigate if discrepancies between a firm's pre-existing maturity profile and a benchmark ma-

[4]During the 2008–2009 financial crisis when rollover risk is likely to have been higher, we find that especially firms with valuable investment opportunities implemented more dispersed debt maturity structures.

turity profile (based on firm characteristics implied by the model) explain bond issuance behavior. Indeed, 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 insensitive to the definition of the benchmarks or buckets, and are also economically significant. Hence firms clearly consider pre-existing maturity profiles when they issue new bonds.

Our paper relates to several models of debt maturity and rollover frictions.[5] 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, Yu, and Yang. (2012) study the link between credit spreads, systematic risk, and lumpy maturity structure. These papers focus on single-bond firms' debt maturity choice. More closely related to ours is a recent paper by Diamond and He (2012), which shows that maturing short-term debt can lead to more debt overhang than non-maturing long-term debt. However, none of these papers examine the decision of 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 is optimal, because only a combination of debt with different rollover dates can reduce inefficiencies due to rollover risk.

Our paper builds on recent empirical and survey research. Based on a global survey, Servaes and Tufano (2006) report that chief financial officers are concerned about losing access to debt markets and, in particular, that debt maturity choice is driven by the objective of managing rollover risk by avoiding maturity concentrations. Almeida et al. (2012) 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.[6] In the context of U.S. Treasury bonds, Greenwood, Hanson, and Stein (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, Ippolito, and

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

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

Li (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. (2013), 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.[7] Unlike these studies, we focus on understanding the dispersion of corporate debt maturities.

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 variation in granularity and Section 5 determines how actively firms manage granularity. Section 6 contains a number of additional robustness tests and Section 7 concludes.

2 A Simple Model of Debt Granularity

In the presence of frictions that lead to rollover risk firms should appropriately adjust 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 normalize the riskless interest rate to zero and assume that the NPV of the project, H, is greater than $I/2$.

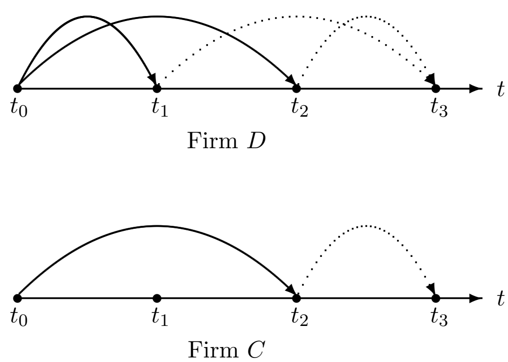
The firm issues straight one- or two-period bonds to raise the required capital of $I - A$. To keep the analysis focused, we do not consider three-period bonds or equity. In a more general model, short maturity debt is optimal due to informational asymmetries (see, e.g., Diamond (1991), Diamond and He (2012), or Milbradt and Oehmke (2012)), and equity is also dominated as long as debt tax shields are sufficiently valuable. Thus, the project is financed by bond issues at time t_0 that must be rolled over before time t_3. However, at times t_1 and t_2, the bond market may freeze with probability λ. Appendix A provides an extended model where market freezes arise endogenously, generating 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 (an alternative interpretation of this inefficiency is that the firm needs to cut back on new investments). Such a partial liquidation reduces the final cash flow and generates an immediate cash flow. We consider

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

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.[8]

Figure 1. Evolution of Debt Rollover



This figure plots the time line of debt rollover for the dispersed maturity structure (or Firm D) with two smaller issues, which expire at time t_1 and t_2, and for 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 or repaid with internally generated cash to realize the project's cash flow.

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.

In practice, bond issuances have a fixed cost component. 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

[8]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.

$2\,k$. 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, Mithal, and Neis (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 ecnomies 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).

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.[9] 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 rollover 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.

As firm D encounters no inefficiencies, it is easy to verify that firm D's equity value 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 λ 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

[9] Thus, in the model the cost of large asset sales is linked to the project's NPV. We believe that it is plausible to assume that it is more difficult to sell a project's NPV than its physical assets, since the NPV will in general depend at least partially on firm-specific organizational and/or human capital which may be difficult to replicate by a potential buyer. More generally, however, there will be heterogeneity in the degree of illiquidity of the project NPV and in addition forced asset sales may be costly even when the project for which the assets were employed had a low or negative NPV.

firm C's equity value 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 benefits of a dispersed maturity structure are given by the difference in equity values, $\Delta E \equiv E^D - E^C$, which is informative about the incentives for creating a granular debt structure:

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

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.

In summary, the above model 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 inefficiency can also be interpreted as passing up valuable investment opportunities. To keep the analysis focused, we have not considered other channels to avoid or manage rollover risk, but we will consider the potential role of these alternatives in the empirical analysis (see Section 4.2).

The model generates a number of empirical predictions for a corporation's incentives to select a concentrated or dispersed debt maturity profile. First, the potential benefits of a dispersed maturity structure increase with the probability of a market freeze, λ. 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, an increase in transaction costs, k, works in favor of a more concentrated maturity structure. This implies that a firm with higher floatation and illiquidity costs will have a lower incentive to implement a more dispersed maturity profile. Since there is evidence that these costs are negatively related to firm age and firm size (see subsection 4.1), corporate bond maturities should be more dispersed for larger and more mature firms.

There are additional observations that follow. Because a firm with a higher value of assets in place, A, needs less debt financing, the rollover problem in the λ 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. Moreover, even though we do not model cash flows from assets in place, observe 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 all of the above predictions should apply both to a comparison 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 contains comprehensive data on over 140,000 corporate bond issues for all credit ratings. The FISD 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. These data sets enable us to measure debt granularity and various firm characteristics for the 1991–2012 period. In addition, we also employ the Capital IQ database for firms' usage of lines of credit. This results in a more restricted sample, which only covers the 2002–2012 period. Following standard practice, 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.

3.2 Variable Construction

We first define our empirical granularity measures. In the model of Section 2, the concentration of a firm's bond maturities can be measured with a version of the Herfindahl index. Specifically, let x_i denote firm j's principal amounts maturing in each maturity bucket i, where the buckets are obtained by grouping bond maturities into the nearest integer years. The fraction of principal maturing in each maturity bucket is then given by $w_i = x_i / \sum_i x_i$. The concentration index of firm

j's debt maturity structure, H_j, is therefore defined as:

$$HERF_j = \sum_i w_i^2, \tag{4}$$

In the theoretical model firm C has a single bond outstanding and thus its Herfindahl index at time t_0 is $HERF^C = 1$. Firm D has two bonds with equal face value outstanding, so that firm D's Herfindahl index at time t_0 is $HERF^D = 0.5 < 1$. Based on this measure, firm C has therefore a more concentrated or less granular debt structure than firm D.

For robustness we introduce a second measure, which is also based on our model and relies on the average squared deviation of a firm's observed maturity profile from the perfectly dispersed one (i.e., distance from perfect granularity). We define perfectly dispersed as a debt structure that has the same maximum debt maturity, but a constant fraction of principal, $1/t_j^{max}$ maturing in each maturity bucket, where the maximum debt maturity t_j^{max} is the longest maturity of the currently outstanding bonds at issuance. Thus, the second concentration measure is defined as:

$$DIST_j = \frac{1}{t_j^{max}} \sum_{i=1}^{t_j^{max}} \big(w_{j,i} - \frac{1}{t_j^{max}}\big)^2. \tag{5}$$

In our theoretical model in section 2, firm C has a single bond outstanding that is rolled over at time t_2 and its distance measure at time t_0 is given by $DIST^C = (1/2)[(0-1/2)^2+(1-1/2)^2] = 0.25$. Firm D issues two bonds with equal face value outstanding, maturing at time t_1 and at time t_2. So firm D's distance measure is $DIST^D = (1/2)[((1/2) - (1/2))^2 + ((1/2) - (1/2))^2] = 0 < 0.25$. Thus, firm D has a more dispersed debt structure than firm C.

To capture dispersion rather than concentration or distance, we define the following granularity measures: inverse of the Herfindahl index, $GRAN1 \equiv 1/HERF$, and negative value of the log of the squared distance from perfect dispersion, $GRAN2 \equiv -\log(DIST)$.[10] 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).

To investigate the empirical predictions from Section 2, we include a number of explanatory and control variables in our regression specifications. The explanatory variables include market-to-book (Q), firm size ($Size$), firm age (Age), leverage (Lev), and profitability ($Prof$). We provide details on the construction of all variables used in this study in Appendix B.

[10]Similar to Lemmon, Roberts, and Zender (2008), we add 0.001 to $DIST$ to prevent $GRAN2$ from being negative infinity.

3.3 Summary Statistics and Stylized Facts

Table 3 contains the summary statistics for our sample of 2,537 firms over the 1991–2012 period, for which we have 19,262 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 \$8.21 (\$1.81) 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 relevance of fixed costs associated with bond issuance. Typical issue sizes of bonds are quite large with a median of \$150 million and an average of \$217.7 million. Observe also that the interquartile range of $BondAmt$ starts at \$91.7 million and ends at \$261 million. The fact that 75% of the bonds in our sample have a face value greater than \$91.7 million is consistent with the presence of a fixed cost element associated with bond issuance.

[Insert Table 3 here]

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 1.1 bonds outstanding (see $NBond$) and the Herfindahl-based granularity measure ($GRAN1$) equals 1.00. In contrast, the highest granularity firms have on average 13.44 bonds outstanding with $GRAN1$ value of 5.66. A perfectly granular firm with $GRAN1 = 13$ would have equal amounts expiring with thirteen different maturities, whereas a firm with $GRAN1 = 6$ would have six different maturities with bonds of equal size.[11] Thus, the Herfindahl-based granularity measure of 5.66 suggests that debt structures are not perfectly granular even for firms with the largest number of bonds outstanding. For the $GRAN2$ tercile groups, the lowest granularity firms have $GRAN2 = 2.25$, which translates to an average standard deviation from perfect granularity of 32.5%, whereas the highest granularity firms' corresponding standard deviation from the perfect granularity is only 8.85%.[12] The sample properties are similar when we use $GRAN2$ to stratify the data in columns 4–6 of Table 4.

[Insert Table 4 here]

[11]The interpretation of $GRAN1$ is 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.

[12]The standard deviations from perfect granularity are obtained from the square root of corresponding $DIST$ values.

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 maturity dates. In particular, we highlight that a large number of firms have very concentrated maturity structures. For example, using $GRAN1$, 8,911 out of 19,231 firm-year observations have perfectly 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 1.1. 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 is 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 the maturity matching principle.

This substantial variation in debt maturity profiles does not seem to be explained by bank loans. In other words, firms do not complement concentration in bond maturities with loan maturities. For the tercile groups based on corporate bonds' percentages of total debt outstanding in columns 7–9 of Table 4, 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, 4.5 bonds outstanding but a $GRAN1$ value of only 2.40, 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.[13] That is, for both granularity-based tercile groups, higher bond maturity dispersion is associated with higher debt maturity dispersion.

