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Granularity of Corporate Debt

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Abstract

We study whether firms spread out debt-maturity dates, which we call *granularity of corporate debt.* In our model, firms that are unable to roll over expiring debt need to liquidate assets. If multiple small asset sales are less inefficient than a single large one, it can be optimal to diversify debt rollovers across time. Using a large sample of corporate bond issuers during the 1991–2012 period, we establish novel stylized facts and evidence consistent with our model's predictions. There is substantial heterogeneity (i.e., firms have both concentrated and dispersed debt structures). Debt maturities are more dispersed for larger and more mature firms and for firms with better investment opportunities, higher leverage, and lower profitability. During the recent financial crisis, firms with valuable investment opportunities implemented more dispersed maturity structures. Finally, firms manage granularity actively and adjust toward target levels.

I. Introduction

Firms have debt outstanding with different maturity dates, although the fixed-cost components of debt issues and secondary market illiquidity should motivate them to concentrate debt issues into a single issue or few issues. What are frictions and trade-offs for firms to avoid or face maturity concentrations? Choi, Hackbarth, and Zechner (2018) offer causal evidence that firms indeed manage debt-rollover dates by spreading out maturities in response to an unexpected increase in rollover

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risk in a well-identified sample. In this article, we extend their study to a large panel spanning 2 decades of corporate bond issuers in the United States and characterize the determinants of firms' decisions to spread out bond maturity dates across time, which we call *granularity of corporate debt.*

Building on Choi, Hackbarth and Zechner (2018), we formalize what factors drive this important, and so far unexplored, dimension of debt structure and generate a number of testable implications. We consider a 3-period model in which rollover risk influences debt structure because it can have real effects. The project can be financed by either a large debt issue with a single rollover date or by two smaller issues with different rollover dates. Thus, each debt issue must be rolled over at least once before the final date. We refer to the former case as a firm with a concentrated maturity structure, or as firm C, because it refinances at one point in time (i.e., at date 1 or 2). The latter case is referred to as a firm with a dispersed maturity structure, or firm D, because it refinances at two points in time.

Along some paths, the bonds can be rolled over and the firm's full final payoffs including noncontractible cash flows are eventually realized. Along other paths, however, the firm can temporarily lose its access to the bond market. The firm's inability to access the bond market may arise endogenously because it can become temporarily exposed to a large risk, which we refer to as a *technology shock.* We show that in such states, investors may not roll over their bonds. As a consequence, the firm's project must be partially liquidated to repay the bondholders, and this may be inefficient (i.e., reduce the firm's net worth).[1]

Firm D only needs to partially liquidate assets so that it can preserve the positive net present value (NPV) of the noncontractible cash flows. By contrast, if firm C cannot roll over its bonds, then it must liquidate more and hence loses the positive NPV of the noncontractible cash flows. Thus, it is less costly to be exposed to small rollover risks at two points in time rather than being exposed to a large rollover risk at one point in time.[2] Yet, a larger bond issue has lower flotation costs (see Lee et al. (1996)) and illiquidity costs (see Longstaff, Mithal and Neis (2005)) than two smaller bond issues. Thus, there is a trade-off in that firm D has a flexibility

[1]See, for example, 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 production after disasters such as Fukushima) or hedge funds (e.g., after the financial crisis); and impending natural catastrophes, such as oil spills, whose exact consequences for businesses such as tourism are unknown for some time (see, e.g., Massa and Zhang (2011)). One such example of a market freeze and rollover risk is the bankruptcy of General Growth Properties in April 2009.

[2]There may be additional motives for firms to issue debt with different maturity dates. Matching the 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 with 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 article remain relevant even in the presence of other motives for spreading debt-maturity dates across time.

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(or real-option) advantage over firm C, whereas firm C has a transaction-cost or bond-liquidity advantage over firm D.

Based on trading off costly project liquidation (or underinvestment) against transaction costs, we derive a number of testable implications. Our model implies that incentives to spread out debt maturities increase with rollover risk and investment opportunities. Moreover, corporate debt should be more dispersed for larger and more mature firms because of their lower transaction costs, for firms with higher leverage ratios, and for less profitable firms because of 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 Income 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 the FISD to measure debt-maturity dispersion.[3] For each firm, we group bond maturities into the nearest integer years and compute the fraction of bond amounts outstanding each year. The first measure of maturity dispersion is the inverse of the maturity profile's Herfindahl index based on this fraction. 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 novel stylized facts about debt granularity. Notably, a firm's average number of bonds outstanding in our sample is 4.9, with an interquartile range between 1.0 and 4.0 but a high standard deviation of 9.4. In other words, although a large fraction of firms have dispersed maturity structures, we also find that numerous firms have 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 manage maturity profiles 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 on the 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, for example, including the number of bonds as an

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

[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.

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explanatory variable, including private debt-maturity profiles in our granularity measures, instrumenting leverage and maturity, and stratifying the sample into firms with high and low proportions of private debt.

In addition, we perform tests showing that firms manage debt-maturity dispersion. 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 toward target levels over time. In particular, speed-of-adjustment regressions reveal fairly high and statistically significant adjustment rates, ranging from 14% to 52% per year. These results also complement those reported by Choi et al. (2018), which show a causal relationship between increased rollover risk and firms' active maturity management.

Our article relates to 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 (2014) 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. He and Milbradt (2016) consider an endogenous, dynamic debt-maturity structure. Chen, Yu, and Yang (2020) study the link between credit spreads, systematic risk, and lumpy maturity structure. These articles focus on single-bond firms' debt-maturity choice. Closer to our work is that of Diamond and He (2014), which shows that maturing short-term debt can create more debt overhang than nonmaturing long-term debt. Most relatedly, Huang, Oehmke, and Zhong (2019) develop a multiperiod model of debt structure in which firms trade off incentives to repay debt and prevent costly early liquidation. However, these articles do not examine the decision of diversifying debt rollovers across dates and, in particular, when it is likely optimal to avoid maturity concentrations. In our setting, neither a single long-term nor a single short-term bond is likely optimal because only a combination of debt with different rollover dates can, at the expense of higher transaction costs, minimize real inefficiencies resulting from rollover risk.

Our article 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 resulting from changes in the maturity of Treasuries. Using syndicated loan data for U.S. firms, Mian, and Santos (2018) find that most creditworthy firms frequently

[5]For earlier theories of maturity structure, see, for example, Brick and Ravid (1985), Diamond (1991), and Flannery (1986).

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

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manage (i.e., extend) loan maturities to reduce liquidity risk. Rauh and Sufi (2010) and Colla, Ippolito, and Li (2013) establish that relative to large, high-credit-quality firms, small, low-rated firms have dispersed or multitiered debt structures, whereas small, unrated firms specialize in fewer types. Finally, Harford, Klasa, and Maxwell (2014), 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. Most other studies exclusively focus on average debt maturity (see, e.g., Barclay and Smith (1995), Guedes and Opler (1996), Johnson (2003), and Saretto and Tookes (2013)). Unlike these studies, we focus on examining the determinants of the granularity of corporate debt.

