Granularity of Corporate Debt: Theory and Tests*

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Abstract

We study the degree to which firms spread out their bonds' maturity dates across time, which we call "granularity" of corporate debt. In our model, a firm's access to the bond market may be hindered temporarily, either because the capital market freezes or because the firm becomes exposed to large risks. Therefore, it can be advantageous to diversify the debt roll-over across maturity dates. Using a large sample of corporate bond issuers during the 1991–2009 period, we find evidence that supports our model's predictions in cross-sectional and time-series tests. In the cross-section, corporate debt is more granular for larger and more mature firms, for firms with better investment opportunities, with more tangible assets, with higher leverage ratios, with lower values of assets in place, and with lower levels of current cash flows. We find that during the recent financial crisis especially firms with valuable investment opportunities implemented more granular debt structures. In the time-series, we also document that firms manage granularity in that newly issued corporate bond maturities complement pre-existing bond maturity profiles.

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1 Introduction

It is not well understood how firms manage the roll-over dates of their bonds by spreading out maturities. Fixed cost components of bond issues and secondary market liquidity considerations should motivate firms to concentrate their debt in a single or few issues. However, even non-financial firms frequently have several bonds outstanding, with different times to maturity. What are the frictions and tradeoffs that drive these decisions? In this paper, we study theoretical and empirical aspects of the degree to which companies spread out their bond maturity dates across time, which we call "granularity" of corporate debt.

We build a three-period model of a firm with two investment projects, which generate non-contractible cash flows at time two. To capture the dynamic nature of the problem, there is also a contractible continuation value at time three. The firm finances the projects by issuing debt with maturity less or equal to two. Thus, investor preferences or frictions, such as moral hazard, are assumed to prevent the firm from issuing very long-term bonds that expire in the final period three. Therefore, the firm must roll over each bond issued at time zero at least once. In this setting, the firm can issue one bond with a single roll-over date (time 1 or time 2) or two bonds with different roll-over dates. That is, the single-bond firm (or firm S) refinances its bond at *one* point in time, whereas the multi-bond firm (or firm M) refinances its bonds at *two* different points in time.

In normal times, the bonds can be rolled over and the risky project cash flows and the firm's continuation value are eventually realized. With some probability, however, the firm can lose its access to the bond market in any given period. The firm's inability to access the bond market may arise endogenously since it can become temporarily exposed to a large risk, which we refer to as a technology shock. We show that, in such states, investors do not roll over the bond. As a consequence, one or both projects must be partially liquidated to repay the bondholders, and this is inefficient.[1]

Uncertainty about project cash flows is resolved gradually over time, so that the firm can ob-

[1] See, e.g., Acharya et al. (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 roll-over risk is the bankruptcy of General Growth Properties in April 2009.

serve whether the non-contractible cash flow component of a project will be high or low, even before it is realized. If bondholders request partial liquidation, the firm therefore knows already its projects' cash flows. Since firm M only needs to partially liquidate one project, it has the real option to retain the better project, i.e. the one with the higher future payoff. By contrast, if firm S cannot roll over its single bond, then it must partially liquidate both projects. Intuitively, the model's trade-off is that firm M has a flexibility (or real option) advantage over firm S, whereas firm S has a transaction cost advantage over firm M, since one larger issue faces lower floatation and illiquidity costs than two smaller issues (see Longstaff et al. (2005) and Mahanti et al. (2008) for evidence on a positive relation between bond issue size and secondary market liquidity).[2]

Based on this trade-off between flexibility benefits and transaction costs, we derive a number of testable implications. The difference in value between firm M and firm S implies that the benefits of debt granularity (i.e. being a multi- rather than a single-bond firm) increase with the probability of market freezes and with the value of investment opportunities. Moreover, the solution of the model indicates that corporate debt should be more granular for larger and more mature firms, for firms with more tangible assets, with higher leverage ratios, with lower values of assets in place, and with lower levels of current cash flows.

To test the theory's predictions, we construct a large panel data set that contains information on firms' granularity, leverage, maturity, and other characteristics (e.g., age, size, Tobin's Q, etc.) by merging data on public debt issues from Mergent's Fixed Investment Securities Database (FISD) with the COMPUSTAT database. For the 1991–2009 period, we obtain an unbalanced panel with 16,593 (9,288) firm-year observations for firms with at least one bond (two bonds) outstanding. Thus, a number of firms forgo the benefits of granularity management, but the majority of firms has multiple bonds outstanding.

We use these firm-level data on corporate bond issues to measure how dispersed firms' maturity structures are through time. For each firm, we group bond maturities into the nearest integer years and use their fractions out of the total amount of bonds outstanding to compute a Herfindahl

[2] There may be additional motives why firms issue debt with different maturity dates. Firms may wish to match the maturities of liabilities with those of assets. This 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, frictions stemming from asymmetric information are likely to be more severe at longer horizons compared to shorter horizons, which further limits firms' ability to match the maturities of liabilities with those of assets. Thus, the tradeoff that we consider in this paper remains relevant even in the presence of other motives for granularity.

index and an Atkinson index (see Atkinson (1970)) each year. To capture dispersion rather than concentration of roll-over dates, we use the inverse of the maturity profile's Herfindahl index and the negative value of the log of the Atkinson index as proxies for the granularity of corporate debt.

Several novel results emerge. Consistent with the model's predictions, we find strong evidence that larger and more mature firms, firms with higher Tobin's Q, more levered firms, and firms with higher asset tangibility exhibit more granular debt structures. In contrast, granularity is negatively associated with profitability. In this first series of tests, most of these firm characteristics remain economically and statistically important even after controlling for industry-level or firm-level fixed effects, suggesting that firms condition on these variables in their granularity management. Our findings are also present in subsamples of firms with a high and a low proportion of private debt, suggesting that granularity management is independently important, because public debt is more difficult to adjust or renegotiate.[3] Moreover, during the 2008–2009 financial crisis when access to primary capital markets was difficult, we find that especially firms with valuable investment opportunities implemented more granular debt structures. In a second series of tests, we establish that debt granularity moves over time towards target levels. In particular, speed-of-adjustment regressions reveal surprisingly high adjustment rates, ranging from 20% to 40% per year.[4]

To provide more direct evidence on firms' granularity management, we also examine whether firms consider pre-existing maturity profiles when they issue new bonds. To do so, we investigate whether discrepancies between a firm's pre-existing maturity profile and a benchmark maturity profile (based on firm characteristics) explain future debt issue behavior. We find strong support for this prediction. If a firm has a large fraction of bonds outstanding in any given maturity bucket relative to its benchmark profile, then it is significantly less likely to issue bonds in those maturity buckets. For example, the probability of issuing additional nine- or ten-year maturity bonds drops by 0.772 of a percentage point for every percentage point that a firm's maturity profile exceeds the benchmark profile in this bucket. The results hold across all maturity buckets, are largely invariant to the definition of the benchmarks or buckets, and are also economically very significant.

[3] 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)). Firms with a large proportion of private debt may therefore not need granular public debt and yet we do not find evidence for such a substitution effect.

[4] Both test results also hold for the subsample of firms with at least two bonds outstanding and for the subsample of firms that have bonds without sinking fund provisions.

Our paper is related to recent contributions on debt maturity and roll-over frictions.[5] By linking corporate bond credit risk and bond market liquidity risk, He and Xiong (2011) show that short-term debt exacerbates roll-over risk. He and Milbradt (2011) endogenize the feedback between secondary market liquidity risk and roll-over risk – reduced liquidity raises equity's rollover losses, leading to earlier endogenous default, which in turn worsens bond liquidity. These papers focus on single-bond firms' maturity choice. Similar to our multi-bond firm is the paper by Diamond and He (2011), which shows that maturing, risky short-term debt can lead to more debt overhang than non-maturing risky long-term debt. However, none of these papers examines the trade-offs faced by firms when diversifying debt roll-overs across maturity dates. In our setting, issuance of a single long-term or a single short-term debt claim may not be optimal. But a combination of debt with different roll-over dates can better balance inefficiencies due to roll-over risk at different points in time.

Our paper is also related to recent empirical research. Almeida et al. (2011) document that firms with a greater fraction of long-term debt maturing at the onset of the 2007 financial crisis had a more pronounced investment decline than otherwise similar firms.[6] In the context of U.S. Treasury bonds, Greenwood et al. (2010) argue that firms vary their debt maturity to act as macro liquidity providers by absorbing supply shocks due to changes in the maturity of Treasuries. Using syndicated loan data for U.S. firms, Mian and Santos (2011) find more active maturity management by credit worthy firms to avoid being exposed to liquidity risk. Finally, Rauh and Sufi (2010) and Colla et al. (2012) find that – relative to large, high credit quality firms – small, low rated firms have dispersed or multi-tiered debt structures, while small, unrated firms specialize in fewer types. Unlike these studies, we focus on testing cross-sectional and time-series implications for the granularity of corporate debt.[7]

The rest of the paper is organized as follows. Section 2 describes the model. Section 3 derives the model's solution and its testable implications. Section 4 presents data sources and summary statistics. Section 5 contains the empirical findings and Section 6 concludes.

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

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

[7] For empirical studies of debt maturity see, e.g., Barclay and Smith (1995), Guedes and Opler (1996), Stohs and Mauer (1996), and Johnson (2003).

2 Model

2.1 Technology

We study a three-period model of an initially all-equity financed firm. The firm has assets in place (or initial net worth), A, and two two-period investment projects. Each project requires a capital outlay, I, at time t_0. If both periods elapse without (partial) early liquidation and without a technology shock, then each project generates two uncorrelated random cash flows at time t_2 plus a non-random continuation value, $\bar{v}$, at time t_3. Each of the two random cash flows, $\widetilde{CF}_1$ and $\widetilde{CF}_2$, can take the realization $c > 0$ or $c + H > c$, with equal probability. Thus, along such paths, each project produces expected cash flows of $2\,c + H$. Uncertainty about cash flows is resolved gradually over time, so the firm can observe at time t_1^- (t_2^-) whether $\widetilde{CF}_1$ ($\widetilde{CF}_2$) of a project will be c or $c + H$. Similar to, e.g., Hart and Moore (1995), cash flows are observable but non-verifiable, while continuation values are also verifiable.