How do firms with concentrated maturity structures manage rollover risk? Although we do not consider other channels for managing rollover risk in our theoretical framework, firms might, in practice, use them too. That is, concentrated firms could hoard larger cash balances, issue more equity, or have more lines of credit. We find evidence for such substitution effects in Table 4 in that low-granularity firms tend to have greater cash balances ($Cash$), larger credit lines ($LCLimit$), and more equity issuances ($EqIssue$). For example, cash holding, lines of credit, and equity issuances

[13]See Appendix B or Section 4.5 for the construction of $GRAN1L$ and $GRAN2L$.

are, on average, 0.14 (0.07), 0.18 (0.11), and 0.03 (0.01) in the low (high) $GRAN1$ tercile group.

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 3.86, 7.50, and 15.66, respectively, whereas average asset maturity is similar across the terciles, 5.15, 6.05, and 5.90. Despite the limitations of interpreting these statistics, it seems unlikely that the intuitive idea behind the maturity matching principle influences firms' behavior in the data.

Figure 2 plots time-series averages of debt maturity dispersion for issuing and non-issuing firms. For issuing firms, maturity dispersion seems to be countercyclical, i.e. firms issue bonds to make maturity structures more dispersed during recessions. Increased rollover risk during recessions appears to 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 business cycle pattern is also consistent with our model, because in recessions the probability of a market freeze, λ, is likely to be higher.

[Insert Figure 2 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 Variation in Debt Granularity

We have argued in Section 2 that firms face trade-offs when they manage their maturities 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 debt maturity structures.

4.1 Baseline Regressions

We begin by estimating the following baseline regression:

$$GRAN_{i,t+1} = \beta X_{i,t} + \alpha_i + y_t + \epsilon_{i,t+1} \tag{6}$$

where $X_{i,t}$ is a vector of explanatory and control variables, α_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.

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.[14] Recall that Figure 2 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, Hanson, and Stein (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 and note that the results are robust to using industry-level clustering of standard errors.

Table 5 gives the estimation results of equation (6) 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.

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

0.422 and 0.499 for $GRAN1$ and $GRAN2$, respectively. The economic significance is also sizable. Consider, for instance, the coefficient estimate of 0.30 on the market-to-book ratio (Q) in the first column of Table 5. It implies that a one standard deviation change (0.98) in the market-to-book ratio changes $GRAN1$ by 0.29, which corresponds to a 11.8% (19.6%) change relative to the sample average (median) of 2.50 (1.50) for $GRAN1$ 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 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 inefficiencies.

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 1.53 according to the first column in the $GRAN1$ panel. 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 bond issuance and illiquidity costs, and are therefore not able to spread out their bonds' maturity dates across time.[15]

Leverage (Lev) is also positively associated with granularity. Although consistent with our prediction, this result can be partly due to endogeneity between granularity and leverage. Firms might consider bond amounts and bond maturity simultaneously when making issuance decisions. We consider endogeneity in Section 4.3 by using instrumental variable regressions.

Cash flow ($Prof$) is negatively associated with granularity, which is also consistent with the trade-off derived in Section 2. 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

[15] 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.

"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 with control variables 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, 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 reliably 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 heterogeneity. The remainder of this section studies several alternative specifications and robustness tests for these baseline results.

4.2 Number and Type of Bonds

While the main explanatory variables in equation 6 are significantly associated with our granularity measures, this does not entirely rule out the possibility of alternative explanations. Specifically, one could 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 could have granular debt structures, because they are more likely to (or just randomly) issue bonds with different maturity dates, which could 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 the number of bonds is not a sufficient statistic for granularity.

Since there are many 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 the 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 fund provisions. Since effective maturities for bonds with options and sinking funds are likely to be much shorter than for straight bonds, re-estimating equation (6) 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 regression setup of Section 4.1 leverage is treated as an exogenous variable. In reality, however, debt granularity and leverage may be determined jointly and be subject to the longest available maturity. That is, firms may determine the level of leverage along with the first two moments of maturity (i.e. average maturity and dispersion of maturity) simultaneously.

In this subsection, we address this concern 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). The first instrument we consider is issuer-level credit rating. In this context it is important to point out that rating agencies mainly focus on debt coverage and cash flows to rate firms.[16] Therefore 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. The second instrument we use is asset maturity. Asset maturity is likely to influence granularity mostly through its potential effect on average debt maturity but is unlikely to have a direct effect on granularity. Johnson (2003) and Saretto and Tookes (2012) also employ asset maturity as an instrument for debt maturity. In our implementation of the 2SLS estimations, we employ both of these instruments.[17]

Columns "IV" of Table 6 report the results from the 2SLS regressions using 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.[18] For example, the effect of Q and Lev more than doubles in the left panel for $GRAN1$.[19] Most of the explanatory variables are statistically significant at the 5% or 10% level with the exception of $Prof$. Taken together, these results provide further evidence of the trade-off in Section 2 that motivates firms' to manage the granularity of their debt.

4.4 Industry Granularity

Given that asset maturity is likely to be more homogeneous within an industry, including industry granularity should diminish the importance of some of the explanatory variables of the baseline regressions in Table 5, especially if firms match maturities of their liabilities with those of their assets (i.e. use the matching principle). So we consider in the sixth columns of Table 6 the possibility

[16] Rating agencies only recently started to take into consideration firms' debt maturity structures according to S&P's 2008 revision of its approach to credit ratings. Further, Gopalan, Song, and Yerramilli (2013) find that credit rating agencies tend to put more weight on shorter debt maturities instead of the overall debt maturity profile. He and Xiong (2012) also argue that rating agencies "need to incorporate the so-called maturity risk, i.e. an effect generated by firms' debt maturity structure on their credit risk."

[17] In untabulated results, we include industry leverage as the third instrument, similar to Saretto and Tookes (2012). The results are qualitatively the same.

[18] In the first stage regression, asset maturity is associated negatively with leverage and positively with debt maturity, while ratings are associated with negatively with market leverage and positively with debt maturity. Coefficient estimates on the instruments and the partial F-statistics are all statistically significant at the 1% level, indicating that weak instruments are not a concern.

[19] This suggests that mangers are concerned about rollover risk in that they select low leverage and high granularity simultaneously. This endogeneity creates a downward bias of the coefficients in our baseline regressions of Table 5.

that industry granularity explains 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 influence the relations between granularity and firm characteristics, which we report in Table 5. In fact, the estimation results suggest that firm characteristics, such as market-to-book or leverage, are independently important. We conclude that some but by no means all variation in granularity is driven by industry granularity and that these findings provide 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. In particular, Blackwell and Kidwell (1988) and Krishnaswami, Spindt, and Subramaniam (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. 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 maturities, and calculate granularity measures based on total instead of public debt maturities. To this end, we augment the corporate bond maturity structures from FISD by debt maturity variables from COMPUSTAT. Specifically, for maturities less than five years, we collect debt maturity information available in COMPUSTAT ($DD1$ to $DD5$). These COMPUSTAT variables include both public and private debt expiring in less than or equal to five years. For maturities greater than five years, we employ bond amounts available in FISD. We then combine debt amounts from these two sources to calculate granularity measures of firms' total debt. Given that most bank loans have stated maturities of less than five years, this procedure should generate fairly good proxies for debt granularity that capture both public and private debt maturity dispersion.[20]

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 equation (6) using the granularity measures that include private debt as dependent variables. The regression results based on these measures are gathered in the seventh 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 debt granularity.

5 Active Granularity Management

The results in the previous section show that variation in firms' debt granularity is consistent with the predictions from our model. In this section, we examine to what extent observed granularity levels are attributable to active granularity management.

5.1 Active vs. Passive Granularity Changes

Even without active granularity management, debt maturity dispersion changes when pre-existing bonds mature, which we call a *passive* granularity change. We define the passive component of a firm's granularity in year t, $PassiveGRAN_t$, as the granularity level that the firm would achieve if it replaces an expiring bond with a new bond that has exactly the same maturity and face value as the expiring bond had at the time of issue. In other words, a firm with a passive granularity management policy simply rolls over a maturing bond with an identical bond. We then define an *active* granularity change as difference between the actual granularity in year t and the passive granularity, $GRAN_t - PassiveGran_t$.[21]

The above decomposition allows an analysis on how much of firms' total granularity change is due to the passive vs. active components. Specifically, we denote the active granularity change as

$$\Delta_A GRAN_{t+1} \equiv GRAN_{t+1} - PassiveGran_{t+1}$$

[20] To validate this approach, we have 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.

[21] We thank an anonymous referee for suggesting this line of inquiry.

and the passive granularity change as

$$\Delta_P GRAN_{t+1} \equiv PassiveGRAN_{t+1} - GRAN_t.$$

Therefore, the actual or total granularity change is the sum of the two components: $\Delta GRAN_{t+1} = \Delta_A GRAN_{t+1} + \Delta_P GRAN_{t+1}$.

In Table 7, we provide averages, standard deviations, and correlations of these components of granularity changes to gauge how much of actual granularity changes are due to active management. As can be seen from the table, most of the variation in granularity changes is driven by firms' active management. The standard deviations of $\Delta GRAN_t$ and $\Delta_A GRAN_t$ are almost the same for both measures and the correlations between $\Delta GRAN_t$ and $\Delta_A GRAN_t$ are 0.97 for $GRAN1$ and 0.99 for $GRAN2$. Therefore, these summary statistics suggest that the active component of granularity changes brings about most of the observed changes in maturity dispersion.

[Insert Table 7 here]

We now test explicitly whether firms are active granularity managers. We proceed in two steps. In the first stage, we estimate the following partial adjustment model:

$$\Delta GRAN_{i,t+1} = \gamma(\beta X_{i,t} - GRAN_{i,t}) + \nu_{i,t+1}, \tag{7}$$

where $X_{i,t}$ is a vector of explanatory variables, such as the ones suggested by our model. Thus, $\beta X_{i,t}$ denotes target maturity dispersion and γ is the speed of adjustment towards target dispersion.

In the second stage, we examine how much of the partial adjustment estimated in (7) is due to the active vs. passive granularity management. The second stage regression is as follows:

$$\Delta_A GRAN_{i,t+1} = \gamma_A(\beta X_{i,t} - GRAN_{i,t}) + \eta_{i,t+1} \tag{8}$$

$$\Delta_P GRAN_{i,t+1} = \gamma_P(\beta X_{i,t} - GRAN_{i,t}) + \omega_{i,t+1} \tag{9}$$

where the granularity gap from the target $(\beta X_{i,t} - GRAN_{i,t})$ is estimated using the coefficients from the first stage regression (7). Since $\Delta GRAN_{t+1} \equiv \Delta_A GRAN_{t+1} + \Delta_P GRAN_{t+1}$, we have $\gamma = \gamma_A + \gamma_P$. If firms manage granularity actively, we will find γ_A to be much greater than γ_P.