The rest of the article is organized as follows: Section II describes the model and its implications. Section III presents data sources, granularity measures, summary statistics, and stylized facts. Section IV provides the empirical analysis of variation in granularity and how actively firms manage it. Section V contains a number of additional robustness tests, and Section VI concludes. The Appendix provides variable definitions.

II. A Simple Theory of Debt Granularity

We develop a simple framework in which firms are unable to refinance their entire debt externally in some states of the world and are therefore forced to engage in inefficient project liquidations or underinvestment. Because multiple small debt rollovers are less risky than a single large one, it can be advantageous to diversify debt rollovers across maturity dates.

A. Environment

We build a model of debt-maturity dispersion that extends the one in Choi, Hackbarth and Zechner (2018) by considering endogenously arising time-varying access to external debt markets and inefficient, early liquidations. We consider an initially all-equity-financed firm at time t_0 over 3 periods (i.e., times t_1, t_2, and t_3) and normalize the riskless interest rate to 0. 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 of $I+H$ at time t_3. Importantly, only the firm's invested assets I are contractible, whereas H represents noncontractible growth options.

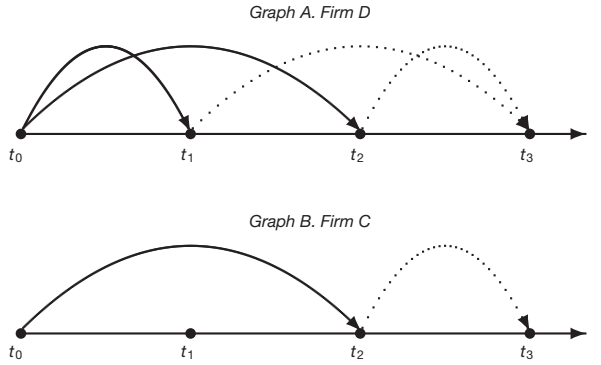
To raise the required capital $I-A$, the firm must issue debt, and given our focus on the effects of rollover risk, we require the debt to mature before the firm's final liquidation period, t_3.[7] Specifically, the firm can choose a *concentrated* (less granular) debt-maturity structure by issuing a single large bond, or it can choose a *dispersed* (more granular) maturity structure by issuing two smaller bonds, one to be rolled over at time t_1 and the other to be rolled over at time t_2 (see Figure 1). Without loss of generality, we assume that the issue size of each bond equals half of

[7]To keep the model focused, we do not introduce other frictions, such as asymmetric information, which could provide an endogenous motive for shorter debt maturities. For the same reason, we do not consider other securities, such as equity or convertibles, or other means to mitigate rollover risk, such as credit lines or cash reserves.

FIGURE 1

Evolution of Rollover Decisions

Figure 1 plots the timeline of rollover decisions for the dispersed maturity structure (or firm D) with two smaller issues, which expire at time t_1 and t_2, and the concentrated maturity structure (or firm C) with one larger issue, which expires at time t_2. An expiring issue needs to be rolled over to time t_3 to realize the firm's noncontractible cash flow.



the required outside capital. We will refer to the former as firm C, for *concentrated*, and to the latter as firm D, for *dispersed.* It is straightforward to show that firm C is indifferent between rolling over its single bond at time t_1 or at time t_2. Without loss of generality, we therefore only consider the latter case. Moreover, each bond issue requires a fixed cost, k, at time t_0. That is, firm C incurs only k and hence has a transaction-cost advantage of k because firm D's two bond issues cost 2 k.

To generate rollover risk, we consider firm-specific shocks that can lead to obsolescence of the firm (see Figure 2). At both times t_1 and t_2, the firm reaches a *high-uncertainty state* with probability λ, respectively. In this high-uncertainty state, the firm may not be able to raise enough capital by issuing new bonds to repay the old one because the firm becomes vulnerable to a technology shock. With probability π the technology shock actually takes place at time t_1^+ or t_2^+, 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 operating just as in the *low-uncertainty state* that arises with probability $1-\lambda$.[8]

B. Equity Values

We will now derive the equity values of firms with different debt granularity. Consider first firm D, which issues two bonds at time t_0, one that needs to be rolled over at time t_1 and one that needs to be rolled over at time t_2. Without loss of generality, we assume that each bond raises half the required outside capital (i.e., $(I-A)/2$ needs to equal the market (present) value of each bond issue). Because the 1-period bond turns out to be riskless, its initial face value is $F_{0,1}^D = (I-A)/2$.

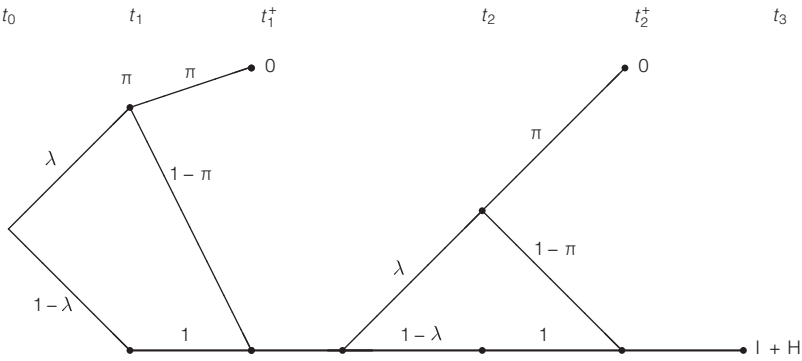
[8]Firm-specific shocks are potentially correlated across firms. Hence, firms may perceive larger rollover risks during economic downturns. This potentially market-wide variation in the effect of rollover risk is discussed in Section V.C.

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FIGURE 2

Evolution of Cash Flows, Risks, and Shocks

Figure 2 plots the timeline of cash flows, risks, and shocks. In each of the 2 periods, there is a probability λ with which firms become vulnerable to a technology shock, which will then occur with probability π. If the technology shock takes place, the firm's value drops to 0. In the absence of any technology shocks, the firm realizes its contractible and noncontractible components $I+H$ at time t_3.



However, the 2-period bond defaults with probability $1-\lambda\pi$, in which case the recovery value is 0. Therefore, its initial face value is $F^D_{0,2}=(I-A)/(2(1-\lambda\pi))$.

To roll over the first bond at time t_1 in state λ, the firm must issue a new bond with a face value of $F_{1,3,\lambda}=(I-A)/(2(1-\pi)(1-\lambda\pi))$ because the rolled-over amount is only repaid with probability $(1-\pi)(1-\lambda\pi)$. Note that the present value of such a bond is exactly $(I-A)/2$, which is required to repay the first bond. Thus, to make the project viable, we assume that $I\geq(I-A)/(2(1-\pi)(1-\lambda\pi))$. To roll over the first bond at time t_1 in the low-uncertainty state $1-\lambda$, the new bond must have a face value of $F_{1,3,1-\lambda}=(I-A)/(2(1-\lambda\pi))$.