However, firms may also evolve along paths, where they are hit by a technology shock. Specifically, in every period, there is a probability λ with which the firm becomes vulnerable to such a potential technology shock, which will then occur with probability π. If the technology shock takes place, then each project only produces a final cash flow of c and its collateral value drops to zero.[8] With probability $1 - \pi$ the technology shock does not follow the λ state, however, and the firm continues its projects as a going concern, just as in the $1 - \lambda$ state.[9]

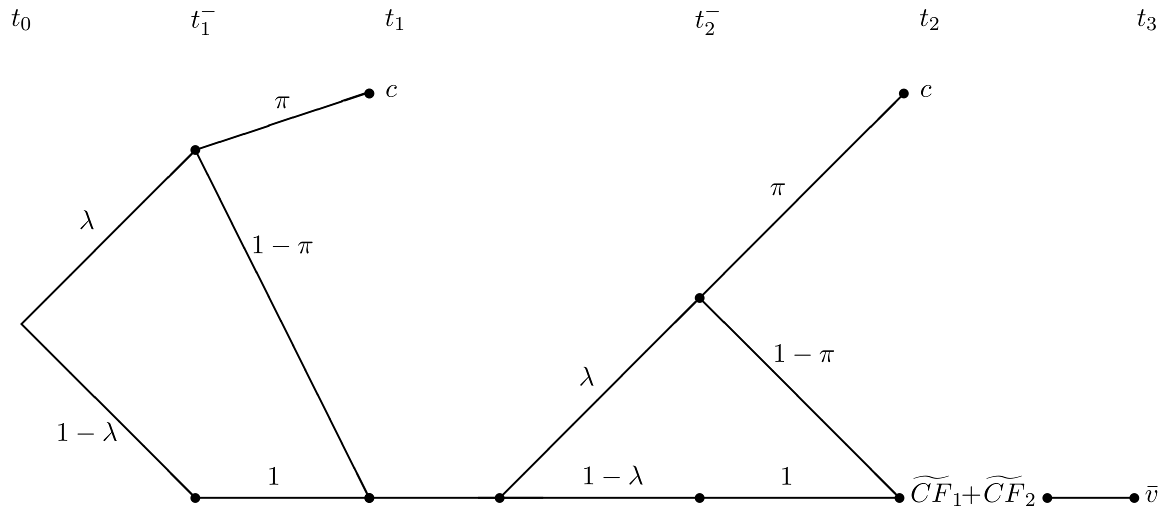
If a bond expires when the firm is vulnerable to a technology shock, then it may not be able to roll it over and, as a consequence, may be forced to partially liquidate one or both projects, depending on the size of the expiring bond. Partial liquidation of a project at time t_i, $i \in \{1, 2\}$, yields collateral value, c, which is contractible, but eliminates the project's non-contractible cash flow, $\widetilde{CF}_i$. Figure 1 provides the evolution of cash flows, risks, and shocks over time.

To provide intuition, we first consider a particularly simple version of the model where the probability of a technology shock is zero (i.e. $\pi = 0$) and the capital market may freeze exogenously. That is, bondholders' roll-over incentives are not explicitly modeled in this version but instead capital markets freeze in each period with probability λ and subsequently reopen. For this version

[8]The final, non-contractible cash flow of c ensures that equityholders have no incentive for early liquidation.
[9]The possibility that the market reopens is why we refer to "partial" rather "full" liquidation in such cases.

of the model we assume that $c > I - \frac{1}{2}A > 0$, so bonds are needed but risk-free.

Figure 1. Evolution of Cash Flows, Risks, and Shocks



This figure plots the time line of cash flows, risks, and shocks. In each of the two periods, there is a probability λ with which firms become vulnerable to a technology shock, which will then occur with probability π. If the technology shock takes place, each project's collateral value drops from c or zero and each project only pays off a final, non-contractible cash flow of c. Project cash flows in the absence of a technology shock, $\widetilde{CF}_1$ and $\widetilde{CF}_2$, are realized at time t_2, and are either c or $c + H$ with equal probability. In the absence of a technology shock, each project's contractible continuation value, $\bar{v}$, is realized at time t_3.

In the more general version of the model, we endogenize bondholders' roll-over decision. To do so, we let the probability of a technology shock be greater than zero (i.e. $\pi > 0$), which will endogenously limit the firm's access to the capital market. To rule out trivial solutions, we require that:

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

and

$$0 \;<\; A \;<\; 2\,I\;. \tag{2}$$

Essentially, the left-hand side of condition (1) ensures that a bond can be rolled over in a state in which the firm is not vulnerable to a technology shock, whereas the right-hand side implies that this is not feasible in a state where the firm may be hit with a technology shock. Condition (2) states that the firm cannot fully fund the projects using its initial net worth, A.

Finally, we also assume that:

$$2\,c \;>\; \frac{2\,I - A}{1 - \lambda\,\pi}\;. \tag{3}$$

As will become apparent later, this condition ensures that there is enough collateral to satisfy bondholders in full when the bond expires and cannot be rolled over. The reason is that the face value of debt will always be less than or equal to $(2\,I - A)/(1 - \lambda\,\pi)$.

2.2 Preferences and Contracts

For simplicity, all investors are assumed to be risk-neutral and the risk-free interest rate is normalized to zero. At time t_0, the firm needs to raise $2\,I - A$ by issuing debt to fund the two investment projects. We restrict firms at time t_0 to issue straight bonds expiring either at time t_1^- or time t_2^-.[10] We consider two initial corporate debt structures that differ by the number of bonds outstanding: the firm can issue one or two bonds at time t_0. We refer to the former as firm S (or single bond firm) and to the latter as firm M (or multi-bond firm). Firm S issues a single bond at time t_0 that matures at time t_2^- and is then rolled over to time t_3 whenever possible. To raise $2I - A$ and to ensure that investors break even in expectation, the initial bond must have a face value of $P_S(t_0, t_2^-) = (2\,I - A)/(1 - \lambda\,\pi)$ since the bond payoff is zero if a technology shock occurs at time t_1, which occurs with probability $\lambda\pi$.[11]

In contrast, firm M issues two bonds at time t_0, a riskless one with face value $P_M(t_0, t_1^-) = I - \frac{1}{2}A$ that is due at t_1^- and another one with face value $P_M(t_0, t_2^-) = (I - \frac{1}{2}A)/(1 - \lambda\,\pi)$ that matures at t_2^-. So the two bonds of firm M need to be rolled over to t_3 at times t_1^- and t_2^-. When firm M rolls over its short-term bond at time t_1 to time t_3, then the new bond's required face value is $P_M(t_1, t_3) = (I - \frac{1}{2}A)/(1 - \lambda\,\pi)$ since bondholders will receive zero if a technology shock occurs at time t_2, which occurs with probability $\lambda\,\pi$. (In case of exogenous market freezes, it can be easily verified that debt is risk-free, i.e. $P_S(t_0, t_2^-) = 2\,I - A$ and $P_M(t_0, t_2^-) = I - \frac{1}{2}A$.)

If a bond cannot be repaid at maturity, then bondholders have the right to seize assets from one or both projects, depending on the face value of the bond, and realize the collateral value. When bondholders request liquidation of a project, the firm already knows each project's cash flow (provided no technology shock occurs). Thus, if the firm only needs to liquidate one project, it has the real option (i.e. flexibility advantage) to keep the one with the higher future payoff. This is the

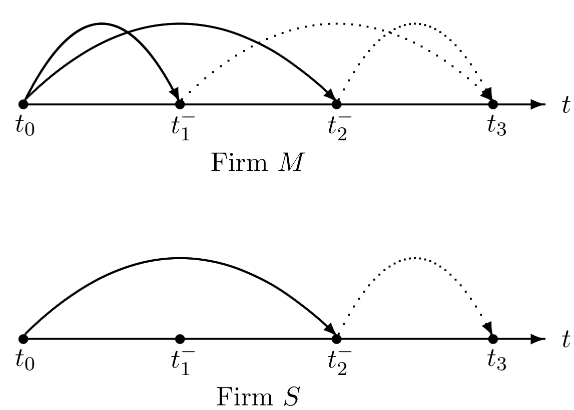
[10] See Milbradt and Oehmke (2012) on the limits of debt maturity when long-term debt markets can break down.

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

case if a firm has issued two bonds and only one expires at time t_i^- and cannot be rolled over. Then it will only liquidate the worse project and thereby only loses CF_i of that project. By contrast, if the firm has issued a single bond that expires at time t_2^- and it cannot be rolled over, then the firm must liquidate both projects and thus loses CF_2 of both projects.[12]

To capture scale economies of larger issues, we assume that the firm pays a fixed transaction cost per issue, k, at time t_0. Alternatively, k can be thought to reflect the fact that a single large bond issue may have a more liquid secondary market, thus leading to a lower illiquidity discount than two smaller bond issues. That is, the single-bond firm has a transaction cost advantage, since it requires a single issue cost k, whereas the multi-bond firm incurs issue costs of $2\,k$. Figure 2 provides the evolution of roll-over decisions over time.

Figure 2. Evolution of Roll-Over Decisions



This figure plots the time line of roll-over decisions of the multi-bond firm (Firm M) with two smaller bond issues, which expire at time t_1^- and t_2^-, and single-bond firm (Firm S) with one large bond issue, which expires at time t_2^-. An expiring bond issue needs to be rolled over into time t_3 to obtain the firm's continuation value.

3 Solution

3.1 Exogenous Market Freezes

We begin by solving the simple model where the probability of a technology shock is equal to zero (i.e. $\pi = 0$), but the market freezes in each period with probability λ and subsequently reopens.

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

Since in this setup bondholders always get the face value back, the face value per bond is either $I - \frac{1}{2}A$ (if two bonds are issued) or $2\,I - A$ (if a single bond is issued).

To determine the value of the single-bond firm, we need to derive its cash flows along each of the possible paths. First, consider the path where the market freezes in both periods, which occurs with probability λ^2. Since firm S does not have a bond expiring at time t_1, it will collect the expected value of $\widetilde{CF}_1$ from both projects, i.e. $2\,c + H$ at time t_2. At time t_2^-, however, firm S faces a roll-over problem since the market freezes again. Therefore, bondholders cause inefficient liquidation of both projects, i.e. $\widetilde{CF}_2$ is lost for both projects, and therefore equityholders' expected total dividends at time t_2 are given by $2\,c + H + 2\,c - (2\,I - A)$. Finally, the continuation value, $2\,\bar{v}$, becomes available at time t_3.

Next consider the two paths where the market only freezes once, i.e. either at time t_1 or at time t_2 but not in both periods. Along both paths, equityholders will again receive the continuation value, $2\,\bar{v}$. If the market freezes when firm S does not have a bond repayment due and is open when it has one due, then it generates an expected value of cash flows equal to $2\,(2\,c + H)$ and repays $2\,I - A$, which happens with probability $\lambda\,(1-\lambda)$. On the other hand, if the market is open at time t_1 but freezes at time t_2, then firm S obtains $2\,c + H$ in the first period, but only $2\,c$ in the second period before repaying $2\,I - A$ to bondholders. This happens with probability $(1-\lambda)\,\lambda$.

Finally, the market does not freeze in either period with probability $(1-\lambda)^2$. Along this path, firm S does not face a roll-over problem and thus generates $2\,(2\,c + H)$ in expected project cash flows, obtains the continuation value, $2\,\bar{v}$, and repays $2\,I - A$ to bondholders. Summing up the values over the four states, equity value of firm S equals:

$$V_S(\lambda) \;=\; A - 2\,I + 4\,c + 2\,\bar{v} + H\,(2-\lambda)\;. \tag{4}$$

Next, consider the multi-bond firm. If the market freezes, then firm M is unable to roll over its bond and must liquidate one project. However, since firms observe cash flows before giving away collateral, firm M will optimally abandon the worse project from the set of feasible project payoffs, $\{\{c+H, c+H\}, \{c, c+H\}, \{c+H, c\}, \{c, c\}\}$. This yields an expected project cash flow equal to $c + \frac{3}{4}\,H$, reflecting the real option (i.e. flexibility advantage) that firm M has in deciding which project to terminate and which one to continue.