Table 8 displays the results for the first stage partial adjustment model (7). Following Flannery and Rangan (2006), we include in the first two columns firm and year fixed effects to control for unobservable firm-specific heterogeneity in target granularity.[22] In addition, we employ panel GMM of Arellano and Bond (1991) and double-differencing estimation of Han and Phillips (2010), because coefficient estimates are inconsistent in a dynamic panel model with fixed effects.

Two observations follow from the first stage regression results in Table 8. First, the coefficient estimates for the target granularity $(\gamma\beta)X_{i,t}$ confirm the predictions from our model in almost all cases. Tobin's Q, firm size, leverage, and profitability are reliably related to target dispersion across all the models considered in a way that is consistent with our hypotheses. Second, we obtain a fairly high speed of adjustment in granularity. The estimates for adjustment are between 0.14 and 0.52 across the models, implying that the half lives of excess granularity are between 0.84 to 4.6 years, depending on the model. Moreover, the estimates for adjustment are statistically highly significant, which indicates that firms have target granularity levels and engage in granularity management.

[Insert Table 8 here]

Having established that firms adjust granularity toward target levels consistent with our theory, we examine how much of the adjustment is due to active granularity changes by estimating the second stage regressions (8) and (9). In Table 9, we report the speed-of-adjustment coefficients γ_A and γ_P after normalizing by γ for easy comparison. Consistent with the correlation analysis above, a substantial portion of granularity adjustment is due to firms' active management. Across all specifications, we find that 88% to 99% of the speed-of-adjustment estimated in Table 8 is attributed to the active component. In other words, the results indicate that firms change granularity actively either through new issuance or retirement when they adjust their granularity towards target levels.

In Table 9, we further separate out granularity changes due to issuance and early retirement from granularity changes to investigate whether firms rely on new issues or buy backs in managing granularity. We define active granularity change through issuance, $GRAN^I_{t+1} - PassiveGRAN_{t+1}$, where $GRAN^I_{t+1}$ is granularity calculated by assuming no early retirement of bonds in $t+1$. Similarly, we define active granularity change through early retirement, $GRAN^R_{t+1} - PassiveGRAN_{t+1}$, where $GRAN^R_{t+1}$ is granularity calculated by excluding new issues in year $t+1$. For the regressions of these two components on the granularity gap, $(\beta X_{i,t} - GRAN_{i,t})$, reported in Table 9, we find that new issues are relatively more important for granularity management than early retirements.

[Insert Table 9 here]

[22] In untabulated results, an F-test for the joint significance of the fixed effects rejects at the 1% level the hypothesis that these terms are all equal, supporting heterogeneity in granularity targets.

Overall, these results support the view that firms actively manage debt maturity dispersion mainly through issuance of new bonds. The speed with which firms make adjustments towards granularity targets is fairly high. Furthermore, granularity targets are explained by firm characteristics in ways that are in line with the predictions of our model and that are also consistent with the baseline results in the previous section.

5.2 Bond Issuance and Granularity Changes

The results in the previous subsection show that firms actively manage granularity toward target levels mainly through new issuances. In this subsection, we investigate this issue further by examining how firms determine the maturity of new issues given pre-existing maturity profile. Specifically, we ask the following question: how important is maturity dispersion when firms determine the maturity of newly-issued bonds?

To answer 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 bond 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 estimate a binomial choice regression for each maturity bucket $j = 1, 2, ..., 7$ for each new issue of bonds:

$$Prob(I_{it}^{j}) = a_1 m_{it}^{1} + a_2 m_{it}^{2} + a_3 m_{it}^{3} + a_4 m_{it}^{4} + a_5 m_{it}^{5} + a_6 m_{it}^{6} + a_7 m_{it}^{7} \ , \tag{10}$$

where I_{it}^{j} is a dummy variable for bond issuance of firm i at time t and m_{it}^{1} to m_{it}^{7} are deviations of the issuing firm's maturity profile from its benchmark profile. The maturity buckets are defined as follows. For maturities shorter than 10 years ($1 \leq j \leq 5$), there are five two-year buckets, each from $2j - 1$ to $2j$ years. For maturities longer than 10 years, there are two maturity buckets, one for 11 to 20 years and the other one for 21 years or longer.

The dependent variable is the bond issuance (dummy) variable, I_{it}^{j}, which equals one if the newly issued bond's amount is greater than a cut-off level and if its maturity falls into bucket j and equals zero otherwise.[23] We estimate a linear probability model for each maturity bucket j, because the economic magnitude of coefficient estimates are easier to interpret. In untabulated results, we estimate a probit model and obtain remarkably similar results. Industry and year fixed effects are

[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.

included in the estimation.[24] Any economy-wide supply side effects on firms' issuance are absorbed by the year fixed effect. Standard errors are clustered at the Fama-French 49 industry level.

The deviation of the firm's maturity profile from its benchmark profile is computed as follows. Each firm's maturity profile is first calculated as fractions of pre-existing bond amounts in each maturity bucket j. To obtain the benchmark maturity profile, firms are sorted into high (top 50%) and low (bottom 50%) groups based on the explanatory variables in Section 4 (i.e. Q, $Size$, Age, Lev, and $Prof$) and average maturity ($BondMat$). This procedure yields 64 maturity profile groups. The benchmark profile of each group is then obtained by averaging maturity profiles in that group. The deviation from the benchmark profile, m_{it}^{j}, is the difference between firm i's maturity profile and the benchmark profile of the group that the issuing firm belongs to.

If firms avoid maturity concentrations by managing bond issuances relative to benchmark profiles, then the probability of issuing a bond in the maturity bucket j should be negatively related to the deviation of the firm's maturity profile in that bucket, m_{it}^{j}. This implies the following testable hypothesis. The diagonal coefficients, a_j for $j = 1, ...7$, should be significantly negative and, on average, smaller than the off-diagonal coefficients for the other maturity buckets, a_l, where $l \neq j$.

The estimation results in Panel A of Table 10 confirm the hypothesis. 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 (1 to 2 year), all diagonal coefficients are negative and statistically significant at 1%, suggesting that firms engage in maturity dispersion management by avoiding maturity towers. For the five to six year maturity bucket, for example, the coefficient a_j is -0.35. That is, the probability of issuing additional five- or six-year maturity bonds drops by 0.35 of a percentage point for every percentage point that a firm's maturity profile exceeds the benchmark maturity profile in bucket 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, 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 maturity structures when the relative size of the new issue is larger.

[Insert Table 10 here]

[24] Firm fixed effects are inappropriate for our sample, as a number of firms issue only one bond in our sample period.

In addition, we examine in Table 10 if the diagonal coefficients are smaller than the average of the other six coefficients in the same binomial choice regression (i.e. column). For this purpose, we test the null hypothesis, H_0: $a_i - \frac{1}{6}\sum_{n\neq i} a_n = 0$, 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 -0.02 to -0.31 in Panel A1. Furthermore, they are all statistically significant at the 1% level, except for the shortest maturity bucket. 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 Additional Robustness Checks

6.1 Other Channels for Managing Rollover Risk

In practice, there are several mechanisms other than maturity dispersion to manage rollover risk. That is, firms with concentrated maturity profiles (see Table 4) may rely on other channels of rollover risk management, which we have not considered so far. In this section, we examine how firms' use of these channels is related to granularity.

The first channel we consider is corporate cash holdings. Given potential losses from higher rollover risk, firms would like to carry cash from good to bad states if their net worth enables them to do so. Recall that a sufficiently high net worth eliminates the inefficiency in Section 2. Another channel is equity issuance, which can also solve the firm's problem in Section 2. Although equity issuances are in general relatively expensive, firms could use equity issuances to avoid inefficiencies. We measure cash holdings, $Cash$, by cash divided by total assets and equity issuance, $EqIssue$, by common or preferred stock sales divided by total assets.

The third channel relates broadly to lines of credit. Firms with lines of credit can better withstand rollover risk and hence may have concentrated debt structures to reduce bond issuance costs. For short-term debt rollovers, firms typically utilize lines of credit and reclassify short-term debt as long-term debt. We adopt the measure *Rec* from Chang, Chen, and Dasgupta (2010), which is defined as reclassified short-term debt under SFAS No. 6 divided by total assets.[25] Under SFAS No. 6, a firm can reclassify short-term debt as long-term if the firm intends to refinance the debt on a long-term basis and it has a non-cancellable financing agreement that allows the refinancing of the short-term debt. According to Chang, Chen, and Dasgupta (2010), reclassified debt is almost always accompanied by credit lines, and thus this measure should capture firms' ability to manage rollover risk through credit lines. In addition, we employ direct measures of credit lines. We obtain data on firms' total credit lines available from Capital IQ. The database facility amounts are for bank overdraft, letters of credit outstanding, and revolving credit. We aggregate these facility amounts for each firm and each year to get total lines of credit available. Our measure for lines of credit is $LimitLC$, which is total lines of credit available divided by total assets.

To examine whether these channels are related to debt granularity, we include $Cash$, $LimitLC$, Rec, and $EqIssue$ in our baseline specification (6) as independent variables. The results are reported in Table 11. Several observations follow. First, cash holdings are not reliably related to our granularity measures. These results suggest that firms do not hoard cash to deal with rollover risk, possibly because cash holdings are relatively expensive. Second, the results in the second columns suggest that firms use credit lines to manage rollover risk of bonds. That is, the debt reclassification variable Rec is negatively and reliably related to granularity. In contrast, a direct measure of credit lines $LimitLC$ is not statistically significant, which suggests that Rec is a cleaner measure of the use of credit lines for debt rollover than $LimitLC$, because firms open credit lines for other reasons as well.[26] Finally, firms do not appear to rely on equity issuances to manage rollover risk. This result is in line with the notion that equity issuances are even costlier than carrying cash.

[Insert Table 11 here]

In sum, the results suggest that, in addition to spreading out debt maturity dates over time,

[25] We are grateful to Yunling Chen and Sudipto Dasgupta for providing us with the data.

[26] In unreported results, we double-sort firms by granularity ($GRAN$) and debt reclassification (Rec) measures. This reveals that larger, older, and less levered with more growth opportunities tend to manage granularity directly (rather than indirectly via credit lines).

firms use other channels of rollover risk management. Firms with significant amounts of credit lines available tend to have concentrated debt structures, because they are more likely to roll over expiring debt without incurring inefficiencies and hence can economize on bond issuance costs.

6.2 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, are useful for managing rollover risk.

To examine this substitution hypothesis, we estimate the model in equation (6) for low and high bank debt subsamples. That is, we investigate in Table 12 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. In addition to the main explanatory variables, we also include the fraction of bank loans to total debt, $BankLoanPct$, to examine whether having more bank loans affects the level of granularity. Notably, the coefficient estimates of the main explanatory variables for both subsamples are qualitatively similar to the full sample results in Table 5. Thus, the baseline results in Table 5 are robust to variation in the proportion of private debt. Interestingly, we find that a substitution effect of private debt, because the coefficient on $BankLoanPct$ is negative especially for the high bank loan subsample. Overall, these results suggest that granularity is mainly relevant for public debt, which supports our arguments in Section 2.