The second bond needs to be rolled over at time t_2. Because the face value of this bond is $F^D_{0,2}=(I-A)/(2(1-\lambda\pi))$, rollover in the high-uncertainty state λ would require a new bond issue with a face value of $F^D_{2,3,\lambda}=(I-A)/(2(1-\pi)(1-\lambda\pi))$. If the available contractible time t_3 cash flow of $I-(I-A)/(2(1-\pi)(1-\lambda\pi))$, where the second term reflects the face value of the bond that has been issued at time t_1, is insufficient to issue such a bond, we assume that the project can be partially liquidated by giving up a time t_3 cash flow of $(I-A)/(2(1-\pi)(1-\lambda\pi))$ and generating a time t_2 cash flow of $(I-A)/(2(1-\lambda\pi))$. That is, such a partial (or small) project liquidation is not inefficient because H is not lost. If the second bond must be rolled over at time t_2 in the low-uncertainty state $1-\lambda$, then the required face value of the new bond is only $F^D_{2,3,\lambda}=(I-A)/(2(1-\lambda\pi))$ (i.e., lower than that required in the high-uncertainty state).

To summarize, firm D issues at time t_0 a 1-period bond with a face value of $F^D_{0,1}=(I-A)/2$, which is rolled over by issuing a new bond that expires at time t_3 and has a face value of $F_{1,3,\lambda}=(I-A)/(2(1-\pi)(1-\lambda\pi))$ or $F_{1,3,1-\lambda}=(I-A)/(2(1-\lambda\pi))$, respectively. Also at time t_0, firm D issues a 2-period bond with a face value of $F^D_{0,2}=(I-A)/(2(1-\lambda\pi))$, which is rolled over at time t_2 either by partially liquidating the project or by issuing a new bond with a face value of $F^D_{2,3,\lambda}=(I-A)/(2(1-\pi)(1-\lambda\pi))$. In the low-uncertainty state $1-\lambda$, the rollover requires pledging time t_3 cash flows of $F^D_{2,3,1-\lambda}=(I-A)/(2(1-\lambda\pi))$ to bondholders. The resulting cash flows to equity holders are displayed in Table 1.

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TABLE 1

Paths, Probabilities, and Cash Flows for Firm D

Table 1 provides the probabilities and the cash flows to equity holders of firm D for all possible state trajectories. At time t_0, firm D issues two bonds: One with face value $F^D_{0,1} = (I-A)/2$ that is rolled over at t_1 by issuing a new bond with face value $F^D_{1,3,\lambda} = (I-A)/2(1-\pi)(1-\lambda\pi)$ (in the high-uncertainty state) or with face value $F^D_{1,3,1-\lambda} = (I-A)/2(1-\lambda\pi)$ (in the low-uncertainty state). Also at time t_0, the firm issues a 2-period bond with face value $F^D_{0,2} = (I-A)/(2(1-\lambda\pi))$, which is rolled over at time t_2 either by partially liquidating the project or by issuing a new bond with face value of $F^D_{2,3,\lambda} = (I-A)/(2(1-\pi)(1-\lambda\pi))$ (in the high-uncertainty state) or $F^D_{2,3,1-\lambda} = (I-A)/(2(1-\lambda\pi))$ (in the low-uncertainty state).

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	$(1-\lambda)(1-\lambda)$	$I+H-\frac{I-A}{1-\lambda\pi}$

Next we derive the equity value for firm C. Recall that firm C only issues a single bond that needs to be rolled over at time t_2 and has a required face value of $F^C_{0,2} = (I-A)/(1-\lambda\pi)$. In the high-uncertainty state λ, the rollover requires issuing a new bond with a face value of $F^C_{2,3,\lambda} = (I-A)/((1-\pi)(1-\lambda\pi))$ because with probability π, the technology shock materializes, and all cash flows are lost. If the time t_3 contractible cash flows are not sufficient to make such a bond issue feasible, then the firm must liquidate the entire project to repay the bond. This is inefficient because we assume that the project has a positive NPV (i.e., $I+H > I/((1-\lambda\pi)^2)$; that is, the required amount to repay the expiring bond is less than the expected project cash flows under continuation.[9] Firm C is unable to refinance its bond in the high-uncertainty state at time t_2 if the *endogenous market-freeze* condition holds:

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

In this case, firm C must generate cash internally by liquidating the entire project. Note that for a more highly levered firm (e.g., A is smaller or I is larger), the left-hand side is more likely to be smaller than the right-hand side, and hence condition (1) is more likely to hold.

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

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

[9]Convex project liquidation costs are assumed here without reliance on any specific functional form. It suffices to assume it is costless to partially liquidate a project, generating the capital needed to repay the dispersed firm's debt face value $F^D_{0,2}$. However, it is costly to fully liquidate a project to generate the capital needed to repay the concentrated firm's debt $F^C_{0,2}$; that is, a radical liquidation of the project implies a loss of the final cash flows $I+H$.

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TABLE 2

Paths, Probabilities, and Cash Flows for Firm C

Table 2 provides the probabilities and the cash flows to equity holders of firm C for all possible state trajectories. At time t_0, firm C issues a single bond with face value $F^C_{0,2} = (I-A)/(1-\lambda\pi)$ that must be rolled over at t_2. In the low-uncertainty state, this requires issuing a new (riskless) bond, expiring at t_3 with the same face value equal to $F^C_{2,3} = (I-A)/(1-\lambda\pi)$. In the high-uncertainty state, contractible cash flows are insufficient to roll over the bond and the entire project must be liquidated to repay the bond.

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	$(1-\lambda)(1-\lambda)$	$I+H-\frac{I-A}{1-\lambda\pi}$

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

Equation (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 equity holders must repay debt holders their contributed capital, $I-A$, in expectation. Finally, the transactions costs are $2k$.

The equity value of firm C is given by:

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

Equation (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 $1-\lambda\pi$). Moreover, at time t_2, firm C's final payoff is always lost in the high-uncertainty state, so its final payoff arises only in the low-uncertainty state, which occurs with probability $1-\lambda$. Finally, notice that firm D generates the final payoff at time t_2 with probability $1-\lambda\pi > 1-\lambda$, which is the source of inefficiency that is traded off against transaction costs.

C. Implications

Comparing equity values allows us to pin down the benefits of spreading out maturity dates, which is defined by the difference in equity values, $\Delta E \equiv E^D - E^C$, which is informative about the incentives for creating a dispersed debt structure:

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

To begin, notice that equation (4) reveals that the model with endogenous market freezes yields testable implications similar to Choi, Hackbarth and Zechner (2018) without asset sales and without endogenous market freezes. The relative advantage of dispersed debt maturities increases with H, and it decreases with k and A (i.e., condition (1) does not hold for a sufficiently large level of A so that ΔE becomes $-k$). It also follows from equation (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).

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The implications for testing are as follows: 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 NPV, H, rises. Put differently, it is optimal for a firm with more profitable projects as measured, for example, 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 flotation and liquidity costs will have a lower incentive to implement a more dispersed maturity profile.