We can now determine the cash flows along the four possible paths. It is straightforward to verify that the resulting firm value to equityholders at time t_0 is:

$$V_M(\lambda) \;=\; A - 2\,I + 4\,c + 2\,\bar{v} + H\,(2 - \tfrac{1}{2}\,\lambda)\;. \tag{5}$$

The difference between the equity values of firm M and firm S after accounting for the transaction cost per issue k at time t_0 is thus given by:

$$V_M(\lambda) - 2\,k - [V_S(\lambda) - k] \;=\; \tfrac{1}{2}\,\lambda\,H - k\;. \tag{6}$$

The benefits of debt granularity (i.e. being a multi- rather than a single-bond firm) rise with the probability of market freezes, λ, and with the value of the firm's investment opportunity or payoff, H, but they decline with the level of transaction costs, k. In other words, the multi-bond firm's flexibility advantage dominates when investment opportunities are more important and when market freezes are more likely, whereas the single-bond firm's transaction cost advantage dominates when floatation and illiquidity costs are more important. Thus, depending on the magnitude of these two countervailing forces, it can be advantageous to have a single issue or multiple issues.

3.2 Endogenous Market Freezes

We now solve the model with endogenous market freezes which may arise when firms become vulnerable to a technology shock. This happens in each period with probability λ and the technology shock subsequently occurs with probability $\pi > 0$. This more general version of the model will generate a number of additional testable implications for our empirical analysis.

3.2.1 Debt Roll-Over and Early Project Liquidation

The debt roll-over decisions for firms S and M are required to determine their value at time t_0, $V_S(\lambda)$ and $V_M(\lambda)$. We start with firm S that has a single bond outstanding that must be rolled over at time t_2^-. We observe that, for bondholders to break even, the face value must equal $P_S(t_0, t_2^-) = (2\,I - A)/(1 - \lambda\,\pi)$. This is so since the bond is risky when issued at time t_0, due to a possible technology shock at time t_1^-. In other words, its face value is only paid back with probability $1 - \lambda\,\pi$, i.e. the probability that the firm's operations are not terminated prematurely due to a shock at time t_1.

It is easy to see that the bond cannot be rolled over when the firm is vulnerable to a technology shock at time t_2^-, i.e. in the λ state. In this state, new investors will not contribute $P_S(t_0, t_2^-)$ to pay back the expiring bond since $-(2\,I - A)/(1 - \lambda\,\pi) + (1 - \pi)\,2\,\bar{v} < 0$ by the right-hand side of condition (1). In this case, the expected value of $\widetilde{CF}_2$ of each project $2\,c + H$, is lost and instead the projects' collateral value, $2\,c$, is realized, of which $(2\,I - A)/(1 - \lambda\,\pi)$ is used to repay bondholders. If the technology shock actually occurs at time t_2, then the firm's continuation value drops to zero, so $2\,\bar{v}$ is lost. Otherwise (i.e. with probability $1 - \pi$), the firm continues its presence in the product market and realizes the projects' continuation value, $2\,\bar{v}$.

In the $1 - \lambda$ state at time t_2^-, when the firm is not vulnerable to a shock, firm S can roll over its bond, because investors are willing to refinance given that $-(2\,I - A)/(1 - \lambda\,\pi) + 2\,\bar{v} > 0$ by the left-hand side of condition (1). As a result, the firm realizes expected project cash flows from both projects, equal to $\mathrm{E}[\widetilde{CF}_2] = 2\,c + H$, plus the continuation value, $2\,\bar{v}$.

Moving back in time, we next consider time t_1^-. Firm S does not need to roll over any debt at that time, and thus it does not lose either of the two project cash flows due to roll-over risk. However, if the technology shock is realized, which happens with probability $\lambda\,\pi$, then operations end (i.e. the projects' continuation values vanish) and the projects only produce one final cash flow of $2\,c$ (cf. path (i) in Table 1). With probability $1 - \lambda\,\pi$ no technology shock occurs at time t_1, and firm S produces an expected cash flow $\mathrm{E}[\widetilde{CF}_1] = 2\,c + H$.

Next, we consider the roll over decisions of firm M. Recall that firm M issues two bonds at time t_0, one with maturity t_1^- and the other with maturity t_2^-. It is easy to see that the former bond is riskless, and thus requires a face value of $(I - \frac{1}{2}A)$, whereas the latter bond is risky, thus requiring a face value of $(I - \frac{1}{2}A)/(1 - \lambda\,\pi)$.

Consider first the λ state at time t_2^-, when the firm is vulnerable to a shock. In this case, firm M cannot roll over the maturing bond, since it can only pledge collateral worth $(1 - \pi)[2\,\bar{v} - (I - \frac{1}{2}A)/(1 - \lambda\,\pi)]$. According to condition (1), this is less than the amount required to roll over the bond, i.e. $(I - \frac{1}{2}A)/(1 - \lambda\,\pi)$. The firm must therefore partially liquidate one project to pay back the face value of the expiring bond.

Next we consider the roll over decision in the $1 - \lambda$ state at time t_2^-, in which the firm is not vulnerable to a shock. In this case, firm M can roll over the maturing bond since it can pledge a collateral value of $2\,\bar{v} - (I - \frac{1}{2}A)/(1-\lambda\,\pi)$. Condition (1) implies that this exceeds $(I - \frac{1}{2}A)/(1-\lambda\,\pi)$, which is the capital required to roll over the maturing bond.

Moving backwards in time to t_1^-, we first consider the roll-over decision in the λ state. The risk-free, short-term bond with face value $I - \frac{1}{2}A$ expires at this time. However, the expected value of collateral that can be pledged to new investors of a bond with maturity t_3 is $(1-\pi)\,(1-\lambda\,\pi)\,2\,\bar{v}$, which is less than $I - \frac{1}{2}A$ by condition (1). Thus, the maturing short-term bond cannot be rolled over and one project must be liquidated.

Finally, we consider the $1-\lambda$ state at time t_1^-. In this state, the expiring, short-term bond can be rolled over, as the expected value of collateral that can be pledged to new bondholders is $(1-\lambda\,\pi)\;2\bar{v}$, which exceeds $I - \frac{1}{2}A$ by the left-hand side of condition (1). Therefore, the short-term bond can be rolled over in this state.

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

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

Having determined in which states the firm can roll over its expiring bonds, it is now straightforward to determine the cash flows generated by the firms along each of the seven possible paths. These are summarized in Tables 1 and 2 below.

Multiplying the cash flows of each possible path by their respective probabilities and summing

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

Paths	Probabilities	Cash Flows
(i)	$\lambda\,\pi$	$c-(I-\frac{1}{2}A)+c$
(ii)	$\lambda\,(1-\pi)\,\lambda\,\pi$	$c-(I-\frac{1}{2}A)+c+\frac{3}{4}H+c-\frac{I-\frac{1}{2}A}{1-\lambda\,\pi}+c$
(iii)	$\lambda\,(1-\pi)\,\lambda\,(1-\pi)$	$c-(I-\frac{1}{2}A)+c+\frac{3}{4}H+c-\frac{I-\frac{1}{2}A}{1-\lambda\,\pi}+c+\frac{3}{4}H+2\,\bar{v}$
(iv)	$\lambda\,(1-\pi)\,(1-\lambda)$	$c-(I-\frac{1}{2}A)+c+\frac{3}{4}H+2\,c+H+2\,\bar{v}-\frac{I-\frac{1}{2}A}{1-\lambda\,\pi}$
(v)	$(1-\lambda)\,\lambda\,\pi$	$2\,c+H+c-\frac{I-\frac{1}{2}A}{1-\lambda\,\pi}+c$
(vi)	$(1-\lambda)\,\lambda\,(1-\pi)$	$2\,c+H+c-\frac{I-\frac{1}{2}A}{1-\lambda\,\pi}+c+\frac{3}{4}H+2\,\bar{v}-\frac{I-\frac{1}{2}A}{1-\lambda\,\pi}$
(vii)	$(1-\lambda)\,(1-\lambda)$	$2\,(2\,c+H)+2\,\bar{v}-\frac{2\,I-A}{1-\lambda\,\pi}$

up, we find the equity values of firms S and M at time t_0, $V_S(\lambda)$ and $V_M(\lambda)$, are:

$$V_S(\lambda) \;=\; A-2\,I+2\,c\,(2-\lambda\,\pi)+2\,\bar{v}\,(1-\lambda\,\pi)^2+H\,(2-\lambda)\,(1-\lambda\,\pi)\;, \tag{7}$$

and

$$V_M(\lambda) \;=\; A-2\,I+2\,c\,(2-\lambda\,\pi)+2\,\bar{v}\,(1-\lambda\,\pi)^2+H\,(2-\lambda\,\pi)\,[1-\tfrac{1}{4}\,\lambda\,(1+3\,\pi)]\;. \tag{8}$$

The expressions for the values of firm S and firm M reveal several intuitive properties, such as values are decreasing in λ and π and increasing in the project payoff, H. However, we are mainly interested in the determinants of the difference in value between firm S and firm M to see under what circumstances granularity of corporate debt is beneficial.

Recalling that each initial bond issue is associated with a fixed transactions cost, k, to capture floatation and illiquidity costs the difference in value between the two strategies is:

$$V_M(\lambda)-2\,k-[V_S(\lambda)-k] \;=\; \tfrac{3}{4}\,\lambda\,H\,(1-\pi)\,(\tfrac{2}{3}-\lambda\,\pi)-k\;. \tag{9}$$

As in the simpler version of the model, the benefits of debt granularity (i.e. being a multi- rather than a single-bond firm) decrease with transactions costs k. However, the effects of the other parameters on the relative value of granularity are now slightly more subtle and depend on the combined magnitude of the probabilities of becoming vulnerable to a shock and the shock taking place. Equation (9) implies that, as long as $\lambda\,\pi < \frac{2}{3}$, the benefits of granularity increase with the project payoff, H. Equation (9) also shows that the benefits of granularity are first increasing with the probability of becoming vulnerable to a shock, λ, and beyond some point (i.e. if $\lambda\,\pi > \frac{1}{3}$) decrease with λ.

Furthermore, equation (9) says that, ignoring transactions costs, the benefit due to debt granularity becomes zero as π goes to one, since early liquidation becomes less inefficient in this special case. In the limit, if $\pi = 1$, liquidating a project early in the λ state or continuing the project generate an identical cash flow of c (although the former liquidating cash flow is contractible and the latter is not). Thus, in the limit, when the technology shock always materializes, the flexibility advantage generated by debt granularity vanishes.

More generally, equation (9) reveals that, for a large range of plausible parameter values, firm M has a flexibility (or real option) advantage over firm S. Thus, in the absence of floatation and illiquidity costs, it is optimal to select a more granular debt structure. Yet, if $\lambda\,\pi > \frac{2}{3}$, i.e. for very large probabilities of a technology shock, a single long-term bond becomes optimal, even when transactions costs are zero. This is so since large values of $\lambda\,\pi$ effectively "discount away" the flexibility advantage of firm M in the second period, so that the higher expected payoff of firm S in the first period (i.e. $2\,c + H > 2\,c + \frac{3}{4}H$) becomes the dominating factor for the difference in value between firm M and firm S. Therefore, the model's solution also implies that, if a technology shock occurs with a sufficiently high probability, then the firm would prefer to have a single large roll-over risk in the distant future, rather than smaller roll-over risks distributed over different maturities.