[Insert Table 12 here]

6.3 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.

In Table 13, we estimate equation (6) for the 2008–2009 crisis period and for the non-crisis period (i.e. 1991 to 2007 and 2010 to 2012). 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 difference 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 0.47, compared to 0.18 for the non-crisis period in the third column. 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 13 here]

7 Conclusion

This paper extends the existing literature by focusing on the dispersion of a 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 or pass up valuable investment opportunities 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 debt issuance costs or illiquidity costs. 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.

Based on a large panel of corporate bond issuers during the 1991–2012 period, we show that there is substantial variation in granularity in that we observe both very concentrated and highly dispersed maturity structures. Moreover, observed variation in granularity supports the model's predictions. Debt maturities are more dispersed and maturity dispersion adjusts faster towards target levels suggested by our model, e.g., 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. We also find that newly issued bond maturities complement pre-existing bond maturity profiles. Hence firms, on the margin, pay attention to debt maturity profiles by actively managing granularity.

Taken together, the model's predictions and test results generate several new 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. Finally, we have largely focused on the corporate finance implications for debt granularity. While it is beyond the scope of this paper to explore the asset pricing implications of debt granularity, this should prove fruitful for future research.

Appendix A. Model With Endogenous Market Freezes

In this appendix, we provide an extension of the model presented in Section 2 to endogenous market freezes. We adjust the assumptions made in Section 2 in the following sense. First, of the final cash flow, $I + H$, only I is contractible, whereas H represents non-contractible growth options. Second, at times t_1 and t_2, there is now a probability λ with which the firm reaches a *high-uncertainty state*. In this case, the firm becomes vulnerable to a technology shock. With probability π the technology shock actually takes place at time t_1^+ or t_2^+. In this case, the firm ceases to exist, and all cash flows are lost. 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 $1-\lambda$.

As in Section 2, the firm issues straight one- or two-period bonds to raise the required capital of $I-A$. Without loss of generality, firm D raises $\frac{I-A}{2}$ by issuing a bond to be rolled over at time t_1 and the remaining $\frac{I-A}{2}$ by issuing a bond to be rolled over at time t_2. It turns out that the former bond is riskless, so its required face value equals $\frac{I-A}{2}$. The latter bond is risky, because the firm may be hit by a technology shock at time t_1^+, and hence its required face value is therefore $\frac{I-A}{2(1-\lambda\,\pi)}$. This ensures that bondholders break even in expectation. Firm C issues a single bond to be rolled over at time t_2. Since it is also risky, its face value must equal $\frac{I-A}{1-\lambda\,\pi}$.

If investors do not roll over an expiring bond in the high-uncertainty state, the firm must transfer cash flows from time t_3 to repay the bondholders. As before, this may be interpreted either as an asset sale or as a cutback of investment at the time when the bond must be refinanced. If firm D needs to refinance its bond at time t_1 in the high-uncertainty state, it requires funds of $\frac{I-A}{2}$ (=face value of debt expiring at time t_1). To generate these funds, it must give up a cash flow at time t_3 of $\frac{I-A}{2(1-\pi)(1-\lambda\,\pi)}$. Note that the present value of this cash flow is exactly $\frac{I-A}{2}$, since in the high-uncertainty state at time t_1 there is only a $(1-\pi)(1-\lambda\,\pi)$ chance that the firm will survive without technology shock until time t_3. Thus, generating funds of $\frac{I-A}{2}$ at time t_1 by reducing investment or selling assets does not generate any deadweight losses, as it requires giving up a cash flow at time t_3 whose present value is exactly equal to $\frac{I-A}{2}$.

If firm D cannot refinance its bond at time t_2, it needs to generate funds equal to $\frac{I-A}{2(1-\lambda\,\pi)}$ (=face value of debt expiring at time t_2). We assume that this can be done by reducing investments or selling assets that reduce time t_3 cash flows by $\frac{I-A}{2(1-\pi)(1-\lambda\,\pi)}$. Thus, as before, generating these funds does not create deadweight losses, since the reduction of time t_3 cash flows exactly equals the funds generated at time t_2. We therefore assume without loss of generality that firm D always repays its expiring debt in the high-uncertainty state by transferring the necessary cash flows from time t_3.

Firm C needs to refinance its bond at time t_2. In the high-uncertainty state at time t_2 investors would be willing to contribute at most $(1-\pi)\,I$ to firm C, since with probability π the technology shock materializes and all cash flows are lost, and H is not contractible. The amount required to repay the face value of debt is $\frac{I-A}{1-\lambda\pi}$ (=face value of firm C's bond). So, firm C is unable to refinance its bond in the high-uncertainty state at time t_2 if the *endogenous market freeze* condition holds:

$$A \;<\; \pi\,[1+\lambda\,(1-\pi)]\,I\ . \tag{A.1}$$

In this case, firm C must generate cash internally by selling assets or cutting back investment. We assume that this is costly in the sense that the firm would need to give up all its cash flows at time t_3, $I+H$. Note that if leverage is larger (e.g. A is smaller or I is larger), then the left-hand side is more likely to be smaller than the right-hand side and hence condition (A.1) is more likely to hold.

Depending on how uncertainty is resolved over time, there are seven possible paths along which firms can evolve. Table 1 summarizes firm D's cash flows to equity net of debt payments for each of these seven paths.

Table 1. Paths, Probabilities, and Cash Flows for Firm D

Paths	Probabilities	Cash Flows to Equity
(i)	$\lambda\,\pi$	0
(ii)	$\lambda\,(1-\pi)\,\lambda\,\pi$	0
(iii)	$(1-\lambda)\,\lambda\,\pi$	0
(iv)	$\lambda\,(1-\pi)\,\lambda\,(1-\pi)$	$I+H-\frac{I-A}{(1-\pi)(1-\lambda\,\pi)}$
(v)	$\lambda\,(1-\pi)\,(1-\lambda)$	$I+H-\frac{I-A}{2(1-\pi)(1-\lambda\,\pi)}-\frac{I-A}{2(1-\lambda\,\pi)}$
(vi)	$(1-\lambda)\,\lambda\,(1-\pi)$	$I+H-\frac{I-A}{2(1-\lambda\,\pi)}-\frac{I-A}{2(1-\pi)(1-\lambda\,\pi)}$
(vii)	$(1-\lambda)\,(1-\lambda)$	$I+H-\frac{I-A}{1-\lambda\,\pi}$

Table 2 displays the cash flows to equityholders for firm C assuming that condition (A.1) holds. If this condition does not hold, then it is easy to show that firm C's cash flows to equityholders are identical to those of firm D, as given in Table 1.

Table 2. Paths, Probabilities, and Cash Flows for Firm C

Paths	Probabilities	Cash Flows to Equity
(i)	$\lambda\,\pi$	0
(ii)	$\lambda\,(1-\pi)\,\lambda\,\pi$	0
(iii)	$(1-\lambda)\,\lambda\,\pi$	0
(iv)	$\lambda\,(1-\pi)\,\lambda\,(1-\pi)$	0
(v)	$\lambda\,(1-\pi)\,(1-\lambda)$	$I+H-\frac{I-A}{1-\lambda\,\pi}$
(vi)	$(1-\lambda)\,\lambda\,(1-\pi)$	0
(vii)	$(1-\lambda)\,(1-\lambda)$	$I+H-\frac{I-A}{1-\lambda\,\pi}$

We obtain equity values by multiplying cash flows to equityholders by their respective probabilities, summing up, and recognizing that firm D's transactions costs are twice the ones incurred by firm C. The equity value of firm D is thus given by:

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

Equation (A.2) is easy to interpret. The firm generates the final cash flow, $I+H$, with the probability that no technology shock occurs, i.e. $(1-\lambda\,\pi)^2$. And equityholders must repay debtholders their contributed capital, $I-A$, in expectation. Finally, the transactions costs are $2\,k$.

The equity value of firm C is given by:

$$E^C \;=\; (1-\lambda)[(1-\lambda\,\pi)\,(I+H)-(I-A)]-k\;. \tag{A.3}$$

Equation (A.3) also shows that the final payoff, $I+H$, is only realized if no technology shock occurs at time t_1 (i.e. with probability of $1-\lambda\,\pi$). However, at time t_2 the final payoff is always lost in the high-uncertainty state for firm C (i.e. it must be fully used to repay debt), not only when the technology shock occurs subsequently. So the final payoff arises only in the low-uncertainty state, which occurs with probability $1-\lambda$. Notice that firm D generates the final payoff at time t_2 with probability $1-\lambda\,\pi > 1-\lambda$, which is the sources of inefficiency that is traded off against transaction costs.

The benefits of a dispersed maturity structure are defined by the difference in equity values, $\Delta E \equiv E^D - E^C$, which is informative about the incentives for creating a granular debt structure:

$$\Delta E \;=\; \begin{cases} \lambda[(1-\pi)\,(1-\lambda\,\pi)\,(I+H)-(I-A)]-k & \text{if condition (A.1) holds,} \\ -k & \text{otherwise.} \end{cases} \tag{A.4}$$

Equation (A.4) reveals that the model with endogenous market freezes yields the same testable implications as the ones we discuss for the model with exogenous market freezes in Section 2. Specifically, it follows that the relative advantage of dispersed debt maturities increases with H and that it decreases with k and A (i.e. condition (A.1) does not hold for a sufficiently large level of A so that ΔE becomes $-k$). Finally, it also follows from equation (A.4) that, for a sufficiently high NPV, the relative benefit of debt granularity increases with λ, i.e. the probability of the high-uncertainty state. In addition to the model with exogenous market freezes, we can see that ΔE decreases with π, i.e. the probability of a technology shock. Intuitively, the main benefit of dispersed debt maturity is to operate the firm's assets even during high-uncertainty times (i.e. the λ-states in our model). However, if in high-uncertainty times the technology shock always materializes, then the benefit of debt granularity vanishes (formally, we have for high values of π that $1-\lambda\,\pi \approx 1-\lambda$).

Appendix B. Variable Definitions

This appendix provides the variable construction of all the variables used in the study. All variables in uppercase letters refer to the COMPUSTAT items.

$GRAN1$: inverse of Herfindahl index of bond maturity fractions (see Section 3.2).

$GRAN2$: negative of log distance from the perfect maturity dispersion (see Section 3.2).

$GRAN1L$: inverse of Herfindahl index of total debt maturity fractions based on $DD1$ to $DD5$ and FISD's bond amounts for maturities greater than five years (see Section 4.6).

$GRAN2L$: negative of log distance from the perfect maturity dispersion based on $DD1$ to $DD5$ and FISD's bond amounts for maturities greater than five years (see Section 4.6).

Q: market-to-book ratio, $(AT + PRCC * CSHO - CDQ - TXDB)/AT$.

$Size$: log of total assets (AT).

Age: number of years in the COMPUSTAT file prior to observations.

Lev: market leverage, $(DLTT + DLC)/(AT + PRCC * CSHO - CEQ - TXDB)$

$Prof$: operating income before depreciation scaled by total assets, $OIBDP/AT$.