There are additional implications 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 $I - A \leq I/2$ for firm C. 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 these predictions should apply to both a comparison of firms with different characteristics and the bond-issuance decisions of a given firm through time.

Finally, ΔE in equation (4) decreases with the probability of a technology shock π. That is, the benefit of debt granularity is to operate the firm's assets even during high-uncertainty times (i.e., the λ states in our model). However, if the technology shock always materializes in high-uncertainty times, then the benefit of debt granularity vanishes because $1 - \lambda\pi \approx 1 - \lambda$ for high values of π.

III. Data Description

A. Data Sources

Corporate bond data are drawn from Mergent's 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 Committee on Uniform Securities Identification Procedures (CUSIP) number 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 the FISD, which begins in the 1980s but becomes comprehensive in the early 1990s. We obtain firms' accounting data from the annual Compustat tapes. Merging these data sources, we measure debt granularity 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 (Standard Industrial Classification (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.

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B. Variable Construction

In Section II, bond-maturity concentration can be measured with a version of the Herfindahl index. Following Choi, Hackbarth, and Zechner (2018), we employ two measures of debt concentration that are also motivated by our model. First, we define the concentration index of firm j's debt maturity structure, H_j as:

$$\text{HERF}_j = \sum_i w_i^2, \tag{5}$$

where w_i denotes the fraction of firm j's principal amounts maturing in each maturity bucket i, and the maturity buckets are obtained by grouping bond maturities into the nearest integer years.

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

Second, the measure 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 perfectly dispersed granularity). Perfectly dispersed granularity consists of 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. Specifically, firm j's distance measure is as follows:

$$\text{DIST}_j = \frac{1}{t_j^{\max}} \sum_{i=1}^{t_j^{\max}} \left(w_{j,i} - \frac{1}{t_j^{\max}} \right)^2. \tag{6}$$

To capture dispersion rather than concentration or distance, we define the following granularity measures: inverse of the Herfindahl index, $\text{GRAN1} \equiv 1/\text{HERF}$, and negative value of the log of the squared distance from perfect dispersion, $\text{GRAN2} \equiv -\log(\text{DIST})$.[10] We use the maturity structure of corporate bonds from the 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 IV.E).

To investigate the empirical predictions from Section II.C, we include a number of explanatory and control variables in our regression specifications. The explanatory variables include market-to-book ratio (Q), firm size (SIZE), firm age (AGE), leverage (LEV), and profitability (PROF). We provide details on the construction of all variables used in this article in the Appendix.

C. 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

[10] In terms of GRAN1, Oehmke and Zawadowski (2017) construct a similar measure of fragmentation, and for GRAN2, we add 0.001 to DIST to prevent it from being negative infinity.

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TABLE 3

Sample Descriptive Statistics

The sample in Table 3 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. The means, standard deviations, 25th percentile, median, and 75th percentile of the main variables are reported. 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 equipment divided by assets), respectively. PROF_VOL is the standard deviation of earnings divided by assets using data from the past 5 years. BOND_MAT is the average of firms' bond maturities weighted by amounts. BOND_PCT is the ratio of the total book value of bonds available in the FISD to the total book debt in Compustat for each firm. BOND_AMT is the average amount of bond issues outstanding for each firm. BOND_AMT/ASSET is BOND_AMT divided by total assets. CASH is cash holdings divided by assets. LIMIT_LC is the total amount of credit lines available divided by assets, and EQ_ISSUE is the sale of common and preferred stocks divided by assets.

Variables	Mean	Std. Dev.	P25	Median	P75
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
PROF_VOL	0.06	0.08	0.03	0.04	0.07
BOND_MAT	9.01	5.82	5.01	7.43	11.59
BOND_PCT	0.65	0.30	0.42	0.69	0.95
BOND_AMT	217.66	300.71	91.66	150.00	261.00
BOND_AMT/ASSET	0.17	0.84	0.03	0.09	0.20
CASH	0.57	0.50	0.00	1.00	1.00
LIMIT_LC	0.15	0.12	0.06	0.12	0.20
EQ_ISSUE	0.02	0.06	0.00	0.00	0.01

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 BOND_PCT). The distribution of principal amounts, BOND_AMT, is informative about the relevance of fixed costs associated with bond issuance. The 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 BOND_AMT 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.

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 a GRAN1 value of 5.66. A perfectly granular firm with GRAN1 = 13 would have equal amounts expiring with 13 different maturities, whereas a firm with GRAN1 = 6 would have 6 different maturities with bonds of equal size.[11] Thus, the Herfindahl-based granularity measure of

[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 1.

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TABLE 4

Sample Descriptive Statistics Across Tercile Groups

Table 4 reports sample statistics for tercile groups based on two granularity measures (GRAN1 and GRAN2), bond percentage (BOND_PCT), and bond maturity (BOND_MAT). We report the 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 similarly to GRAN1 and GRAN2, respectively, but use Compustat's DD1–DD5 variables for maturities of 1 to 5 years and bond amounts in Mergent's Fixed Income Security Database (FISD) for maturities greater than 5 years. NBOND is the number of bonds outstanding for each firm. NMAT is the number of bond maturities grouped into the nearest integer years 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 is profitability (operating income divided by assets). BOND_MAT is the average of firms' bond maturities weighted by amounts. ASSET_MAT 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. BOND_PCT is the ratio of the total book value of bonds available in the FISD to total book debt in Compustat for each firm. BOND_AMT is the average amount of bond issues outstanding for each firm. CASH is cash holdings divided by assets. LIMIT_LC is the total amount of credit lines available divided by assets, and EQ_ISSUE is the sale of common and preferred stocks divided by assets.

	GRAN1			GRAN2			BOND_PCT			BOND_MAT		
Variables	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)
NMAT	1.00	2.60	7.94	1.02	1.89	6.98	2.78	3.91	3.15	2.10	2.85	4.93
	(1.00)	(2.00)	(6.00)	(1.00)	(2.00)	(5.00)	(1.00)	(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)

(continued on next page)

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TABLE 4 (continued)

Sample Descriptive Statistics Across Tercile Groups

	GRAN1			GRAN2			BOND_PCT			BOND_MAT		
Variables	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High
BOND_MAT	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)
ASSET_MAT	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)
BOND_PCT	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)
BOND_AMT	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)
BOND_AMT/ASSET	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)
LIMIT_LC	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)
EQ_ISSUE	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)
No. of 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

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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 a 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.

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 structures (i.e., GRAN1 = 1) and are all allocated to the low tercile. 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 they 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 Table 4 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, those in the high-BOND_PCT group have 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, for example, 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 (LIMIT_LC), and more equity issuances (EQ_ISSUE). For example, cash holding, lines of credit, and equity issuances are, on average, 0.14 (0.07), 0.18 (0.11), and 0.03 (0.01) in the tercile group with low (high) GRAN1.

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

[13]See the Appendix or Section IV.E for the construction of GRAN1L and GRAN2L.