3.3 Testable Hypotheses

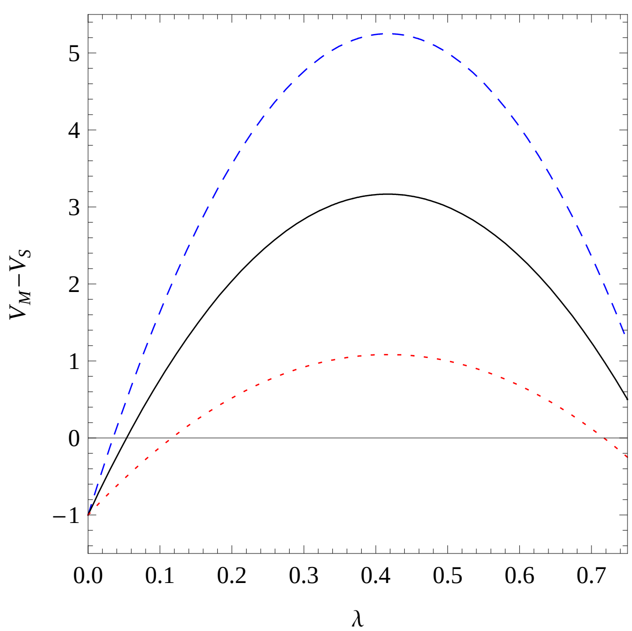
We select the following base case parameter values to plot the benefits of debt granularity (i.e. the expression in equation (9)): the non-contractible project cash flow, H, is equal to 200, the collateral value, c, and the investment cost, I, are equal to 300, the probability of a technology shock, π, is equal to 0.8, the continuation value, $\bar{v}$, is equal to 750, and the transaction costs, k, is equal to 1.[13]

With transaction costs, firm S initially dominates firm M for λ-values in the right neighbor-

[13]Note that condition (1) implies that the admissible values for π are generally in the $[\frac{1}{2}, 1]$ interval and that, for these base case parameter values, the admissible values for λ are in the $[0, \frac{3}{4}]$ interval.

hood of zero where $V_M < V_S$. As λ rises, however, the flexibility advantage of firm M becomes increasingly important, whereas the transaction cost advantage of firm S is of course invariant to λ. As a result, the difference in value grows and hence λ has to be sufficiently far away from zero for $V_M > V_S$ to hold. Eventually, the difference in value declines again and, in some cases, it may become negative for sufficiently high λ-values, because the earlier period's cash flows, where firm S does not face a roll-over problem, can be relatively more important than the later period's cash flows.

Figure 3. Benefits of Debt Granularity (H)



This figure plots the effect of the non-contractible cash flow H on the difference in value of firms M and S, $V_M - V_S$, as a function of the probability of becoming vulnerable to a technology shock λ. The base case depicted by the black, solid line, assumes that the non-contractible project cash flow H is equal to 200, the collateral value, c, and the investment cost, I, are equal to 300, the probability of a technology shock π is equal to 0.8, the continuation value, $\bar{v}$ is equal to 750, and the transaction costs k is equal to 1. The blue, dashed line assumes $H = 300$ and the red, dotted line assumes $H = 100$.

As seen in Figure 3, increasing transaction costs works in favor of firm S, because it produces a downward shift of the $V_M - V_S$ curve. This implies that a firm with higher frictions will have a lower incentive to implement a more granular debt structure. Since transaction costs are generally regarded to be inversely related to firm age and firm size (see, e.g., Fischer et al. (1989)), we obtain our first testable hypothesis.

Hypothesis 1 *Corporate debt is more granular for larger and more mature firms.*

Figure 3 plots the difference in value of firms M and S, $V_M - V_S$, as a function of λ for three different levels of the non-contractible project cash flow, H. That is, we vary the base case profitability of $H = 200$ represented by the solid line to higher profitability $H = 300$ (given by the dashed line) or to lower profitability $H = 100$ (given by the dotted line). As seen in all cases, there is always an initial region, in which firm S dominates due to its transaction cost advantage irrespective of the size of the investment opportunity. So, on the one hand, the graphical illustration suggests that firm S can also dominate firm M for any positive λ-values when the investment project is not very valuable (i.e. approximately when $H < 50$). On the other hand, debt granularity management will be increasingly valuable when the project's payoff rises. Put differently, it is optimal for firms with more valuable growth opportunities as measured, e.g., by a higher value of Tobin's Q, to have a more granular debt structure. This logic produces our second testable implication.

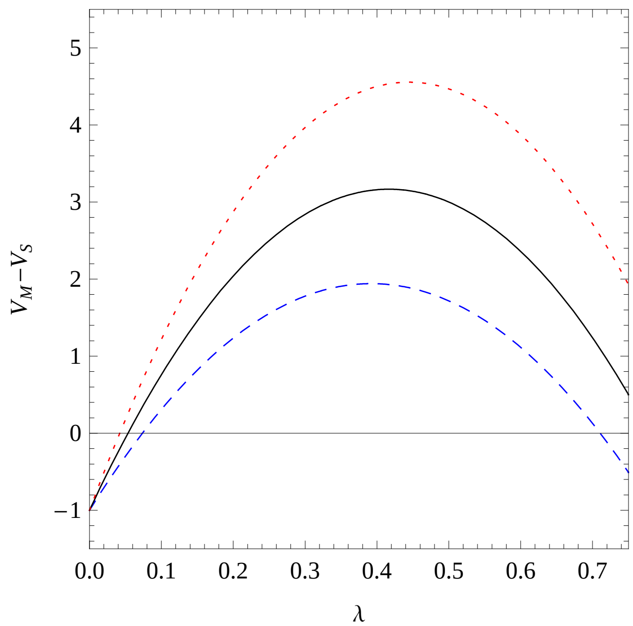
Hypothesis 2 *Corporate debt is more granular for firms with higher values of Tobin's Q.*

Figure 4 continues the graphical analysis by focusing on three different cases for the probability of a technology shock, π, which we set to 0.8 in the base case. In particular, the dashed line considers lower collateral quality in that the probability of collateral to become worthless is higher (i.e. $\pi = 0.85$), while the dotted line assumes $\pi = 0.75$, so that collateral is more likely to withstand bad times. We can therefore interpret a lower value of π as a higher degree of asset tangibility. Intuitively, firms with more tangible assets are less likely to be hit by a technology shock. The figure reveals that a lower (higher) probability of a technology shock increases (decreases) the benefits of a granular debt structure; i.e. firm M is increasingly more valuable than firm S when the probability of a technology declines. Thus, we obtain the next testable implication.

Hypothesis 3 *Corporate debt is more granular for firms with higher asset tangibility.*

Finally, there are two more testable hypotheses that follow from firm characteristics that influence condition (1), which we invoke to avoid solutions where firm S always dominates firm M. Observe that firms with a higher initial net worth A (or more loosely speaking firms with higher cash flows from assets in place, which would imply a larger value of A in a present value sense) need to borrow less than $2\,I$ (or can refinance using internal funds in the λ-state).

Figure 4. Benefits of Debt Granularity (π)



This figure plots the effect of the profitability of a shock π on the difference in value of firms M and S, $V_M - V_S$, as a function of the probability of becoming vulnerable to a technology shock λ. The base case depicted by the black, solid line, assumes that the non-contractible project cash flow H is equal to 200, the collateral value, c, and the investment cost, I, are equal to 300, the probability of a technology shock π is equal to 0.8, the continuation value, $\bar{v}$ is equal to 750, and the transaction costs k is equal to 1. The blue, dashed line assumes $\pi = 0.85$ and the red, dotted line assumes $\pi = 0.75$.

As a consequence, the roll-over problem of firm S will disappear in the λ-state when initial net worth is sufficiently high (or cash flows from assets in place are sufficiently high). Therefore, if leverage is sufficiently low, because initial net worth is sufficiently high, firm S dominates firm M and hence less granular debt structures should be observed in the data.

Hypothesis 4 *Corporate debt is more granular for firms with higher leverage ratios.*

Even though we do not model cash flows from assets in place, it is clearly true that higher cash flows from assets in place correspond, in a present value sense, to a higher value of assets in place. Hence we obtain the fifth prediction of the model.

Hypothesis 5 *Corporate debt is more granular for firms with lower cash flows from assets in place.*

4 Data Description

4.1 Sample Selection and Variable Construction

Corporate bond data are drawn from Mergent's Fixed Income Security Database (FISD), which contains comprehensive data on over 140,000 public bond issues for all credit ratings.[14] We obtain issue dates, maturity, initial and historical amounts outstanding, and other relevant information from the database. Accounting data are drawn from the annual COMPUSTAT tapes. We exclude financial firms (SIC codes 6000-6999) and utilities (SIC codes 4900-4999), and winsorize the top and bottom 0.5% of variables to minimize the impact of data errors and outliers. The combined data set covers the period from 1991 to 2009.

Granularity of corporate debt is measured by the dispersion of debt maturity structures. We employ measures of maturity dispersion based on a Herfindahl index and an Atkinson inequality index (Atkinson (1970)) of bond maturity concentrations. For each firm, we group bond maturities into the nearest integer years i and use their fractions of the total amount of bonds outstanding w_i to compute the Herfindahl index, $HERF = \sum_i w_i^2$. The Atkinson index is essentially the ratio between the geometric and the arithmetic mean: $ATKIN = 1-(\prod_i x_i)^{1/N}/\overline{x}$, where x_i equals $1-w_i$, $\overline{x}$ is the mean of x_i, and N is the maximum maturity of outstanding bonds. Based on these concentration indices, two measures of granularity (i.e. dispersion) are considered: the inverse of the Herfindahl index ($GRAN1 \equiv 1/HERF$) and the negative value of the log of the Atkinson index of bond fractions ($GRAN2 \equiv -\log(ATKIN)$).[15] Because we measure granularity of public debt, $GRAN1$ and $GRAN2$ do not consider maturity structures of private debt (i.e. bank loans).[16] In the empirical analysis, we address this issue by considering the proportion of private debt as explanatory variable.

Being an inverse of the Herfindahl index, $GRAN1$ reflects the number of bonds a firm has outstanding in an intuitive way. If the firm has n bonds with equal face values, $GRAN1$ will be n. If the firm has a more concentrated debt structure, e.g., n bonds with different face values, $GRAN1$ will be less than n. For this reason, $GRAN1$ tends to be positively skewed. On the other hand, $GRAN2$ measures inequality among different debt maturity distributions. Due to the way we construct $GRAN2$, the measure is sensitive to the longest maturity of a firm, whereas $GRAN1$

[14] FISD includes all fixed income securities that already have or probably will have a CUSIP in the near future.
[15] Similar to Lemmon et al. (2008), we add 0.001 to $ATKIN$ to prevent $GRAN2$ from being negative infinity.
[16] See Mian and Santos (2011) for a study on the maturity management of syndicate loans.

is not. Also, $GRAN2$ tends to be slightly negatively skewed, so it complements $GRAN1$ in terms of distributional characteristics.