Tan: plant, property, and equipment scaled by total assets, $PPENT/AT$.

$BondMat$: average of firms' bond maturities weighted by amounts.

$ProfVol$: standard deviation of operating income before depreciation divided by total assets ($OIBDP/AT$) using the past five years.

$NBond$: number of bonds outstanding.

$BondPct$: ratio of total book value of bonds available to total book debt for each firm.

$BondAmt$: average amount of bonds outstanding for each firm.

$BondAmt/Asset$: average amount of bonds outstanding divided by total assets.

$Cash$: cash holdings divided by total assets, CH/AT.

$LimitLC$: credit lines based on Capital IQ (for the 2002–2012 period) divided by total assets AT (see Section 4.2).

$EqIssue$: sale of common and preferred stocks divided by total assets ($SSTK/AT$).

Rec: reclassified short-term debt under SFAS No. 6 divided by total assets.

$AssetMat$: 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 ($ACT/COGS$), and the maturity of net property, plant, and equipment is that amount divided by annual depreciation expense ($PPENT/DP$).

$IndGRAN$: median values of granularity within Fama-French 49 industry groups each year.

$PassiveGRAN_t$: a granularity level that a firm would achieve in t if it replaces an expiring bond with a new bond that has exactly the same maturity and face value as the expiring bond.

$\Delta_A GRAN_{t+1}$: defined as $GRAN_{t+1} - PassiveGran_{t+1}$.

$\Delta_P GRAN_{t+1}$: defined as $PassiveGRAN_{t+1} - GRAN_{t+1}$.

$GRAN_t^I$: granularity calculated by assuming no early retirement of bonds in t.

$GRAN_t^R$: granularity calculated by excluding new issues in year $t + 1$.

$BankLoanPct$: percentage of bank loans with respect to the total amounts of debt.

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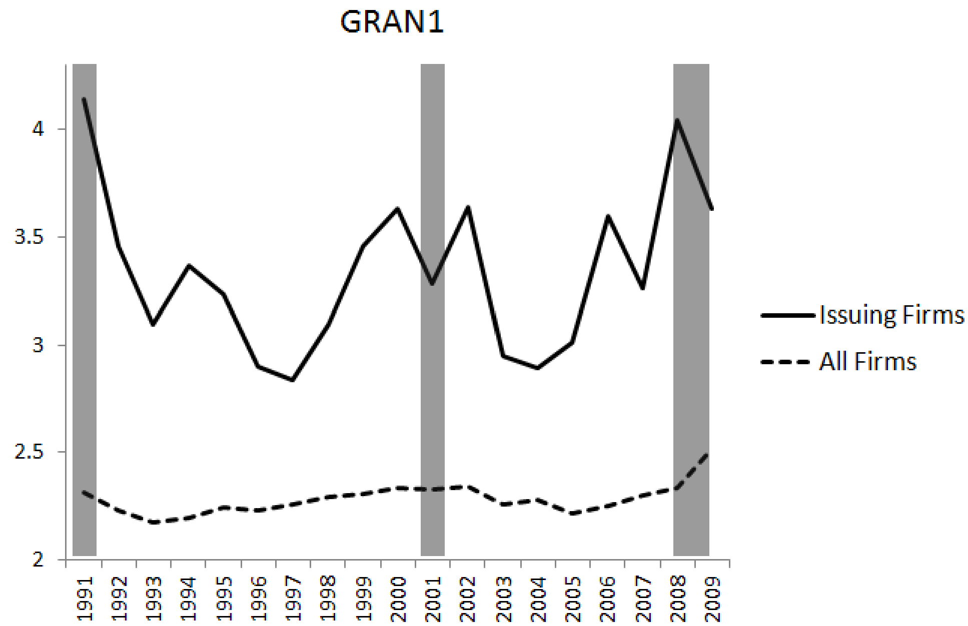
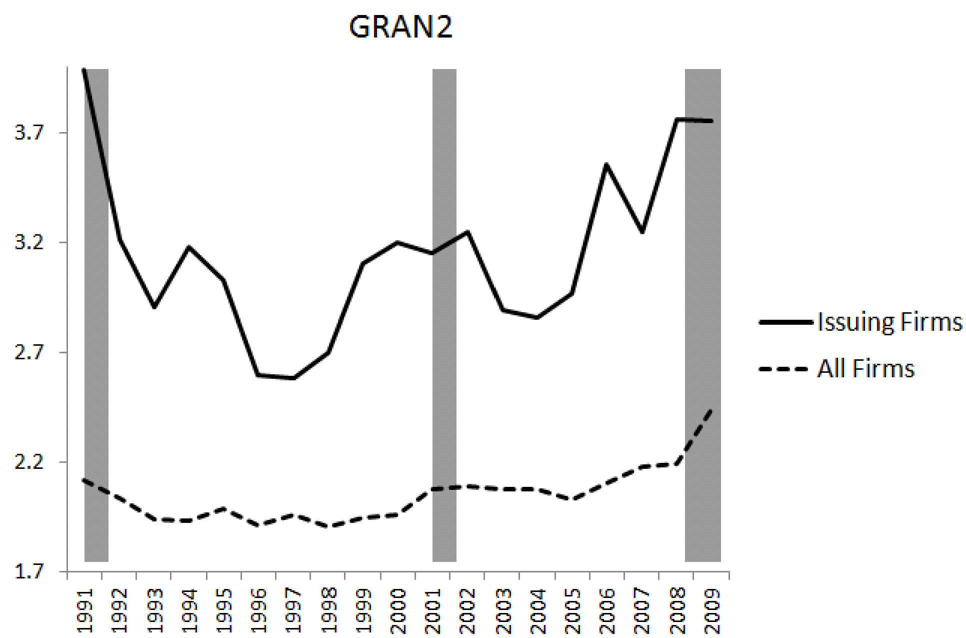
Figure 2. Time Series of Debt Maturity Dispersion





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 Herfindahl index of bond maturity fractions. $GRAN2$ is the negative value of the log 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 2012. Panel A reports means, standard deviations, 25%, median, and 75% of main variables. $GRAN1$ is the inverse of the Herfindahl index of bond maturity fractions. $GRAN2$ is the negative of the log distance from the perfect maturity dispersion. $NBond$ is the number of bonds outstanding for each firm. $Size$ 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 profitability (operating income divided by assets) and tangibility (property, plant, and equipments divided by assets), respectively. $ProfVol$ is the standard deviation of earnings divided by assets using the past five years. $BondMat$ is the average of firms' bond maturities weighted by amounts. $BondPct$ 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 amount of bond issues outstanding for each firm. $BondAmt/Asset$ is $BondAmt$ divided by total assets. $Cash$ is cash holdings divided by assets. $LimitLC$ is the total amount of credit lines available divided by assets and $EqIssue$ is sale of common and preferred stocks divided by assets.

	Mean	Stdev	25%	Median	75%
$GRAN1$	2.50	2.45	1.00	1.50	2.94
$GRAN2$	3.42	1.17	2.40	3.19	4.25
$Nbond$	4.9	9.4	1.0	2.0	4.0
$Size$	7.55	1.63	6.45	7.50	8.61
Age	22.15	13.76	9.00	20.00	34.00
Q	1.67	0.98	1.09	1.38	1.87
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	0.27	0.49
$ProfVol$	0.06	0.08	0.03	0.04	0.07
$BondMat$	9.01	5.82	5.01	7.43	11.59
$BondPct$	0.65	0.30	0.42	0.69	0.95
$BondAmt$	217.66	300.71	91.66	150.00	261.00
$BondAmt/Asset$	0.17	0.84	0.03	0.09	0.20
$Cash$	0.57	0.50	0.00	1.00	1.00
$LCLimit$	0.15	0.12	0.06	0.12	0.20
$EqIssue$	0.02	0.06	0.00	0.00	0.01

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 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. $Size$ 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. $Prof$ is profitability (operating income divided by assets). $BondMat$ 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 amount of bond issues outstanding for each firm. $Cash$ is cash holdings divided by assets. $LimitLC$ is the total amount of credit lines available divided by assets and $EqIssue$ is sale of common and preferred stocks divided by assets.