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Finally, the last 3 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 (ASSET_MAT) is neither clearly increasing with nor reliably related to debt maturity. For the low, mid, and high terciles, the average maturity is 3.86, 7.50, and 15.66, respectively, whereas the average asset maturity is similar across the terciles, 5.15, 6.05, and 5.90, respectively. 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 3 plots the time-series averages of debt-maturity dispersion for issuing and nonissuing firms. For issuing firms, maturity dispersion seems to be countercyclical; that is, firms issue bonds to make maturity structures more dispersed during recessions. Increased rollover risk during recessions appears to push firms toward more dispersed debt structures, even though the 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.

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 the 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.

IV. Empirical Analysis of Variation in Debt Granularity

We have argued in Section II 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 III. In this section, we examine whether firm characteristics that proxy for different incentives for granularity management are reliably related to the observed variation in the dispersion of debt maturity structures.

A. Baseline Regressions

We begin by estimating the following baseline regression:

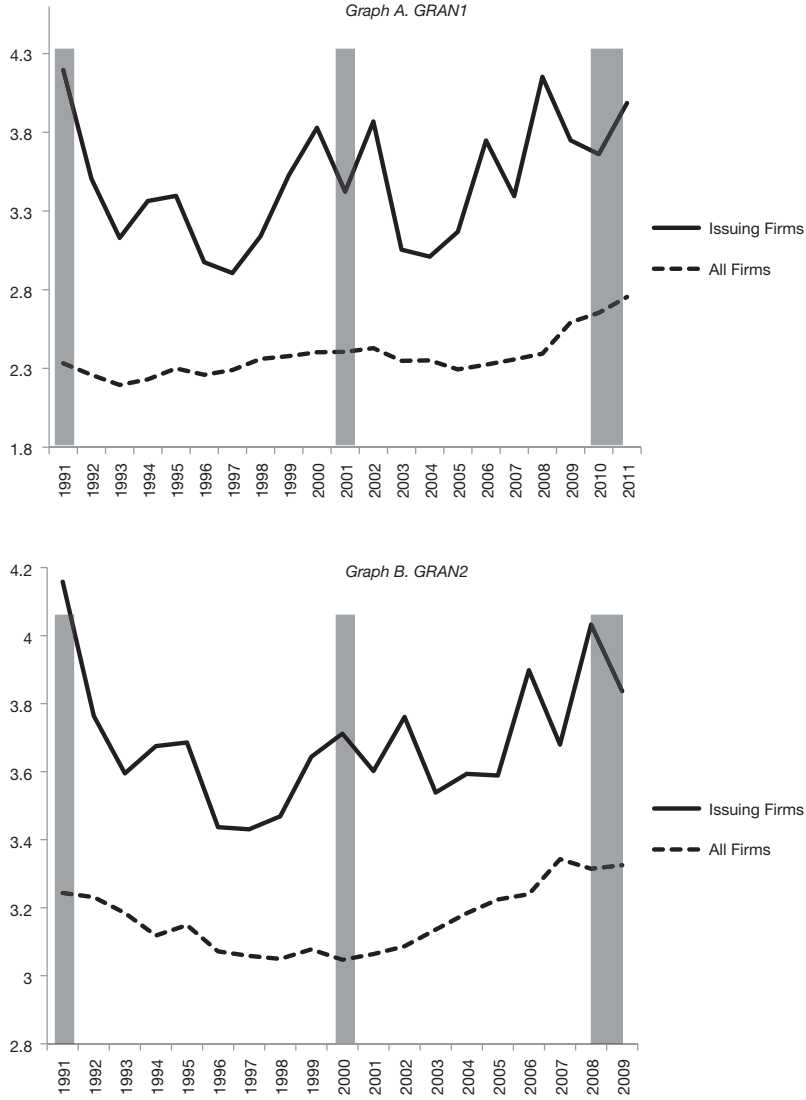
$$\text{GRAN}_{i,t+1} = \beta X_{i,t} + \alpha_i + y_t + \epsilon_{i,t+1} \tag{7}$$

where $X_{i,t}$ is a vector of explanatory and control variables, α_i is an industry- or firm-level fixed effect, and 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 ratio (Q), leverage (LEV), firm size (SIZE), firm age

FIGURE 3

Time Series of Debt Maturity Dispersion

Figure 3 plots the time series of aggregate debt-granularity measures, GRAN1 (Graph A) and GRAN2 (Graph B), 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 National Bureau of Economic Research (NBER) recessions.



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(AGE), and profitability (PROF) as explanatory variables, given that these variables are related to debt granularity according to our framework in Section II. 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 (BOND_MAT) because we want to study the incremental effect of firm characteristics on maturity dispersion. Finally, cash-flow volatility (PROF_VOL) might affect a firm's ability to roll over 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., as a result of 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 3 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 (7) for the measures GRAN1 (in the left panel) and GRAN2 (in the right panel). Overall, the estimated coefficients are mostly statistically significant, and their explanatory power is large. For example, in the first columns of the table for both granularity measures, all the variables are significant at the 1% level. Also, the R^2 is quite high (i.e., 0.422 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 1-standard-deviation change (0.98) in the market-to-book ratio changes GRAN1 by 0.29, which corresponds to an 11.8% (19.6%) change relative to the sample average (median) of 2.50 (1.50) for GRAN1 in Table 3.

Furthermore, the relation between the explanatory variables and debt-maturity dispersion is consistent with our arguments in Section II. 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 the log of total book assets, are reliably positive across all specifications in Table 5. Economically, firm size is highly significant. Observe that with a 1-standard-deviation change in the log of total assets (1.63), the dependent variable is predicted to change by approximately 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

[14]We employ the Fama–French 49-industry classification. The results are robust to other industry specifications, for example, 2-digit SIC codes.

TABLE 5

Baseline Regression

The sample in Table 5 includes firms with corporate bond and accounting information available in Mergent's Fixed Income Security Database (FISD) and the Compustat annual database 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 (FE), and y_t is a year FE. 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 equipment divided by assets), respectively. BOND_MAT is the average of firms' bond maturities, and PROF_VOL is the standard deviation of earnings divided by assets using data from the past 5 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)
BOND_MAT		0.05		0.05		0.02		0.07		0.07		0.04
		(6.99)		(7.04)		(3.16)		(27.92)		(28.69)		(15.43)
PROF_VOL		1.42		1.65		0.17		0.20		0.30		−0.24
		(4.91)		(5.23)		(0.37)		(1.46)		(2.05)		(−0.84)
No. of 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

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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, which is consistent with the results of Choi et al. (2018). They establish that the causal link between increased rollover risk and debt-maturity management is particularly pronounced among high-leverage firms. In Section IV.C, we further examine the link between leverage and granularity by using instrumental-variable regressions.

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

Moving to the extended baseline specification 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 II. For example, the reliably positive coefficient for BOND_MAT 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). Although 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 the 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.[16]

B. Number and Type of Bonds

Although the main explanatory variables in equation 7 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

[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.

[16]The baseline results reported in Table 5 are insensitive to controlling for maximum maturity.

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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.

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). These 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 the residuals from the regression of granularity on the number of bonds as a dependent variable 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.