To investigate the empirical predictions of the model, we include a number of explanatory and control variables in our regression specifications. In particular, firm size ($Size$) is total assets: COMPUSTAT's AT. Firm age (Age) is measured as the number of years in the COMPUSTAT database prior to each observation. Asset tangibility (Tan) is measured as plant, property, and equipment scaled by total assets: $PPENT/AT$. Profitability ($Prof$) is operating income before depreciation scaled by total assets: $OIBDP/AT$, which measures cash flows. Leverage (Lev) is book debt over market assets: $(DLTT + DLC)(AT + PRCC \cdot CSHO - CEQ - TXDB)$. We use the market-to-book ratio (Q) as a proxy of the firm's investment opportunities: $(AT + PRCC \cdot CSHO - CDQ - TXDB)/AT$. To control for corporate liquidity (or financial slack), we include cash holdings: CHE/AT. Finally, *Rating* is the issuer-level S&P rating, where smaller values of *Rating* represent higher ratings.

4.2 Summary Statistics

Descriptive statistics of our sample are reported in Table 3. Compared to all COMPUSTAT firms, the sample consists of larger and higher leverage firms, because they are required to have issued corporate bonds to be included in our sample. For example, in the sample of firms with at least two bonds outstanding, the average and median assets are \$11.9 and \$3.5 billion, and the average and median leverage are 0.28 and 0.24. In the sample of all COMPUSTAT firms during the 1991–2009 period (untabulated), the average and median assets are \$2.0 and \$7.1 billion, and the average and median leverage are 0.18 and 0.20.

[Insert Table 3 here]

Panel A of Table 3 reveals that a number of firms have only one bond outstanding. Within the 16,593 observations, there are 7,189 observations of single-bond firms (or 43%). They are typically younger firms (13 years vs. 28 years median age) with smaller amounts of assets (\$1,776 million vs. \$11,908 million average assets) and shorter average bond maturities (8.2 years vs. 10.1 years average maturity). Single-bond firms might have also considered being granular, because they could have split the face values and spread out roll-over dates by issuing multiple smaller bonds with different maturities. Despite of similar median Tobin's Q values, they did not do so, possibly because they are younger and smaller, so that they have lower incentives to become granular due to higher transaction costs. Panel B reports summary statistics for firm-years, in which bonds have been issued (about 31% of all observations) and for those where no bonds have been issued (about 69% of all observations). So, adjustments (or issuances) take place, on average, every three years. Bond issuers adjust debt structures, while non-issuers are passive. At adjustment points, firms are larger and older, firms have higher values of Tobin's Q and more tangible assets, and firms have higher granularity measures. This evidence is in accordance with the predictions from our model.

The empirical distributions of the granularity measures, $GRAN1$ and $GRAN2$, for firms with at least two bonds are reported in Figure 5 and 6, respectively. $GRAN1$ is skewed to the right partly because it is an inverse of the Herfindahl index. There are a few peaks in Figure 5. For example, the peak at one represents firms that have the same maturities for all the bonds outstanding, meaning that these firms are not spreading out maturity structures. As noted before, $GRAN2$ in Figure 6 is a bit skewed to the left. These histograms reveal that our two measures of granularity have complementary distributional characteristics.

[Insert Figures 5 and 6 here]

Figure 7 plots time-series averages of granularity for issuing and non-issuing firms. For issuing firms, granularity is countercyclical, i.e. firms issue bonds to make debt structures more granular during recessions. Higher roll-over risk during recessions appears to push firms towards more granular debt structures. Thus, firms clearly manage debt granularity over the business cycle. This pattern over the business cycles is also consistent with our model, because in recessions the probability of a market freeze, λ, is likely to be higher.

[Insert Figure 7 here]

Table 4 reports univariate correlations of our variables. On the one hand, granularity is strongly positively correlated with size, age, and tangibility, revealing that large, mature firms with pledgable assets (i.e. collateral) tend to have more granular debt structures. On the other hand, granularity is negatively correlated with Tobin's Q and leverage, which appears inconsistent with our theory, possibly because simple univariate correlation analysis does not capture the complex relations among these variables. The correlations of granularity measures with the number of bonds ($NBond$) are also positive. Hence firms with more bonds tend to have more granular debt structures. Also, if some firms can only issue very short-term debt rather than various layers of long-term debt, then such firms would have a limited ability to design granular debt structures. This explains the positive correlation of granularity and average bond maturity (Mat). Overall, this table suggests that controlling for these variables will be important in the multivariate regression analysis that follows.

[Insert Table 4 here]

5 Empirical Tests

5.1 Cross-Sectional Results

In this section, we test our model's main predictions using the following panel regression:

$$GRAN_{i,t+1} = \alpha_i + y_t + \beta X_{i,t} + \epsilon_{i,t+1} \tag{10}$$

where $X_{i,t}$ is a vector of explanatory and control variables, α_i is a firm- or industry-level fixed effect, and y_t represents a year fixed effect. Given the model's predictions, explanatory variables include market-to-book, leverage, size, age, tangibility, and profitability. We include the number of bonds as a control variable, because there could be a mechanical relation with granularity as firms issue more bonds. Also, firms that can issue long-term bonds have a higher chance of being granular compared to firms that can only issue short-term bonds. We therefore control for average maturity too. Standard errors are clustered at the Fama-French 48 industry level to account for within-industry correlations.

Panel A of Table 5 provides the estimation results of equation (10) using $GRAN1$ as dependent variable. Overall, the independent variables are associated with granularity as predicted by our model. For example, the market-to-book ratio is reliably positively associated with granularity in all specifications. The economic significance is also sizable. In the first column of Panel A, for example, a one standard deviation change in Q moves $GRAN1$ by 0.21. This evidence supports Hypothesis 2 that firms with more valuable growth opportunities have a higher incentive to spread out their bonds' maturity dates across time to protect their valuable projects from inefficient liquidation.

The coefficient estimates on firm size, as measured by total book value of assets, are reliably positive across all regression models. Economically, firm size is also important. Observe that, given a one standard deviation change in log assets (1.63), $GRAN1$ changes by 1.31 in the first column of Panel A. Firm age is also positively related to granularity, although its effect becomes weaker and statistically insignificant when firm fixed effects included. These findings are consistent with Hypothesis 1, which states that small, young firms plagued by high transaction costs and limited access to the financial markets, are not able to spread out their bonds' maturity dates across time.[17]

[Insert Table 5 here]

Asset tangibility and cash flow are reliably related to granularity as predicted by our model as well. In line with Hypothesis 3, tangibility tends to be positively related, although its statistical significance becomes marginal or disappear when we control for firm fixed effects or when firms are required to have at least two bonds outstanding. Cash flow is negatively associated with granularity especially among the full sample of firms, which confirms Hypothesis 5. For one standard deviation changes in the two variables, $GRAN1$ changes by 0.25 and 0.16, respectively, in the first column of Panel A, confirming their economic significance. Other control variables, such as total number of bonds and average debt maturity, are positively associated, but they do not reduce the explanatory power of other key variables, underscoring the robustness of results.

Market leverage is also positively associated with granularity and is precisely measured across all the models considered. Although consistent with Hypothesis 4, this result can be partly due to endogeneity between granularity and leverage. A more granular debt structure can enhance debt capacity and therefore may lead firms to select higher leverage. Another endogeneity channel is that firms might consider amounts of bond issuance and bond maturity simultaneously. However, we find in Table 6 that the relation between leverage and granularity tends to be more positive during the 2008–2009 financial crisis. To the extent that market leverage changes driven by the stock market crash are exogenous, this evidence suggests that firms with high leverage maintain more granular debt structures.

Several robustness checks are performed. In the seventh and eighth columns of Table 5, we

[17]Prior research argues size and age proxy for financial constraints. As firms need to have access to the corporate bond market to enter the sample, it is unlikely that the results are largely driven by firms' financial constraint status.

include firm-year fixed effects after excluding single-bond firms. Since there are many firms with only one bond in the sample, it is possible that the results in Table 5 are mainly driven by one bond firms. If one-bond firms are not able to issue multiple bonds with different maturities for reasons not captured by the control variables, having too many one-bond firms in the sample can be an issue. The results are similar to those with the full sample. Market-to-book, size, age, leverage and tangibility are mostly related positively, and profitability is negatively to granularity. Overall, the results are not driven by single-bond firms.

In the last two columns of Table 5, we exclude bonds with sinking fund provisions. Since effective maturities for sinking fund bonds are much shorter than for straight bonds, our tests are more informative for the sample without those bonds. Indeed, we find stronger or similar results for this well-identified subsample compared to the results for the full sample.

We use the Atkinson index ($GRAN2$) in Panel B of Table 5, because the results for $GRAN1$ in Panel A could be unique to the Herfindahl-based definition of granularity. The results for $GRAN2$ are similar to or stronger than the results for $GRAN1$ and thus reinforce the relevance of our model's predictions.[18] For example, the economic significance of Q increases in case of $GRAN2$. In the first column of Panel B, a one standard deviation change in Q moves $GRAN2$ by 0.36.

In sum, the evidence in Table 5 establishes that firm characteristics, such as Q, $Size$, Age, Lev, Tan, and $Prof$, can explain cross-firm variation in debt granularity in a way consistent with our theory. Without any fixed effects or firm-level controls, the R^2's of the regressions on these variables (the first columns of Panel A and B) are 45.6% and 47.1%, respectively. The economic magnitudes of the variables are also fairly high with one standard deviation changes in the variables typically explaining 10% to 100% of one standard deviation of the granularity measures.

In addition to our main sample, we examine whether firms' motives to have a granular maturity structure are stronger during the 2008–2009 financial crisis, when roll-over risk was likely to be higher. Table 6 reports estimation results of equation (10) for the pre-crisis period and the crisis period. Compared to the pre-crisis period, the effect of Tobin's Q is more precisely measured in the crisis subsample. In untabulated results, the differences in coefficients between the two subsamples are in most cases statistically significant at the 1% level. Overall, these estimation results suggest

[18]Unreported results for the negative value of the Herfindahl index also yield qualitatively identical results.

that given the higher likelihood of investment inefficiencies due to roll-over risk during the crisis, especially firms with valuable investment opportunities (i.e. higher Tobin's Q) selected reliably higher granularity.

[Insert Table 6 here]

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 private debt may not need granular public debt. We therefore investigate in Table 7 whether a larger fraction of bank debt affects firms' bond granularity decisions. Since private debt is easier to adjust and renegotiate than public debt, firms might effectively maintain a high degree of total debt granularity by managing bank debt granularity, leaving bond maturity structure less granular. To examine this substitution hypothesis, we estimate the model in equation (10) for low and high bank debt subsamples, where bank debt is proxied by total debt in COMPUSTAT minus bond amounts in the FISD. Notably, the estimation results for both subsamples are qualitatively similar to the full sample results. Thus, the cross-sectional results in Table 5 are robust to variation in private debt outstanding.