	GRAN1			*GRAN2*			*BondPct*			*BondMat*		
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High
GRAN1	1.00	1.95	5.66	1.00	1.60	4.98	2.15	2.96	2.40	1.71	2.23	3.57
	(1.00)	(1.96)	(4.69)	(1.00)	(1.66)	(4.00)	(1.00)	(1.95)	(1.17)	(1.00)	(1.39)	(2.00)
GRAN1L	2.00	2.77	3.81	1.94	2.63	3.61	2.93	3.02	2.18	2.18	2.90	3.06
	(1.65)	(2.53)	(3.66)	(1.61)	(2.40)	(3.49)	(2.76)	(2.79)	(1.77)	(1.95)	(2.67)	(2.86)
GRAN2	2.46	3.48	4.97	2.25	3.22	4.85	3.31	3.62	3.33	2.78	3.24	4.21
	(2.40)	(3.39)	(4.95)	(2.30)	(3.20)	(4.76)	(3.07)	(3.33)	(3.07)	(2.46)	(3.04)	(4.12)
GRAN2L	2.99	3.86	5.08	2.76	3.66	4.99	3.96	3.95	3.44	3.16	3.66	4.53
	(2.96)	(3.81)	(5.10)	(2.59)	(3.64)	(4.97)	(3.94)	(3.84)	(3.24)	(3.09)	(3.58)	(4.59)
Nbond	1.10	3.14	13.44	1.12	2.18	11.58	4.28	6.05	4.48	2.93	4.09	7.86
	(1.00)	(2.00)	(8.00)	(1.00)	(2.00)	(6.00)	(2.00)	(2.00)	(2.00)	(1.00)	(2.00)	(3.00)
Size	6.58	7.71	9.09	6.60	7.19	8.89	7.89	7.63	7.13	7.15	7.43	8.08
	(6.57)	(7.64)	(9.03)	(6.59)	(7.24)	(8.85)	(7.79)	(7.59)	(7.03)	(7.12)	(7.37)	(8.09)
Age	17.3	22.2	30.5	16.0	20.9	29.8	22.5	23.2	20.7	20.8	20.1	25.5
	(13.0)	(20.0)	(33.0)	(12.0)	(18.0)	(32.0)	(22.0)	(22.0)	(16.0)	(17.0)	(16.0)	(28.0)
Q	1.71	1.66	1.61	1.71	1.67	1.62	1.52	1.60	1.89	1.74	1.58	1.68
	(1.37)	(1.38)	(1.38)	(1.37)	(1.37)	(1.39)	(1.29)	(1.36)	(1.51)	(1.40)	(1.33)	(1.40)
Lev	0.28	0.29	0.25	0.30	0.28	0.25	0.32	0.28	0.22	0.28	0.31	0.23
	(0.24)	(0.25)	(0.22)	(0.26)	(0.24)	(0.21)	(0.29)	(0.24)	(0.18)	(0.23)	(0.29)	(0.20)
Prof	0.10	0.12	0.13	0.09	0.11	0.13	0.12	0.12	0.09	0.09	0.12	0.13
	(0.11)	(0.12)	(0.13)	(0.11)	(0.12)	(0.13)	(0.12)	(0.13)	(0.11)	(0.11)	(0.12)	(0.13)
BondMat	8.08	8.77	10.84	5.55	10.08	11.68	8.94	9.19	8.89	3.86	7.50	15.66
	(6.46)	(7.25)	(9.83)	(5.54)	(7.72)	(10.85)	(7.44)	(7.71)	(6.96)	(4.14)	(7.44)	(14.78)
AssetMat	5.17	5.89	6.44	5.40	5.38	6.31	6.18	5.83	5.10	5.15	6.05	5.90
	(3.65)	(4.53)	(5.23)	(3.75)	(4.01)	(5.12)	(4.93)	(4.52)	(3.56)	(3.73)	(4.68)	(4.52)
BondPct	0.63	0.66	0.69	0.64	0.65	0.66	0.29	0.69	0.97	0.66	0.64	0.66
	(0.66)	(0.69)	(0.72)	(0.67)	(0.70)	(0.70)	(0.31)	(0.69)	(1.00)	(0.73)	(0.66)	(0.70)
BondAmt	169.0	252.5	271.8	174.1	208.8	272.1	170.5	217.5	265.0	207.0	221.1	228.8
	(125.0)	(171.5)	(212.6)	(143.8)	(145.0)	(191.7)	(125.0)	(164.7)	(175.0)	(144.7)	(166.7)	(155.0)
BondAmt/Assets	0.28	0.13	0.04	0.26	0.21	0.04	0.08	0.14	0.30	0.23	0.17	0.12
	(0.18)	(0.08)	(0.02)	(0.19)	(0.11)	(0.03)	(0.05)	(0.09)	(0.16)	(0.11)	(0.11)	(0.05)
Cash	0.14	0.11	0.07	0.14	0.13	0.07	0.06	0.08	0.21	0.14	0.09	0.11
	(0.07)	(0.06)	(0.04)	(0.07)	(0.06)	(0.04)	(0.03)	(0.04)	(0.14)	(0.07)	(0.04)	(0.05)
LCLimit	0.18	0.14	0.11	0.18	0.16	0.11	0.16	0.15	0.13	0.16	0.15	0.14
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(-0.01)	(0.00)	(0.00)	(0.00)
EqIssue	0.03	0.02	0.01	0.04	0.02	0.01	0.02	0.02	0.03	0.03	0.03	0.02
	(0.04)	(0.03)	(0.02)	(0.04)	(0.03)	(0.02)	(0.05)	(0.03)	(0.01)	(0.03)	(0.04)	(0.02)
Obs.	8,911	5,161	5,159	6,806	6,086	6,339	6,348	6,449	6,434	6,411	6,417	6,403

Table 5. Baseline Regression

The sample includes firms with corporate bond and accounting information available in the FISD and COMPUSTAT Annual databases for the period from 1991 to 2012. 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, α_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. Q is the market-to-book ratio and Lev is the market value of leverage. Age is the number of years in the COMPUSTAT file prior to observations. $Prof$ and Tan are 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	0.30	0.29	0.32	0.27	0.20	0.19	0.10	0.13	0.10	0.13	0.08	0.09
	(3.29)	(3.35)	(3.75)	(3.17)	(2.13)	(2.02)	(2.37)	(3.78)	(2.54)	(3.60)	(2.03)	(2.37)
$Size$	0.94	0.91	0.90	0.88	0.74	0.73	0.45	0.41	0.44	0.40	0.33	0.31
	(21.70)	(22.03)	(22.22)	(22.40)	(10.66)	(10.46)	(30.43)	(30.78)	(28.95)	(29.65)	(12.57)	(12.87)
Age	0.03	0.03	0.03	0.03	0.26	0.18	0.02	0.02	0.02	0.02	0.02	-0.08
	(9.73)	(10.15)	(10.57)	(10.72)	(1.42)	(0.96)	(14.47)	(16.01)	(14.41)	(15.32)	(0.18)	(-0.78)
Lev	1.85	1.80	1.49	1.48	1.61	1.64	0.62	0.83	0.49	0.71	0.80	0.93
	(9.31)	(8.92)	(6.99)	(7.01)	(7.72)	(7.64)	(6.44)	(9.48)	(4.88)	(8.01)	(7.95)	(9.74)
$Prof$	-1.61	-1.71	-1.81	-1.76	-0.78	-0.79	-0.40	-0.58	-0.49	-0.65	-0.23	-0.33
	(-6.72)	(-7.27)	(-7.19)	(-7.31)	(-3.94)	(-4.05)	(-3.46)	(-5.92)	(-4.14)	(-6.43)	(-2.33)	(-3.77)
Tan		0.93		1.04		-0.18		0.31		0.32		-0.19
		(4.57)		(4.16)		(-0.54)		(4.96)		(4.03)		(-1.46)
$BondMat$		0.05		0.05		0.02		0.07		0.07		0.04
		(6.99)		(7.04)		(3.16)		(27.92)		(28.69)		(15.43)
$ProfVol$		1.42		1.65		0.17		0.20		0.30		-0.24
		(4.91)		(5.23)		(0.37)		(1.46)		(2.05)		(-0.84)
Obs.	19,146	19,089	19,146	19,089	19,146	19,089	19,262	19,089	19,262	19,089	19,262	19,089
R^2	0.422	0.443	0.440	0.458	0.761	0.763	0.499	0.613	0.513	0.623	0.796	0.833
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. 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 2012. 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, α_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. Q is the market-to-book ratio and Lev is the market value of leverage. $Size$ is the log of total assets. Age is the number of years in the COMPUSTAT file prior to observations. $Prof$ and Tan are 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 asset maturity and issuer-level credit rating 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	0.15	0.12	0.30	0.22	1.39	0.18	0.19	0.08	0.07	0.11	0.13	0.40	0.09	0.07
	(2.48)	(2.13)	(2.30)	(3.18)	(2.01)	(1.92)	(2.31)	(2.46)	(2.28)	(1.98)	(3.30)	(1.69)	(2.51)	(1.89)
$Size$	0.50	0.39	1.08	0.55	0.73	0.71	0.76	0.24	0.18	0.36	0.29	0.34	0.31	0.31
	(8.48)	(8.04)	(9.13)	(9.79)	(6.73)	(10.16)	(12.86)	(10.69)	(8.89)	(10.47)	(10.18)	(11.65)	(12.83)	(14.19)
Age	0.05	-0.01	0.71	-0.12	0.08	0.16	-0.13	-0.12	-0.15	0.18	-0.20	0.02	-0.08	-0.12
	(0.36)	(-0.11)	(1.63)	(-0.66)	(2.26)	(0.87)	(-0.67)	(-1.34)	(-1.92)	(0.93)	(-1.91)	(2.26)	(-0.84)	(-1.23)
Lev	1.04	0.74	2.10	1.15	7.93	1.64	2.04	0.75	0.58	0.79	0.81	2.56	0.92	1.07
	(6.06)	(4.08)	(5.07)	(6.83)	(2.01)	(7.74)	(9.61)	(8.57)	(6.53)	(5.24)	(8.15)	(2.07)	(9.71)	(11.78)
$Prof$	-0.53	-0.40	-0.80	-0.80	0.17	-0.76	-0.54	-0.25	-0.18	-0.25	-0.34	-0.02	-0.35	-0.21
	(-3.03)	(-2.25)	(-1.98)	(-5.13)	(0.24)	(-3.95)	(-2.83)	(-3.06)	(-2.11)	(-1.67)	(-3.63)	(-0.10)	(-3.93)	(-2.31)
Tan	0.14	0.29	0.28	-0.24	-0.76	-0.21	0.38	-0.09	0.00	-0.05	-0.18	-0.37	-0.20	0.07
	(0.47)	(0.88)	(0.52)	(-0.91)	(-1.29)	(-0.63)	(1.17)	(-0.74)	(-0.01)	(-0.35)	(-1.31)	(-1.89)	(-1.61)	(0.65)
$BondMat$	0.02	0.02	0.03	0.00	0.31	0.02	0.03	0.04	0.04	0.04	0.04	0.06	0.04	0.04
	(3.68)	(3.66)	(2.37)	(-0.02)	(1.69)	(3.12)	(4.89)	(17.25)	(17.10)	(10.84)	(12.39)	(1.14)	(15.23)	(17.61)
$ProfVol$	0.32	0.39	1.08	0.28	-0.72	0.08	-0.35	-0.19	-0.15	0.41	0.04	-0.32	-0.24	-0.44
	(0.80)	(0.97)	(1.02)	(0.71)	(-0.62)	(0.18)	(-0.75)	(-0.72)	(-0.57)	(0.83)	(0.15)	(-0.72)	(-0.86)	(-1.67)
$Nbond$	0.13							0.04						
	(7.74)							(7.88)						
$IndGRAN$						0.27							0.17	
						(5.50)							(6.70)	
$Obs.$	19,089	19,089	11,051	12,592	15,274	19,089	19,089	19,089	19,089	11,051	12,592	15,274	19,089	19,089
R^2	0.822	0.539	0.736	0.819	0.754	0.765	0.750	0.859	0.734	0.827	0.827	0.807	0.836	0.822
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. Summary Statistics on Active and Passive Granularity Changes

This table provides the average, standard deviation, and correlations of the granularity change $\Delta GRAN_t$, the passive granularity change $\Delta_P GRAN_t (\equiv PassiveGRAN_t - GRAN_t)$, and the active granularity change $\Delta_A GRAN_t (\equiv GRAN_t - PassiveGRAN_t)$. The passive granularity change $PassiveGRAN_t$ is defined as a granularity level that the firm would achieve if it replaces an expiring bond with a new bond that has exactly the same maturity and face value as the expiring bond.

Panel A: $GRAN1$

	$\Delta GRAN_t$	$\Delta_P GRAN_t$	$\Delta_A GRAN_t$		Correlations		
					$\Delta GRAN_t$	$\Delta_P GRAN_t$	$\Delta_A GRAN_t$
Mean	0.08	-0.03	0.11	$\Delta GRAN_t$	1		
Std. Dev	0.86	0.21	0.86	$\Delta_P GRAN_t$	0.11	1	
N	17,374	17,374	17,374	$\Delta_A GRAN_t$	0.97	-0.15	1

Panel B: $GRAN2$

	$\Delta GRAN_t$	$\Delta_P GRAN_t$	$\Delta_A GRAN_t$		Correlations		
					$\Delta GRAN_t$	$\Delta_P GRAN_t$	$\Delta_A GRAN_t$
Mean	0.04	-0.01	0.05	$\Delta GRAN_t$	1		
Std. Dev	0.46	0.05	0.46	$\Delta_P GRAN_t$	0.07	1	
N	17,534	17,534	17,534	$\Delta_A GRAN_t$	0.99	-0.05	1

Table 8. First Stage Regression: Adjustment Toward Target Granularity

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. $GRAN1$ 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 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). In column *Han-Phillips*, we provide the results of Han and Phillips (2010) double-differencing estimation. Numbers in parentheses are t-statistics for which standard errors are clustered at the firm level. The sample period is from 1991 to 2012.