Because 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 "$N \geq 2$" 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 ratio, 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 20% of their total bond amounts in bonds with option features and sinking fund provisions. Because effective maturities for bonds with options and sinking funds are likely to be much shorter than those for straight bonds, reestimating equation (7) for the subsample that is composed mostly of straight bonds is potentially more informative. Indeed, the columns labeled "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 with the full sample).

C. Instrumental Variable Regressions

In the regression setup of Section IV.A, 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. Choi, Hackbarth and

TABLE 6

Robustness Checks

The sample in Table 6 includes firms with corporate bond and accounting information available in Mergent's Fixed Income Security Database (FISD) and the Compustat annual database 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 (FE), and y_t is a year FE. 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 equipment divided by assets), respectively. BOND_MAT is the average of firms' bond maturities, and PROF_VOL is the standard deviation of earnings divided by assets using data from the past 5 years. IND_GRAN is the industry-level granularity, measured as median granularity. In the "NBOND" column, we control for the number of bonds. In the "RESID" column, 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 the "$N >= 2$" column, we include firms with more than or equal to two bonds outstanding in the regressions. The column labeled "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 the "IV" column, we run 2-stage least squares using asset maturity and the issuer-level credit rating for the firm's leverage and maturity. The "IND_GRAN" column reports the regression results with industry-level granularity controls. In the "LOANS" column, the dependent variables are GRAN1L and GRAN2L, which use Compustat's DD1–DD5 variables for maturities of 1–5 years and bond amounts in the FISD for maturities greater than 5 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	IND_GRAN	LOANS	NBOND	RESID	$N >= 2$	Straight	IV	IND_GRAN	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)
BOND_MAT	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)
PROF_VOL	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)						
IND_GRAN						0.27							0.17	
						(5.50)							(6.70)	
No. of 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

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Zechner (2018) address this endogeneity concern by employing a triple difference-in-differences regression in a quasi-natural experiment setting. In this subsection, we complement their results by performing 2-stage least squares (2SLS) regressions. Specifically, we instrument leverage and maturity using variables that are likely to affect granularity indirectly through leverage and maturity (but not directly). The first instrument we consider is the 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.[17] Therefore, granularity is likely to be of little or no importance in determining credit ratings. This observation implies that the credit 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 (2013) also employ asset maturity as an instrument for debt maturity. In our implementation of the 2SLS estimations, we employ both of these instruments.[18]

The columns labeled "IV" in 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 with the baseline results.[19] For example, the effect of Q and LEV more than doubles in the left panel for GRAN1.[20] 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 II that motivates firms to manage the granularity of their debt.

D. 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 the maturities of their liabilities with those of their assets (i.e., use the matching principle). So in the sixth columns of Table 6, we consider the possibility that industry granularity explains our baseline results. It turns out that IND_GRAN is economically and statistically significant when we add it to the regression

[17]Rating agencies only recently started to take firms' debt-maturity structures into consideration according to Standard & Poor's (S&P's) 2008 revision of its approach to credit ratings. Further, Gopalan, Song and Yerramilli (2014) 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."

[18]In untabulated results, we include industry leverage as the third instrument, similar to Saretto and Tookes (2013). The results are qualitatively the same.

[19]In the first-stage regression, asset maturity is negatively associated with leverage and positively with debt maturity, whereas ratings are negatively associated with market leverage and positively associated with debt maturity. The 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.

[20]This suggests that managers 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.

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 ratio 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 for the matching principle in our sample.

E. 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 (2018)). 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 are 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 greater for public debt than for private debt, which includes bank loans. In addition, Carey, Prowse, Rhea, and Udell (1993) find that public debt is cost-effective only above $100 million, whereas bank debt and nonbank 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 II.

Nonetheless, we examine whether our results are robust to the 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 the FISD by debt maturity variables from Compustat. Specifically, for maturities less than 5 years, we collect debt-maturity information available in Compustat (DD1–DD5). These Compustat variables include both public and private debt expiring in less than or equal to 5 years. For maturities greater than 5 years, we employ bond amounts available in the 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 5 years, this procedure should generate fairly good proxies for debt granularity that capture both public and private debt-maturity dispersion.[21]

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 reestimate equation (7) 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,

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

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and their signs are consistent with the ones predicted by the model in Section II. Overall, these results indicate that the firm characteristics we consider are also associated with total debt granularity.

F. Active Versus Passive Granularity Changes

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

Even without active granularity management, debt-maturity dispersion changes when preexisting bonds mature, which we call a *passive* granularity change. We define the passive component of a firm's granularity in year t, $\text{PASSIVE}_{\text{G}}\text{RAN}_t$, as the granularity level that the firm would achieve if it were to replace 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 the difference between the actual granularity in year t and the passive granularity, $\text{GRAN}_t - \text{PASSIVE_GRAN}_t$.[22]

This decomposition allows an analysis of how much of firms' total granularity change is attributable to the passive versus active components. Specifically, we denote the active granularity change as

$$\Delta_A \text{GRAN}_{t+1} \equiv \text{GRAN}_{t+1} - \text{PASSIVE_GRAN}_{t+1},$$

and we denote the passive granularity change as

$$\Delta_P \text{GRAN}_{t+1} \equiv \text{PASSIVE_GRAN}_{t+1} - \text{GRAN}_t.$$

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

In Table 7, we provide averages, standard deviations, and correlations of these components of granularity changes to gauge how much of the actual granularity change is attributable 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 ΔGRAN_t and $\Delta_A\text{GRAN}_t$ are almost the same for both measures, and the correlations between ΔGRAN_t and $\Delta_A\text{GRAN}_t$ 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.

We now test explicitly whether firms are active granularity managers. We proceed in 2 steps. In the first stage, we estimate the following partial-adjustment model:

$$\Delta\text{GRAN}_{i,t+1} = \gamma(\beta X_{i,t} - \text{GRAN}_{i,t}) + v_{i,t+1}, \tag{8}$$

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

[22]We thank the anonymous referee for suggesting this line of inquiry.

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TABLE 7

Summary Statistics on Active and Passive Granularity Changes

Table 7 provides the average, standard deviation, and correlations of the granularity change $\Delta GRAN_t$, the passive granularity change $\Delta_P GRAN_t (\equiv PASSIVE_GRAN_t - GRAN_t)$, and the active granularity change $\Delta_A GRAN_t (\equiv GRAN_t - PASSIVE_GRAN_t)$. The passive granularity change $PASSIVE_G RAN_t$ is defined as a granularity level that the firm would achieve if it were to replace an expiring bond with a new bond that has exactly the same maturity and face value as the expiring bond.