[Insert Table 7 here]

5.2 Speed-Of-Adjustment Results

The regression specification (10) assumes implicitly that observed granularity is also firms' target granularity. In a world without adjustment costs, this would be plausible. With adjustment costs, however, granularity is likely to deviate from the target level, and firms will typically make partial adjustments towards their targets. If firms manage granularity, then their granularity will revert to target levels rapidly. In contrast, if there is no target granularity, or if adjustment costs are too high, then firms are passive and adjustment speeds should be slow.

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

$$\Delta GRAN_{i,t+1} = \gamma(\beta X_{i,t} - GRAN_{i,t}) + \nu_{i,t+1}, \tag{11}$$

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

$$GRAN_{i,t+1} = (\gamma\beta)X_{i,t} + (1-\gamma)GRAN_{i,t} + \nu_{i,t+1}. \tag{12}$$

Equation (12) says that, in a world of partial adjustments, next year's granularity, $GRAN_{i,t+1}$, is a linear combination of target granularity ($\beta X_{i,t}$) and actual granularity ($GRAN_{i,t}$) this year.

Table 8 displays again results separately for $GRAN1$ in Panel A and for $GRAN2$ in Panel B. The first two columns in both panels present the pooled OLS estimation results of equation (12) without firm or year fixed effects. The estimated SOA coefficients are around 0.11 (the first column of Panel A) to 0.25 (the second column of Panel B). Economically, these estimates on lagged granularity imply the half lives of excess granularity are between 2.41 to 5.95 years. Moreover, the estimated SOA coefficients are statistically highly significant, which indicates that firms have target granularity levels and are involved in granularity management.

[Insert Table 8 here]

These relatively low adjustment speeds can be due to unobservable heterogeneity in target granularity. As pointed out by Flannery and Rangan (2006), the lack of fixed effects potentially biases the SOA coefficients towards zero. Therefore, we include firm and year fixed effects in columns three and four of both panels in Table 8. With fixed effects, the SOA estimates dramatically increase and are also highly statistically significant. In the forth column of Panel B, for example, the coefficient on $GRAN2$ equals 0.499. At this high rate of adjustment, firms close the granularity gap approximately by 75% within two years. In untabulated results, an F-test for the joint significance of the fixed effects rejects the hypothesis that these terms are all equal ($F(2175, 11983) = 1.84$; p-value=0.00), supporting heterogeneity in granularity targets.

The rapid adjustment speeds with fixed effect estimations require careful interpretation, because equation (12) is a dynamic panel model. It is well-known that coefficient estimates are inconsistent with fixed effects in a dynamic panel. To address this issue, we employ a panel GMM estimation using lags of granularity as instruments as in Arellano and Bond (1991) in the fifth and sixth columns in Table 8. With this approach, the estimated speeds of adjustment are quite similar to the results with fixed effects. In the sixth column of Panel A, for example, the estimated SOA coefficient is

0.483, which indicates that a typical firm adjusts approximately 70% of granularity towards its target granularity within two years. These results based on instrumental variables strongly suggest that firms manage debt granularity even when allowing for non-zero adjustment costs.

As robustness checks, we also report SOA estimations for the subsample of firms with at least two bonds or more outstanding and for the subsample of bonds without sinking fund provisions in the remaining columns of Table 8. The results are qualitatively similar or even stronger, especially when one-bond firms are eliminated from the sample. The estimates are highly statistically significant and the SOA coefficients range from 0.32 to 0.74. Across different specifications and granularity measures, we find that firms reliably adjust granularity levels towards their target granularity levels.

In addition to the SOA estimates in the first line, Table 8 also provides coefficient estimates for $(\gamma\beta)X_{i,t}$, which allow us to deduce granularity targets as a function of firm characteristics. Note that the estimated granularity targets also confirm the predictions from our theory. Tobin's Q, firm size, and leverage are reliably positively related to target granularity across all the models considered. The other variables (i.e. firm age, tangibility, and profitability) also tend to be associated with target granularity in a way that is consistent with our hypotheses.

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

5.3 Time-Series Results

In this section, we provide more direct evidence on firms' granularity management. Specifically, we ask the following question: how important is granularity management when firms determine the maturity of newly-issued bonds?

To address this question, we construct a novel time-series test, which is informative about whether newly-issued bonds' maturities are consistent with debt granularity management. For this purpose, we run a series of binomial choice regressions:

$$Prob(I_i^{K_j}) = a_1 m_i^{K_1} + a_2 m_i^{K_2} + a_3 m_i^{K_3} + a_4 m_i^{K_4} + a_5 m_i^{K_5} + a_6 m_i^{K_6} + a_7 m_i^{K_7} + \alpha_n + y_t \ , \quad (13)$$

where K_j represent maturity buckets, $I_i^{K_j}$ issuance dummies for each newly-issued bond i, and $m_i^{K_j}$ are deviations of the issuing firm's maturity profile from its benchmark's. The maturity buckets K_j are defined as follows. For maturity shorter than 10 years, there are five two-year buckets. In other words, for $1 \leq j \leq 5$, K_j is from $2j-1$ to $2j$ years. For maturities longer than 10 years, there are two maturity buckets K_6 and K_7. K_6 corresponds to years from 11 to 20 and K_7 to years from 21 or longer. α_n is a firm fixed effect for the issuing firm n and y_t denotes a year fixed effect.[19]

The independent variable $m_i^{K_j}$ (the deviation of maturity profiles from the benchmark) is defined in the following way. Each firm's maturity profiles are first calculated as fractions of pre-existing bond amounts in each maturity bucket K_j. To obtain the benchmark maturity profile, firms are sorted into high (top 50%) and low (bottom 50%) groups based on the firm characteristics (Q, market leverage, age, size, tangibility, profitability, and average maturity). This procedure yields 128 maturity profile groups. The benchmark profile of each group is then obtained by averaging maturity profiles in that group. The deviations from the benchmark profiles are obtained by subtracting average maturity profiles of the group that the issuing firm belongs to.

The dependent variable is the issuance variable, $I_i^{K_j}$, which takes a value of one if the bond's maturity falls in the K_j bucket. If the bond issued has a different maturity, then $I_i^{K_j}$ is zero. For the new issue to be sufficiently important, we experiment with different relative issuance size cut-offs. We note that this time-series analysis is conditional in that it estimates a maturity choice problem given the firm issues a bond.

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

Results in Panel A of Table 9 confirm the model's key insights. Panel A1 provides the results

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

based on the sample of bonds with issue sizes greater than 3% of firms' total pre-existing bond amounts. Except for the shortest maturity bucket (K_1), all diagonal coefficients are negative and statistically significant at 1% or 5% level, suggesting that firms engage in granularity management by avoiding maturity towers. For the five to six year maturity bucket, for example, the coefficient on K_3 is -0.423. That is, the probability of issuing additional five- or six-year maturity bonds drops by 0.423 of a percentage point for every percentage point that a firm's maturity profile exceeds the benchmark maturity profile in the bucket K_3. Perhaps because bank loans and other private debt are confounding our analysis for shorter maturities, the weakest result is found at the shortest maturity bucket (K_1), which is still negative and statistically significant at the 10% level. Non-diagonal coefficients are in many cases positive and not significant. The results in Panel A2 based on the sample with the issue cutoff at 5% are even stronger, further confirming firms' motives to maintain granular bond maturity structures when the relative size of the new issue is larger.

[Insert Table 9 here]

In addition, we examine in Table 9 whether the diagonal coefficients are, on average, smaller than the other six coefficients in the same binomial choice regression (i.e. column). For this purpose, we test the following null hypothesis, H_0, in the last rows of Table 9: $a_i - \frac{1}{6}\sum_{n\neq i} a_n = 0$. The results reveal that the diagonal coefficients are always smaller than the average of non-diagonal coefficients. The difference ($a_i - \frac{1}{6}\sum_{n\neq i} a_n$) is negative across all maturity buckets, ranging from -0.07 to -0.99 in Panel A1. Furthermore, they are all statistically significant at the 5% level, except for the seven to eight maturity bucket, in which case the statistical significance is marginal. When the 5% issue cutoff is used in Panel A2, the results are stronger with the hypothesis rejected in all cases at the 5% level.

In Panels B1 and B2 of Table 9, we perform the same tests after excluding all option-embedded bonds, such as callable, convertible, and putable bonds, and bonds with sinking fund provisions, as a robustness check. This exercise is important and informative because effective maturities could be shorter with these option-embedded bonds. Compared to the ones in the full sample, the results are qualitatively similar in the sample of straight bonds.

Overall, these findings reinforce the results from the previous subsection. That is, they also support the view that firms manage debt granularity, especially when they issue new bonds.

6 Conclusion

In this paper, we study the degree to which firms spread out their bonds' maturity dates across time, which we call "granularity" of corporate debt. We build a three-period model with roll-over risk, which has adverse effects on the firm's real investment process, to derive a number of novel, testable implications. In our setting, it can be advantageous to diversify the debt roll-over times across different maturity dates. Our model predicts that corporate debt should be more granular for larger and more mature firms, for firms with better investment opportunities, with more tangible assets, with higher leverage ratios, with lower values of assets in place, and with lower levels of current cash flows.

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

Taken together, our model predictions and test results suggest several novel insights for the joint choice of capital structure and debt structure. In essence, we establish that there is heterogeneity in regards to 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. Hence our understanding of corporate financial decision-making can be improved by recognizing that firms simultaneously use different types, sources, and maturities of debt, which means debt granularity management matters in theory and in practice.