	$GRAN1$				$GRAN2$			
	Industry FE	Firm FE	Arellano-Bond	Han-Phillips	Industry FE	Firm FE	Arellano-Bond	Han-Phillips
$GRAN_{t-1}$	0.14	0.31	0.28	0.25	0.36	0.56	0.52	0.25
	(15.67)	(23.84)	(6.37)	(8.97)	(32.87)	(40.19)	(13.39)	(8.65)
Q	0.09	0.16	0.24	0.72	0.06	0.10	0.10	0.13
	(4.79)	(3.56)	(4.25)	(2.39)	(5.75)	(4.46)	(5.18)	(1.04)
$Size$	0.10	0.26	0.42	0.31	0.08	0.11	0.14	0.07
	(11.65)	(8.79)	(7.70)	(4.76)	(15.81)	(7.76)	(7.88)	(2.55)
Age	0.00	0.19	-0.03	-0.01	0.00	0.04	0.01	0.00
	(-1.53)	(0.92)	(-3.91)	(-1.53)	(4.05)	(0.42)	(2.23)	(0.12)
Lev	0.31	0.75	0.88	1.69	0.22	0.46	0.41	0.66
	(6.28)	(6.83)	(6.42)	(2.46)	(7.71)	(8.27)	(7.10)	(2.30)
$Prof$	-0.21	-0.28	-0.37	-1.05	-0.17	-0.15	-0.13	0.26
	(-4.00)	(-2.80)	(-3.49)	(-0.89)	(-5.06)	(-2.67)	(-2.55)	(0.53)
Tan	0.09	0.03	0.16	-0.30	0.05	-0.02	-0.02	-0.03
	(1.94)	(0.19)	(0.80)	(-0.53)	(2.10)	(-0.21)	(-0.32)	(-0.13)
$BondMat$	-0.02	-0.04	-0.06	0.05	-0.02	-0.02	-0.04	0.00
	(-6.05)	(-5.18)	(-4.66)	(2.70)	(-8.73)	(-7.73)	(-9.17)	(0.50)
$ProfVol$	0.23	-0.05	-0.24	-1.87	0.09	-0.16	-0.43	-1.73
	(3.34)	(-0.22)	(-0.84)	(-0.66)	(2.01)	(-1.08)	(-2.51)	(-1.47)
Obs.	17,261	17,261	14,214	16,554	17,327	17,327	14,269	16,616
R^2	11.1%	14.2%			33.6%	45.4%		
Year FE	Yes	Yes			Yes	Yes		
Industry FE	Yes	No			Yes	No		
Firm FE	No	Yes			No	Yes		

Table 9. Second Stage Regression: Active vs. Passive Management

This Table reports the estimation results of the second stage regression in (8) and (9):

$$\Delta_A GRAN_{i,t+1} = \gamma_A(\beta X_{i,t} - GRAN_{i,t}) + \eta_{i,t+1}$$

$$\Delta_P GRAN_{i,t+1} = \gamma_P(\beta X_{i,t} - GRAN_{i,t}) + \omega_{i,t+1}$$

where $\Delta_A GRAN_{t+1}(\equiv GRAN_{t+1} - PassiveGran_{t+1})$ is the active granularity change and $\Delta_P GRAN_{t+1}(\equiv PassiveGRAN_{t+1} - GRAN_t)$ is the passive granularity change. The granularity gap, $\beta X_{i,t} - GRAN_{i,t}$, is estimated in the first stage regression (7). We report coefficient estimates after normalization using the sum of the coefficients, $\gamma_A + \gamma_P$. We also provide regression results of granularity changes due to issuance (Active Issue) and early retirement (Active Retire). Granularity change through issuance is defined as $GRAN^I_{t+1} - PassiveGRAN_{t+1}$ where $GRAN^I_{t+1}$ is granularity calculated by assuming no early retirement of bonds in $t+1$. Granularity change through early retirement is defined as $GRAN^R_{t+1} - PassiveGRAN_{t+1}$, where $GRAN^R_{t+1}$ is granularity calculated by excluding new issues in year $t+1$. The reported coefficients are normalized using the speed-of-adjustment coefficients estimated for each model in Table 8. Numbers in parentheses are t-statistics for which standard errors are clustered at the firm level. The sample period is from 1991 to 2012.

Panel A: $GRAN1$

	Industry Fixed Effect				Firm Fixed Effect			
	Passive	*Active*	*Active Issue*	*Active Retire*	*Passive*	*Active*	*Active Issue*	*Active Retire*
$\beta X_{i,t} - GRAN_{i,t}$	0.12	0.88	0.77	0.38	0.10	0.91	0.75	0.43
	(10.86)	(18.70)	(16.70)	(11.13)	(10.97)	(23.95)	(20.24)	(11.49)
N	17,261	17,261	17,261	16,604	17,261	17,261	17,261	16,604
R^2	3.2%	9.0%	8.7%	3.8%	3.1%	11.7%	13.1%	2.6%
	Arellano-Bond				**Han-Phillips**			
	Passive	*Active*	*Active Issue*	*Active Retire*	*Passive*	*Active*	*Active Issue*	*Active Retire*
$\beta X_{i,t} - GRAN_{i,t}$	0.07	0.93	0.87	0.31	0.09	0.91	0.85	0.27
	(9.89)	(28.69)	(27.71)	(13.17)	(14.80)	(36.50)	(37.68)	(13.93)
N	16,554	16,554	16,554	15,940	16,554	16,554	16,554	15,940
R^2	0.7%	7.1%	7.5%	2.0%	0.7%	4.1%	4.3%	1.2%

Panel B: $GRAN2$

	Industry Fixed Effect				Firm Fixed Effect			
	Passive	*Active*	*Active Issue*	*Active Retire*	*Passive*	*Active*	*Active Issue*	*Active Retire*
$\beta X_{i,t} - GRAN_{i,t}$	0.02	0.98	0.81	0.51	0.02	0.98	0.77	0.43
	(7.80)	(36.58)	(35.14)	(22.37)	(7.97)	(41.94)	(36.54)	(19.04)
N	17,327	17,327	17,327	17,327	17,327	17,327	17,327	17,327
R^2	1.3%	32.5%	28.5%	7.5%	0.3%	44.2%	37.1%	8.9%
	Arellano-Bond				**Han-Phillips**			
	Passive	*Active*	*Active Issue*	*Active Retire*	*Passive*	*Active*	*Active Issue*	*Active Retire*
$\beta X_{i,t} - GRAN_{i,t}$	0.01	0.99	0.76	0.40	0.02	0.98	0.79	0.44
	(4.08)	(31.37)	(28.41)	(16.18)	(5.92)	(34.10)	(32.48)	(19.56)
N	16,616	16,616	16,616	16,616	16,616	16,616	16,616	16,616
R^2	0.3%	26.1%	19.7%	3.8%	0.3%	19.6%	16.3%	3.5%

Table 10. Bond Issuance Regressions

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

$$Prob(I_{it}^{j}) = a_1 m_{it}^{1} + a_2 m_{it}^{2} + a_3 m_i^3 + a_4 m_i^4 + a_5 m_i^5 + a_6 m_i^6 + a_7 m_i^7,$$

where 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^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 j. After firms are sorted into 64 ($=2^6$) groups based on six 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_{it}^{j} is one if the bond i's maturity falls in bucket j, and is zero if the bond has a different maturity than bucket j. We include Fama-French 49 industry fixed effects for the issuing firm i and year fixed effects. 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 10%. Panel B1 and B2 exclude all bonds with option features (callability, convertibility, putability and sinking fund provisions) from the sample. The hypothesis test ($H_0\colon\ a_i - \frac{1}{6}\sum_{n \neq i} a_n = 0$) 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 2012.

	Panel A1: Issue Cutoff at 3%, All Bonds						
	1-2 Yr	3-4 Yr	5-6 Yr	7-8 Yr	9-10 Yr	11-20 Yr	21- Yr
m^1	**-0.01**	-0.07	-0.23	-0.06	-0.03	0.05	0.17
	(-0.18)	(-1.67)	(-3.47)	(-0.82)	(-0.47)	(0.64)	(2.44)
m^2	0.05	**-0.09**	-0.28	-0.08	-0.04	0.14	0.16
	(2.86)	**(-3.28)**	(-6.92)	(-1.85)	(-0.94)	(2.85)	(3.83)
m^3	-0.02	0.00	**-0.35**	-0.05	-0.05	0.13	0.05
	(-1.44)	(0.00)	**(-9.98)**	(-1.25)	(-1.26)	(2.83)	(1.25)
m^4	0.02	0.01	-0.11	**-0.18**	-0.05	0.05	-0.01
	(1.25)	(0.28)	(-3.13)	**(-5.26)**	(-1.34)	(1.24)	(-0.38)
m^5	0.00	0.02	0.00	-0.10	**-0.18**	0.14	-0.07
	(0.16)	(0.77)	(0.14)	(-3.01)	**(-5.42)**	(3.41)	(-2.22)
m^6	0.01	0.05	0.05	0.02	-0.11	**-0.15**	-0.22
	(0.79)	(1.93)	(1.28)	(0.41)	(-3.01)	**(-3.21)**	(-5.81)
m^7	0.06	0.10	0.16	0.08	-0.23	-0.31	**-0.30**
	(3.75)	(3.54)	(3.73)	(1.85)	(-5.18)	(-5.94)	**(-6.82)**
Observations	7,376	7,376	7,376	7,376	7,376	7,376	7,376
H_0	-0.02	-0.10	-0.29	-0.16	-0.11	-0.17	-0.31
t-stat	(-0.81)	(-3.62)	(-7.99)	(-4.31)	(-3.07)	(-3.70)	(-6.65)