	$\Delta GRAN_t$	$\Delta_P GRAN_t$	$\Delta_A GRAN_t$		Correlations		
					$\Delta GRAN_t$	$\Delta_P GRAN_t$	$\Delta_A GRAN_t$
Panel A. GRAN1							
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							
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

adjustment toward target dispersion. Because we estimate equation (8) using the full sample of firms, γ represents the average speed of adjustment across all firms. In unreported results, we estimate the speed of adjustment firm by firm by relaxing the implicit assumption that equation 8 is the same across firms. We obtain qualitatively similar results.[23]

In the second stage, we examine how much of the partial adjustment estimated in equation (8) is attributable to the active versus passive granularity management. The second-stage regression is as follows:

$$\Delta_A \text{GRAN}_{i,t+1} = \gamma_A(\beta X_{i,t} - \text{GRAN}_{i,t}) + \eta_{i,t+1} \tag{9}$$

$$\Delta_P \text{GRAN}_{i,t+1} = \gamma_P(\beta X_{i,t} - \text{GRAN}_{i,t}) + \omega_{i,t+1} \tag{10}$$

where the granularity gap from the target $(\beta X_{i,t} - \text{GRAN}_{i,t})$ is estimated using the coefficients from the first-stage regression (equation (8)). Because $\Delta\text{GRAN}_{t+1} \equiv \Delta_A\text{GRAN}_{t+1} + \Delta_P\text{GRAN}_{t+1}$, 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 (8). Following Flannery and Rangan (2006), we include firm and year fixed effects in the first two columns to control for unobservable firm-specific heterogeneity in target granularity as well as any market-wide effects on maturity management.[24] 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. In addition, we employ the panel generalized method of moments (GMM) of Arellano and Bond (1991) and the double-differencing estimation of Han and Phillips (2010) because coefficient estimates are inconsistent in a dynamic-panel model with fixed effects.

[23]We thank the anonymous referee for this suggestion.

[24]For example, firms can exploit the shape of the yield curve by picking maturities with low interest rates. In untabulated results, we further address this channel of maturity management by showing that firms' maturity choices are not particularly affected by market-wide effects. We thank the anonymous referee for this suggestion.

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TABLE 8

First-Stage Regression: Adjustment Toward Target Granularity

Table 8 provides results for the following panel-regression equation: $\Delta GRAN_{i,t+1} = -\gamma GRAN_{i,t} + (\gamma\beta)X_{i,t} + v_{i,t+1}$, 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 equipment divided by assets), respectively. BOND_MAT is the average of firms' bond maturities, and PROF_VOL is the standard deviation of earnings divided by assets using data from the past 5 years. In the columns labeled "Industry FE" and "Firm FE," we report the estimation results by including industry-year fixed effects (FE) and firm-year FE, respectively. In the "Arellano–Bond" column, we report the estimation results employing a panel generalized method of moments (GMM) estimation using lags of maturity dispersion as instruments, following Arellano and Bond (1991). In the "Han–Phillips" column, we provide the results of the double-differencing estimation of Han and Phillips (2010). 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)
BOND_MAT	−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)
PROF_VOL	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)
No. of 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		

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 and 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.

Having established that firms adjust granularity toward target levels consistent with our theory, we examine how much of the adjustment is attributable to active granularity changes by estimating the second-stage regressions in equations (9)

TABLE 9

Second-Stage Regression: Active Versus Passive Management

Table 9 reports the estimation results of the second-stage regression in equations (9) and (10): $\Delta_A \text{GRAN}_{i,t+1} = \gamma_A(\beta X_{i,t} - \text{GRAN}_{i,t}) + \eta_{i,t+1}$ $\Delta_P \text{GRAN}_{i,t+1} = \gamma_P(\beta X_{i,t} - \text{GRAN}_{i,t}) + \omega_{i,t+1}$, where $\Delta_A \text{GRAN}_{t+1}(\equiv \text{GRAN}_{t+1} - \text{PASSIVE_GRAN}_{t+1})$ is the active granularity change, and $\Delta_P \text{GRAN}_{t+1}(\equiv \text{PASSIVE_GRAN}_{t+1} - \text{GRAN}_t)$ is the passive granularity change. The granularity gap, $\beta X_{i,t} - \text{GRAN}_{i,t}$, is estimated in the first-stage regression (equation (8)). We report coefficient estimates after normalization using the sum of the coefficients, $\gamma_A + \gamma_P$. 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 FE		Firm FE	
	Passive	Active	Passive	Active
$\beta X_{i,t} - \text{GRAN}_{i,t}$	0.12	0.88	0.10	0.91
	(10.86)	(18.70)	(10.97)	(23.95)
N	17,261	17,261	17,261	17,261
R^2	3.2%	9.0%	3.1%	11.7%
	Arellano–Bond		Han–Phillips	
	Passive	Active	Passive	Active
$\beta X_{i,t} - \text{GRAN}_{i,t}$	0.07	0.93	0.09	0.91
	(9.89)	(28.69)	(14.80)	(36.50)
N	16,554	16,554	16,554	16,554
R^2	0.7%	7.1%	0.7%	4.1%

Panel B. GRAN2

	Industry FE		Firm FE	
	Passive	Active	Passive	Active
$\beta X_{i,t} - \text{GRAN}_{i,t}$	0.02	0.98	0.02	0.98
	(7.80)	(36.58)	(7.97)	(41.94)
N	17,327	17,327	17,327	17,327
R^2	1.3%	32.5%	0.3%	44.2%
	Arellano–Bond		Han–Phillips	
	Passive	Active	Passive	Active
$\beta X_{i,t} - \text{GRAN}_{i,t}$	0.01	0.99	0.02	0.98
	(4.08)	(31.37)	(5.92)	(34.10)
N	16,616	16,616	16,616	16,616
R^2	0.3%	26.1%	0.3%	19.6%

and (10). 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 previous correlation analysis, a substantial portion of granularity adjustment is attributable to firms' active management. Across all specifications, we find that 88%–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 toward target levels.

Overall, these results support the view that firms actively manage debt-maturity dispersion. The speed with which firms make adjustments toward 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.

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V. Additional Robustness Checks

A. 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 II. Another channel is equity issuance, which can also solve the firm's problem in Section II. 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, EQ_ISSUE, 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 Statement of Financial Accounting Standards (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 noncancelable 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 LIMIT_LC, which is total lines of credit available divided by total assets.

To examine whether these channels are related to debt granularity, we include CASH, LIMIT_LC, REC, and EQ_ISSUE in our baseline specification (equation (7)) as independent variables. The results are reported in Table 10. 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 the rollover risk of bonds. That is, the debt-reclassification variable REC is negatively and reliably related to granularity. In contrast, the direct measure of credit lines LIMIT_LC is not statistically significant, which suggests that REC is a cleaner measure of the use of credit lines for debt rollover than LIMIT_LC because firms open credit lines for

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

TABLE 10

Other Channels of Rollover Risk Management

The sample in Table 10 includes firms with corporate bond and accounting information available in Mergent's Fixed Income Security Database (FISD) and the Compustat annual database 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 (FE), and y_t is a year FE. 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. LIMIT_LC is the total amount of credit lines available divided by assets. REC is the short-term debt reclassified under Statement of Financial Accounting Standards (SFAS) No. 6 as long-term debt divided by total assets. EQ_ISSUE is the 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 equipment divided by assets), respectively. BOND_MAT is the average of firms' bond maturities, and PROF_VOL is the standard deviation of earnings divided by assets using data from the past 5 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)		
LIMIT_LC			−0.03				−0.16	
			(−0.15)				(−1.55)	
EQ_ISSUE				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)
BOND_MAT	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)
PROF_VOL	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)
No. of 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

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.