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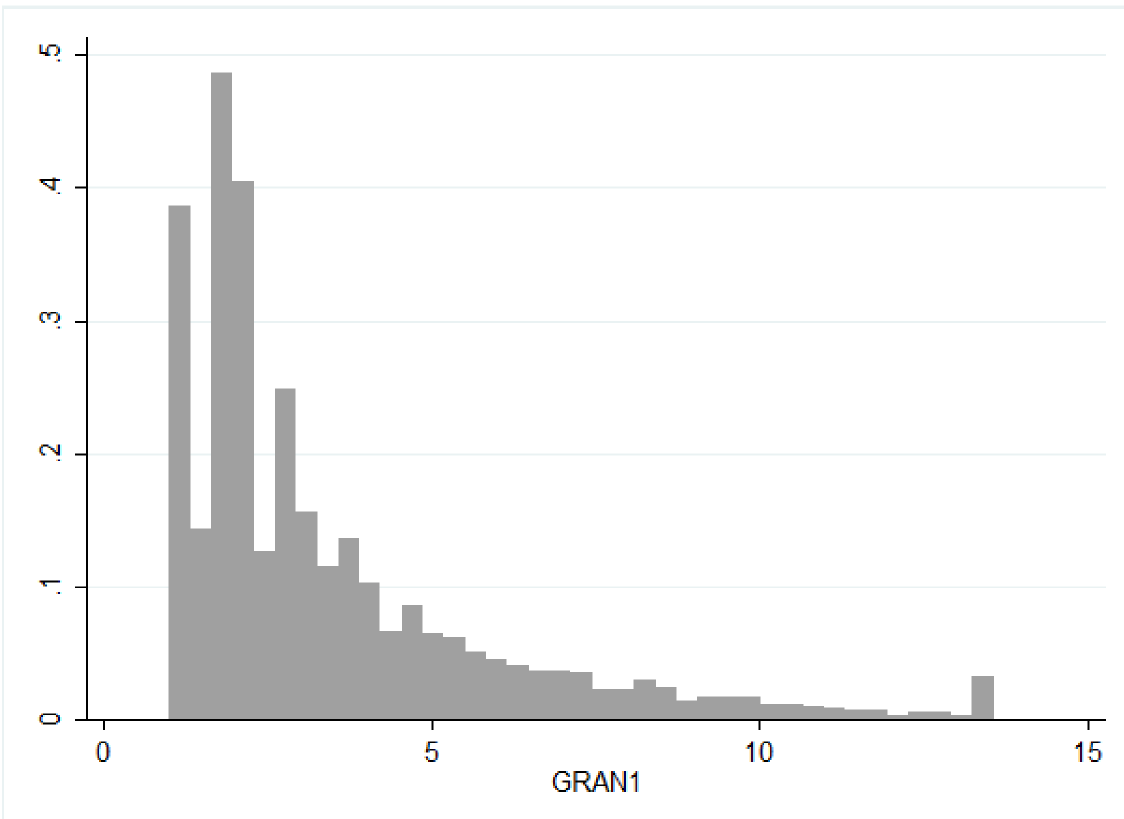
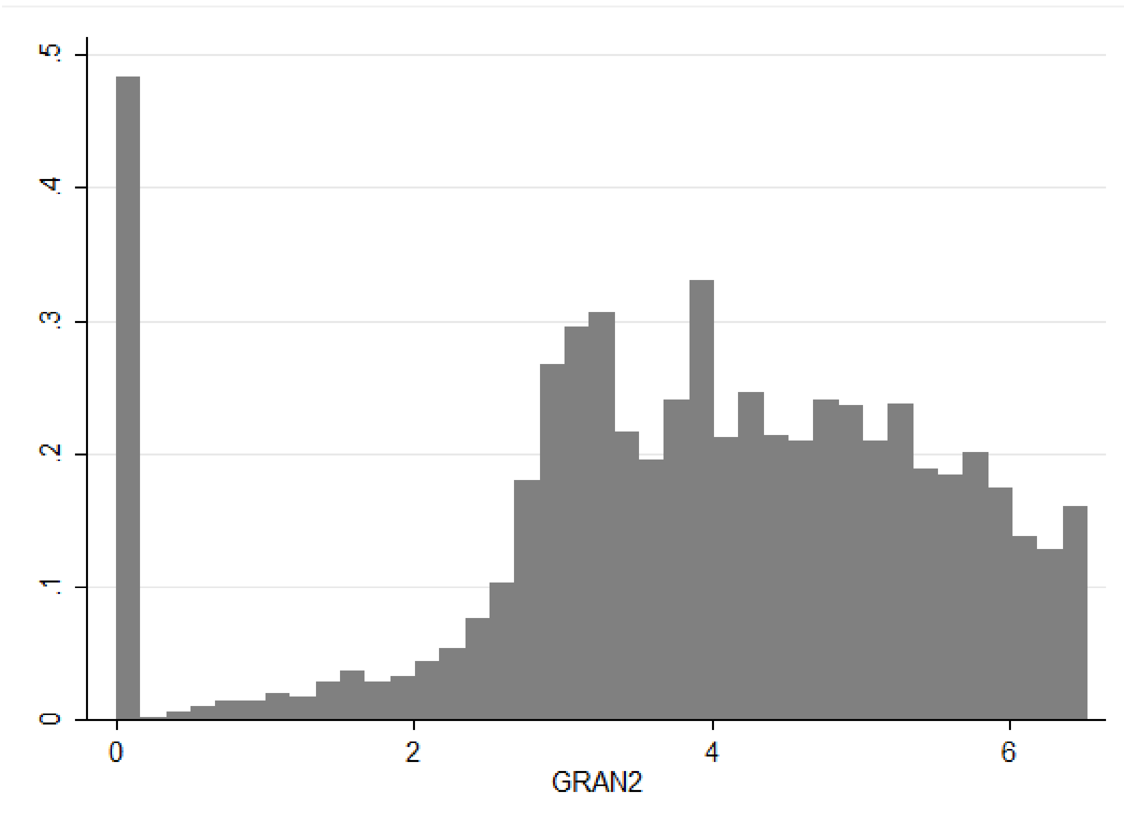
Figure 5. Distribution of Granularity Measures ($GRAN1$)



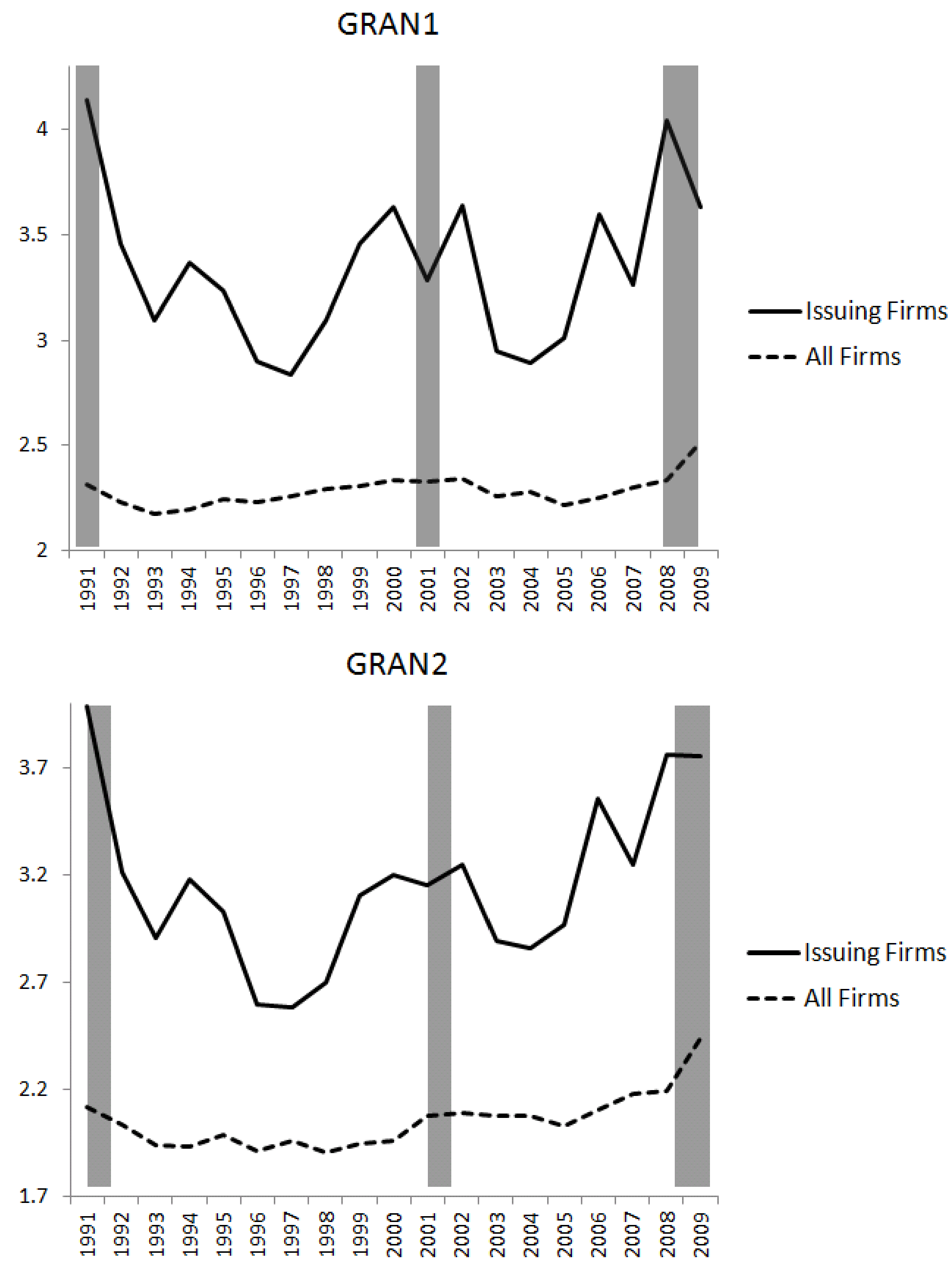
This figure plots the histogram of the granularity measure, $GRAN1$, winsorized at the top and bottom 0.5%. Firms are required to have more than or equal to two bonds outstanding to be included in the sample. $GRAN1$ is defined as an inverse of the Herfindahl index of bond fractions. The bond fractions are calculated by first grouping maturities into the nearest integer years and then calculating fractions out of total bond outstanding.

Figure 6. Distribution of Granularity Measures (*GRAN*2)



This figure plots the histogram of the granularity measure, $GRAN2$, winsorized at the top and bottom 0.5%. Firms are required to have more than or equal to two bonds outstanding to be included in the sample. $GRAN2$ is defined as the negative value of the log of the Atkinson index of bond fractions. The bond fractions are calculated by first grouping maturities into the nearest integer years and then calculating fractions out of total bond outstanding.

Figure 7. Time Series of Granularity



This figure plots the time series of aggregate granularity measures, $GRAN1$ and $GRAN2$, for bond issuing firms only and for all firms. $GRAN1$ is defined as the inverse of the Herfindahl index of bond fractions, and $GRAN2$ is defined as the negative value of the log of the Atkinson index of bond fractions. To obtain bond 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. Shaded areas are NBER recessions.

Table 3. Sample Descriptive Statistics

The sample is drawn from the Fixed Income Security Database (FISD) from Mergent and the annual COMPUSTAT files, excluding financial and utility firms, for the period from 1991 to 2009. Panel A reports summary statistics for firms with one bond ($NBond = 1$) and for firms with at least two bonds ($NBond \geq 2$). $GRAN1$ is defined as an inverse of the Herfindahl index of bond fractions. The bond fractions are calculated by first grouping maturities into the nearest integer years and then calculating fractions out of total bond outstanding. $GRAN2$ is defined as the negative value of the log of the Atkinson index of bond fractions. 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. Tan and $Prof$ are the tangibility and profitability. $NBond$ is the number of bonds outstanding and Mat is the average of firms' bond maturities. Panel B reports statistics for firms issuing bonds (issuers) and for firms not issuing bonds (non-issuers). $NIssue$ is the number of bonds issued by the issuing firms.