	Panel A2: Issue Cutoff at 10%, All Bonds						
	1-2 Yr	3-4 Yr	5-6 Yr	7-8 Yr	9-10 Yr	11-20 Yr	21- Yr
m^1	**-0.05**	-0.23	-0.38	0.02	0.07	0.18	0.12
	(-2.25)	(-5.41)	(-5.08)	(0.27)	(0.80)	(1.92)	(1.57)
m^2	-0.01	**-0.14**	-0.31	-0.06	-0.02	0.16	0.15
	(-0.58)	**(-5.90)**	(-7.39)	(-1.38)	(-0.40)	(2.90)	(3.58)
m^3	-0.02	-0.01	**-0.37**	-0.03	-0.01	0.12	0.03
	(-1.68)	(-0.57)	**(-9.98)**	(-0.84)	(-0.29)	(2.63)	(0.90)
m^4	0.00	-0.01	-0.11	**-0.17**	-0.04	0.05	-0.02
	(0.40)	(-0.63)	(-3.07)	**(-4.39)**	(-1.06)	(1.09)	(-0.60)
m^5	0.00	0.01	-0.03	-0.10	**-0.19**	0.16	-0.06
	(-0.16)	(0.56)	(-0.80)	(-2.68)	**(-5.24)**	(3.69)	(-1.79)
m^6	0.02	0.03	0.13	0.07	-0.07	**-0.23**	-0.29
	(1.43)	(1.33)	(3.40)	(1.73)	(-1.59)	**(-4.66)**	(-7.50)
m^7	0.06	0.11	0.25	0.19	-0.18	-0.40	**-0.60**
	(4.33)	(4.08)	(5.30)	(3.69)	(-3.39)	(-6.57)	**(-12.88)**
Obs.	6,079	6,079	6,079	6,079	6,079	6,079	6,079
H_0	-0.06	-0.13	-0.30	-0.18	-0.16	-0.27	-0.59
t-stat	(-2.57)	(-5.06)	(-7.86)	(-4.48)	(-3.97)	(-5.21)	(-11.95)

	Panel B1: Issue Cutoff at 3%, Straight Bonds Only						
	1-2 Yr	3-4 Yr	5-6 Yr	7-8 Yr	9-10 Yr	11-20 Yr	21- Yr
m^1	**0.01**	-0.05	-0.34	-0.03	-0.06	0.01	0.10
	(0.20)	(-0.46)	(-2.73)	(-0.24)	(-0.52)	(0.09)	(0.87)
m^2	0.12	**-0.08**	-0.32	0.05	-0.11	0.16	0.11
	(2.88)	**(-1.38)**	(-4.25)	(0.77)	(-1.68)	(2.04)	(1.57)
m^3	-0.06	-0.04	**-0.43**	0.01	0.03	0.21	0.07
	(-1.46)	(-0.62)	**(-6.23)**	(0.09)	(0.44)	(2.97)	(1.06)
m^4	0.05	0.09	-0.07	**-0.17**	-0.04	0.05	-0.14
	(1.41)	(1.66)	(-1.02)	**(-2.80)**	(-0.62)	(0.66)	(-2.33)
m^5	-0.01	-0.02	-0.04	-0.03	**-0.18**	0.15	-0.11
	(-0.37)	(-0.39)	(-0.55)	(-0.43)	**(-3.27)**	(2.28)	(-1.81)
m^6	0.01	0.06	-0.10	-0.12	-0.18	**0.10**	-0.13
	(0.38)	(1.15)	(-1.61)	(-2.12)	(-3.38)	**(1.50)**	(-2.19)
m^7	0.07	0.09	0.00	-0.02	-0.21	-0.22	**-0.23**
	(1.82)	(1.56)	(-0.01)	(-0.31)	(-3.42)	(-3.04)	**(-3.54)**
Observations	2,573	2,573	2,573	2,573	2,573	2,573	2,573
H_0	-0.13	-0.10	-0.31	-0.15	0.05	-0.22	-0.21
t-stat	(-0.18)	(-1.73)	(-4.26)	(-1.75)	(0.69)	(-3.22)	(-2.96)

	Panel B2: Issue Cutoff at 10%, Straight Bonds Only						
	1-2 Yr	3-4 Yr	5-6 Yr	7-8 Yr	9-10 Yr	11-20 Yr	21- Yr
m^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^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^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^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^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^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^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	-0.09	-0.09	-0.37	-0.19	-0.13	-0.04	-0.35
t-stat	(-1.38)	(-1.35)	(-4.35)	(-2.48)	(-1.98)	(-0.49)	(-4.43)

Table 11. Other Channels of Rollover Risk Management

The sample includes firms with corporate bond and accounting information available in the FISD and COMPUSTAT Annual databases for the period from 1991 to 2012. 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, α_i is a firm 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. $Cash$ is cash holdings divided by assets. $LimitLC$ is the total amount of credit lines available divided by assets. Rec is the short-term debt reclassified under SFAS No. 6 as long-term debt divided by total assets. $EqIssue$ is sale of common and preferred stocks divided by assets. Q is the market-to-book ratio and Lev is the market value of leverage. Age is the number of years in the COMPUSTAT file prior to observations. $Prof$ and Tan are 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.

	$GRAN1$				$GRAN2$			
$Cash$	-0.02				0.00			
	(-0.13)				(0.02)			
Rec		-3.06				-1.53		
		(-6.95)				(-7.69)		
$LimitLC$			-0.03				-0.16	
			(-0.15)				(-1.55)	
$EqIssue$				0.19				-0.05
				(1.23)				(-0.64)
Q	0.19	0.33	0.25	0.18	0.09	0.12	0.15	0.09
	(2.02)	(2.73)	(2.41)	(1.84)	(2.37)	(2.57)	(2.82)	(2.34)
$Size$	0.73	0.85	0.78	0.74	0.31	0.34	0.39	0.32
	(10.44)	(8.89)	(8.99)	(10.47)	(12.82)	(10.23)	(10.79)	(12.82)
Age	0.18	0.48	0.31	0.14	-0.08	0.14	0.04	-0.07
	(0.96)	(1.14)	(1.75)	(0.71)	(-0.78)	(0.55)	(0.23)	(-0.66)
Lev	1.63	2.74	2.12	1.64	0.93	1.42	1.27	0.93
	(7.66)	(7.91)	(7.99)	(7.49)	(9.74)	(9.47)	(9.98)	(9.42)
$Prof$	-0.79	-0.24	-0.90	-0.83	-0.33	-0.14	-0.33	-0.37
	(-4.08)	(-0.75)	(-3.99)	(-4.23)	(-3.79)	(-1.07)	(-2.95)	(-4.16)
Tan	-0.18	0.46	-0.67	-0.08	-0.18	0.04	-0.36	-0.16
	(-0.51)	(0.84)	(-1.80)	(-0.23)	(-1.33)	(0.22)	(-2.19)	(-1.22)
$BondMat$	0.02	0.02	0.01	0.02	0.04	0.04	0.04	0.04
	(3.15)	(2.54)	(0.48)	(3.01)	(15.40)	(12.61)	(8.22)	(15.26)
$ProfVol$	0.18	0.32	-0.36	0.23	-0.23	-0.06	-0.62	-0.22
	(0.38)	(0.28)	(-0.66)	(0.49)	(-0.83)	(-0.11)	(-1.47)	(-0.77)
Obs.	19,087	10,343	8,081	18,475	19,087	10,343	8,081	18,475
R^2	0.763	0.789	0.858	0.767	0.833	0.845	0.893	0.834
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 12. 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 2012. 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, α_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. $BankLoanPct$ is the percentage of non-bond debt with respect to the total amounts of debt. $Size$ 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 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
$BankLoanPct$	-0.50	-5.03	-0.71	-5.71	-0.40	-1.85	-0.53	-2.65
	(-1.44)	(-8.16)	(-2.01)	(-6.21)	(-3.58)	(-7.52)	(-4.89)	(-7.52)
Q	0.21	0.29	0.25	0.36	0.12	0.05	0.11	0.01
	(2.54)	(1.92)	(2.50)	(1.86)	(3.30)	(0.63)	(2.75)	(0.13)
$Size$	1.08	0.63	0.85	0.83	0.49	0.30	0.36	0.33
	(23.10)	(11.31)	(9.05)	(4.62)	(34.08)	(13.59)	(11.73)	(4.39)
Age	0.03	0.02	0.18	0.42	0.02	0.02	-0.04	0.09
	(9.41)	(4.93)	(0.75)	(1.15)	(13.20)	(7.01)	(-0.31)	(0.49)
Lev	2.87	1.75	2.43	2.09	1.36	0.63	1.38	0.91
	(11.25)	(4.22)	(8.48)	(3.82)	(13.31)	(3.83)	(10.85)	(3.20)
$Prof$	-2.04	-1.02	-0.69	0.01	-0.66	-0.43	-0.20	0.02
	(-8.02)	(-1.67)	(-3.23)	(0.01)	(-5.96)	(-1.42)	(-1.93)	(0.05)
Tan	1.27	0.18	-0.26	0.12	0.30	0.10	-0.08	-0.05
	(4.27)	(0.67)	(-0.69)	(0.18)	(3.40)	(0.78)	(-0.54)	(-0.16)
$BondMat$	0.03	0.04	0.00	0.03	0.06	0.06	0.04	0.05
	(4.18)	(2.93)	(-0.17)	(1.30)	(22.60)	(14.18)	(9.88)	(6.07)
$ProfVol$	1.34	1.79	-0.30	2.42	0.23	0.22	-0.45	0.08
	(4.06)	(1.93)	(-0.56)	(0.87)	(1.45)	(0.49)	(-1.24)	(0.06)
Obs.	9,410	2,926	9,410	2,926	9,410	2,926	9,410	2,926
R^2	0.59	0.433	0.864	0.776	0.72	0.591	0.902	0.861
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 13. 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 2012. 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 2010–2012) and the crisis (2008–2009) periods. $X_{i,t}$ is a vector of explanatory variables, α_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 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	0.25	0.45	0.18	0.47	0.11	0.29	0.08	0.18
	(2.89)	(3.01)	(1.78)	(2.98)	(3.09)	(4.27)	(2.02)	(2.04)
$Size$	0.88	0.89	0.73	0.72	0.40	0.44	0.31	0.34
	(22.22)	(15.13)	(10.17)	(3.10)	(29.49)	(19.78)	(12.48)	(3.17)
Age	0.03	0.03	0.18	0.20	0.02	0.02	-0.09	0.18
	(10.62)	(7.46)	(0.97)	(3.12)	(15.32)	(9.45)	(-0.84)	(5.05)
Lev	1.47	1.64	1.66	1.40	0.69	0.95	0.94	0.59
	(6.99)	(4.31)	(7.29)	(2.95)	(7.77)	(5.56)	(9.20)	(2.13)
$Prof$	-1.74	-1.95	-0.78	-0.56	-0.65	-0.71	-0.35	-0.15
	(-6.93)	(-4.99)	(-3.76)	(-1.28)	(-6.30)	(-3.84)	(-3.66)	(-0.82)
Tan	1.07	0.77	-0.13	-0.60	0.35	0.04	-0.15	-0.26
	(4.27)	(1.97)	(-0.40)	(-0.63)	(4.39)	(0.27)	(-1.13)	(-0.52)
$BondMat$	0.05	0.03	0.02	-0.03	0.07	0.06	0.04	0.01
	(7.02)	(3.56)	(3.19)	(-1.46)	(28.17)	(15.99)	(15.35)	(0.84)
$ProfVol$	1.74	1.08	0.22	0.72	0.29	0.37	-0.25	0.53
	(5.43)	(1.97)	(0.45)	(0.81)	(2.03)	(1.38)	(-0.84)	(0.93)
Obs.	17,398	1,691	17,398	1,691	17,398	1,691	17,398	1,691
R^2	0.458	0.466	0.759	0.962	0.623	0.627	0.831	0.963
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