In sum, the results suggest that in addition to spreading out debt maturity dates over time, firms use other channels of rollover risk management. Firms with significant amounts of credit lines available tend to have concentrated debt

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

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structures because they are more likely to roll over expiring debt without incurring inefficiencies and hence can economize on bond-issuance costs.

B. Proportion of Private Debt

In addition to the results provided in Table 6 for including private debt-maturity profiles in 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, because 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 (7) for low- and high-bank-debt subsamples. That is, in Table 11, we investigate whether a larger fraction of bank debt affects firms' granularity decisions. Firms are categorized as low-bank-loan firms if corporate bonds in the 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, BANK_LOAN_PCT, 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 are robust to variation in the proportion of private debt. Interestingly, we find a substitution effect of private debt because the coefficient on BANK_LOAN_PCT 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 II.

C. Granularity During the Financial Crisis

During the 2008–2009 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. Choi, Hackbarth, and Zechner (2018) show that firms increased their maturity dispersion when faced with higher rollover risk during the GM–Ford downgrade event in 2005. Building on the prior literature, we therefore examine whether firms' incentives to implement a more dispersed maturity structure are stronger during the 2008–2009 financial crisis.

In Table 12, we estimate equation (7) for the 2008–2009 crisis period and for the noncrisis period (i.e., 1991–2007 and 2010–2012). Compared with the noncrisis 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

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TABLE 11

Low- and High-Bank-Loan Subsamples

The sample in Table 11 includes firms with corporate bond and accounting information available in Mergent's Fixed Income Security Database (FISD) and the Compustat annual database 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 high-bank-loan subsamples. Firms are categorized as low-bank-loan firms if corporate bonds in the 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 (FE), and y_t is a year FE. 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. BANK_LOAN_PCT is the percentage of nonbond 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 equipment divided by assets), respectively. BOND_MAT is the average of firms' bond maturities, and PROF_VOL is the standard deviation of earnings divided by assets using data from the past 5 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
BANK_LOAN_PCT	−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)
BOND_MAT	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)
PROF_VOL	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)
No. of 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

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 with 0.18 for the noncrisis 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 as a result of rollover risk during the crisis, especially firms with valuable investment opportunities (as measured by a higher Q) select reliably higher maturity dispersions.

VI. Conclusion

This article extends the existing literature by focusing on the dispersion of a firm's debt maturities instead of its average debt maturity. Maturity structure matters because of rollover risk, that is, 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

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TABLE 12

Noncrisis and Crisis Subsamples

The sample in Table 12 includes firms with corporate bond and accounting information available in Mergent's Fixed Income Security Database (FISD) and the Compustat annual database 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 noncrisis (1991–2007 and 2010–2012) and crisis (2008–2009) periods. $X_{i,t}$ is a vector of explanatory variables, α_i is a firm- or industry-level fixed effect (FE), and y_t is a year FE. 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 equipment divided by assets), respectively. BOND_MAT is the average of firms' bond maturities, and PROF_VOL is the standard deviation of earnings divided by assets using data from the past 5 years. Numbers in parentheses are *t*-statistics, for which standard errors are clustered at the firm level.

	GRAN1				GRAN2			
	Noncrisis	Crisis	Noncrisis	Crisis	Noncrisis	Crisis	Noncrisis	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)
BOND_MAT	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)
PROF_VOL	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)
No. of 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

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. Because 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 larger and more mature firms; and for firms with more profitable investment projects, more tangible assets, higher leverage ratios, lower values of assets in place, and 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, the observed variation in granularity supports the model's predictions. Debt maturities are more dispersed, and maturity dispersion adjusts faster toward target levels, as suggested by our model, for example, for larger and more mature firms and for firms with better investment opportunities, more tangible assets, higher leverage ratios, lower values of assets in place, and lower levels of current cash flows. Hence, firms on the margin pay attention to debt-maturity profiles by actively managing granularity.

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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. Although it is beyond the scope of this article to explore the asset pricing implications of debt granularity, this should prove fruitful for future research.

Appendix. Variable Definitions

This Appendix provides the definitions of all the variables used in the article. All variables in uppercase letters refer to the Compustat items.

GRAN1: Inverse of Herfindahl index of bond maturity fractions (see Section III.B).

GRAN2: Negative of log distance from the perfect maturity dispersion (see Section III.B).

GRAN1L: Inverse of Herfindahl index of total debt-maturity fractions based on DD1–DD5 and the FISD's bond amounts for maturities greater than 5 years (see Section IV.F).

GRAN2L: Negative of log distance from the perfect maturity dispersion based on DD1–DD5 and the FISD's bond amounts for maturities greater than 5e years (see Section IV.F).

Q: Market-to-book ratio, $(\mathrm{AT} + \mathrm{PRCC} \times \mathrm{CSHO} - \mathrm{CDQ} - \mathrm{TXDB})/\mathrm{AT}$.

SIZE: Log of total assets (AT).

AGE: Number of years in the Compustat file prior to observations.

LEV: Market leverage, $(\mathrm{DLTT} + \mathrm{DLC})/(\mathrm{AT} + \mathrm{PRCC} \times \mathrm{CSHO} - \mathrm{CEQ} - \mathrm{TXDB})$.

PROF: Operating income before depreciation scaled by total assets, $\mathrm{OIBDP}/\mathrm{AT}$.

TAN: Plant, property, and equipment scaled by total assets, PPENT/AT.

BOND_MAT: Average of firms' bond maturities weighted by amounts.

PROF_VOL: Standard deviation of operating income before depreciation divided by total assets (OIBDP/AT) using data from the past 5 years.

NBOND: Number of bonds outstanding.

NMAT: Number of bond maturities grouped into the nearest integer years.

BOND_PCT: Ratio of total book value of bonds available to total book debt for each firm.

BOND_AMT: Average amount of bonds outstanding for each firm.

BOND_AMT/ASSET: Average amount of bonds outstanding divided by total assets.

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

LIMIT_LC: Credit lines based on Capital IQ (for the 2002–2012 period) divided by total assets AT (see Section IV.B).

EQ_ISSUE: 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.

ASSET_MAT: 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).

IND_GRAN: Median values of granularity within Fama–French 49-industry groups each year.

PASSIVE_GRAN$_t$: A granularity level that a firm would achieve in t if it were to replace an expiring bond with a new bond that has exactly the same maturity and face value as the expiring bond.

Δ_AGRAN$_{t+1}$: Defined as GRAN$_{t+1}$ − PASSIVE_GRAN$_{t+1}$.

Δ_PGRAN$_{t+1}$: Defined as PASSIVE_GRAN$_{t+1}$ − GRAN$_{t+1}$.

BANK_LOAN_PCT: Percentage of bank loans with respect to the total amounts of debt.

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