Panel A: Subsamples Based on Number of Bonds

	$NumBond \geq 2$			$NumBond = 1$		
	Mean	Std Dev	Median	Mean	Std Dev	Median
$GRAN1$	3.48	2.65	2.62			
$GRAN2$	3.88	1.66	4.01			
$Size$	11907.9	35835.5	3478.4	1775.6	6888.2	662.5
Age	24.9	13.4	28.0	16.9	11.8	13.0
Q	1.66	0.95	1.38	1.70	1.04	1.38
Lev	0.28	0.18	0.24	0.28	0.19	0.24
Tan	0.36	0.23	0.31	0.30	0.24	0.23
$Prof$	0.12	0.10	0.13	0.10	0.13	0.11
$NBond$	8.2	15.3	4.0	1.0	0.0	1.0
Mat	10.1	6.2	8.4	8.2	6.1	6.6
$Obs.$	9404			7189		

Panel B: Subsamples Based on Bond Issues

	Issuers			Non-Issuers		
	Mean	Std Dev	Median	Mean	Std Dev	Median
$GRAN1$	3.33	3.04	2.00	1.86	1.70	1.00
$GRAN2$	3.09	2.33	3.64	1.59	2.09	0.00
$Size$	10370.5	31848.3	2500.9	5542.9	24579.6	1164.8
Age	21.6	13.9	20.0	20.4	12.9	17.0
Q	1.77	1.08	1.43	1.64	0.97	1.35
Lev	0.28	0.17	0.24	0.29	0.19	0.25
Tan	0.37	0.25	0.32	0.33	0.23	0.27
$Prof$	0.12	0.11	0.13	0.11	0.12	0.12
$NBond$	8.6	17.7	3.0	3.2	7.4	1.0
Mat	10.3	5.7	9.1	8.5	6.4	6.7
$NIssue$	2.2	3.9	1.0			
$Obs.$	5117			11476		

Table 4. Correlations

The sample is from the Fixed Income Security Database (FISD) from Mergent and the annual COMPUSTAT files, excluding financial and utility firms for the period from 1991 to 2009. $GRAN1$ is defined as a negative of the Herfindahl index of bond fractions. The bond fractions are calculated by first grouping maturities into the nearest integer years and then calculating fractions out of total bond outstanding. $GRAN2$ is defined as the negative value of the log of the Atkinson index of bond fractions. $Size$ is the total assets in million dollars. Age is the number of years in the COMPUSTAT file prior to observations. Q is the market-to-book ratio and Lev is the market value of leverage. Tan and $Prof$ are tangibility and profitability. $NBond$ is the number of bonds outstanding and Mat is the average of firms' bond maturities. The sample period is from 1991 to 2009 and there are total of 16,593 firm-year observations.

	$GRAN1$	$GRAN2$	$Size$	Age	Q	Lev	Tan	$Prof$	Mat	$NBond$
$GRAN1$	1									
$GRAN2$	0.80	1								
$Size$	0.60	0.65	1							
Age	0.36	0.40	0.41	1						
Q	-0.03	-0.01	0.03	-0.02	1					
Lev	-0.07	-0.08	-0.27	-0.23	-0.54	1				
Tan	0.16	0.14	0.08	-0.02	-0.16	0.19	1			
$Prof$	0.12	0.16	0.28	0.20	0.13	-0.21	0.16	1		
Mat	0.26	0.28	0.22	0.14	0.03	-0.15	0.05	0.11	1	
$NBond$	0.66	0.46	0.40	0.24	-0.03	-0.04	0.13	0.06	0.13	1

Table 5. Cross-Sectional Analysis

This table provides results for the following panel regression equation:

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

where $X_{i,t}$ is a vector of explanatory variables, α_i is a firm or industry level fixed effect, and y_t is a year fixed effect. Panel A and Panel B report results based on $GRAN1$ and $GRAN2$, respectively. In columns named All Firms, the entire sample of firms is considered in the regressions. In the next two columns, only firms with at least two bonds outstanding are included in the regressions. The last two columns reports results from the sample without bonds with sinking fund provisions. $GRAN1$ and $GRAN2$ are the inverse of Herfindahl index and the negative value of the log of the Atkinson index of bond fractions, respectively. To obtain bond fractions, we group bond maturities into the nearest integer years and compute their fractions out of the total amount of bonds outstanding. $Size$ is the total assets in million dollars. Age is the number of years in the COMPUSTAT file prior to observations. Q is the market-to-book ratio and Lev is the market value of leverage. Tan and $Prof$ are tangibility and profitability. $NBond$ is the number of bonds outstanding and Mat is the average of firms' bond maturities. $Cash$ is the cash holdings of firms, and $Rating$ is the issuer-level S&P rating, where smaller values of $Rating$ represent higher ratings. Numbers in parentheses are t-statistics for which standard errors are clustered at the Fama-French 48 industry level. The sample period is from 1991 to 2009.

Panel A: $GRAN1$										
	All Firms						Num. Bonds ≥ 2		Straight Bonds	
Q	0.220	0.122	0.230	0.099	0.190	0.155	0.290	0.231	0.251	0.200
	(3.07)	(1.67)	(2.79)	(1.34)	(2.37)	(1.86)	(1.85)	(1.56)	(2.80)	(2.05)
$Size$	0.805	0.637	0.817	0.632	0.646	0.632	0.974	0.912	0.685	0.646
	(13.14)	(9.49)	(12.43)	(8.76)	(8.62)	(7.10)	(9.49)	(7.04)	(9.24)	(7.08)
Age	0.028	0.017	0.03	0.018	0.186	0.12	0.393	0.641	0.232	0.185
	(8.88)	(6.32)	(11.41)	(7.14)	(1.36)	(0.78)	(1.31)	(1.86)	(1.64)	(1.27)
Lev	1.37	1.447	1.181	1.274	1.3	1.006	1.632	1.155	1.36	1.046
	(5.33)	(6.92)	(4.34)	(6.34)	(5.08)	(4.79)	(3.77)	(3.41)	(4.46)	(4.02)
Tan	1.104	0.516	0.961	0.718	-0.061	0.490	0.433	0.935	0.029	0.527
	(3.73)	(2.62)	(3.10)	(2.38)	(-0.20)	(1.19)	(0.89)	(1.61)	(0.10)	(1.33)
$Prof$	-1.567	-0.657	-1.798	-0.627	-0.485	-0.242	-0.383	-0.016	-0.479	-0.230
	(-4.63)	(-2.31)	(-4.07)	(-2.09)	(-1.98)	(-0.92)	(-0.79)	(-0.03)	(-2.07)	(-0.86)
$NBond$		0.006		0.006		0.005		0.003		0.058
		(3.28)		(3.44)		(3.08)		(3.10)		(3.72)
Mat		0.004		0.004		0.003		0.003		0.03
		(3.82)		(3.81)		(2.42)		(3.11)		(4.66)
$Cash$		-0.009		0.233		0.143		0.099		0.158
		(-0.05)		(1.11)		(0.64)		(0.23)		(0.77)
$Rating$		0.008		0.011		0.137		0.135		0.116
		(0.13)		(0.19)		(1.37)		(1.15)		(1.10)
$Rating^2$		-0.001		-0.001		-0.004		-0.004		-0.004
		(-0.33)		(-0.33)		(-1.28)		(-1.08)		(-1.07)
$Obs.$	16593	14084	16593	14084	16593	14084	9288	8668	15546	13427
R^2	0.456	0.5	0.469	0.504	0.735	0.745	0.701	0.709	0.765	0.791
Year FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	No	No	No	No	No	No
Firm FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: $GRAN2$										
	All Firms						Num. Bonds ≥ 2		Straight Bonds	
Q	0.381	0.442	0.401	0.403	0.379	0.365	0.248	0.199	0.466	0.420
	(4.84)	(4.56)	(5.17)	(4.50)	(5.90)	(5.19)	(3.16)	(2.31)	(8.05)	(6.59)
$Size$	0.865	0.784	0.883	0.784	0.756	0.751	0.617	0.574	0.8	0.779
	(29.28)	(18.75)	(25.78)	(16.77)	(11.66)	(10.52)	(11.92)	(10.43)	(12.97)	(11.26)
Age	0.033	0.026	0.032	0.026	-0.052	-0.3	0.325	0.418	0.033	-0.177
	(10.01)	(9.33)	(11.66)	(9.43)	(-0.26)	(-1.42)	(1.59)	(1.76)	(0.15)	(-0.85)
Lev	1.790	2.251	1.717	2.104	2.295	2.278	1.227	0.998	2.456	2.365
	(8.21)	(9.08)	(8.30)	(8.07)	(8.79)	(10.01)	(4.37)	(4.40)	(8.41)	(9.34)
Tan	0.876	0.471	0.676	0.557	-0.075	0.259	0.184	0.326	-0.062	0.233
	(5.36)	(2.46)	(3.67)	(2.64)	(-0.25)	(0.68)	(0.65)	(1.19)	(-0.22)	(0.71)
$Prof$	-0.953	-0.93	-1.221	-0.836	-0.588	-0.564	-0.22	-0.14	-0.484	-0.407
	(-3.94)	(-2.70)	(-4.48)	(-2.57)	(-2.48)	(-1.91)	(-0.72)	(-0.46)	(-2.08)	(-1.36)
$NBond$		0.033		0.034		0.032		0.018		0.031
		(3.49)		(3.83)		(3.39)		(3.45)		(3.42)
Mat		0.063		0.063		0.045		0.058		0.046
		(8.15)		(8.04)		(7.25)		(16.78)		(6.12)
$Cash$		-0.219		0.214		0.421		0.298		0.499
		(-0.84)		(0.88)		(1.39)		(1.07)		(1.73)
$Rating$		0.05		0.06		0.082		0.071		0.054
		(1.16)		(1.52)		(1.30)		(1.74)		(0.78)
$Rating^2$		-0.004		-0.004		-0.002		-0.002		-0.002
		(-1.92)		(-2.25)		(-1.17)		(-1.66)		(-0.72)
Obs.	16593	14084	16593	14084	16593	14084	9288	8668	15546	13427
R^2	0.471	0.52	0.492	0.531	0.751	0.756	0.75	0.761	0.752	0.758
Year FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	No	No	No	No	No	No
Firm FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes

Table 6. Cross-Sectional Analysis: Pre-Crisis and Crisis Subsamples

This 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 pre-crisis (2007 or earlier) and the crisis (2008 or later) periods. $X_{i,t}$ is a vector of explanatory variables, α_i is a firm or industry level fixed effect, and y_t is a year fixed effect. Panel A and Panel B report results based on $GRAN1$ and $GRAN2$, respectively. In columns named All Firms, the entire sample of firms is considered in the regressions. In the next two columns, only firms with at least two bonds outstanding are included in the regressions. The last two columns reports results from the sample without bonds with sinking fund provisions. $GRAN1$ and $GRAN2$ are the inverse of Herfindahl index and the negative value of the log of the Atkinson index of bond fractions, respectively. To obtain bond fractions, we group bond maturities into the nearest integer years and compute their fractions out of the total amount of bonds outstanding. $Size$ is the total assets in million dollars. Age is the number of years in the COMPUSTAT file prior to observations. Q is the market-to-book ratio and Lev is the market value of leverage. Tan and $Prof$ are tangibility and profitability. $NBond$ is the number of bonds outstanding and Mat is the average of firms' bond maturities. $Cash$ is the cash holdings of firms, and $Rating$ is the issuer-level S&P rating, where smaller values of $Rating$ represent higher ratings. Numbers in parentheses are t-statistics for which standard errors are clustered at the Fama-French 48 industry level. The sample period is from 1991 to 2009.

Panel A: $GRAN1$

	Pre-Crisis					Crisis				
Q	0.082	0.055	0.127	0.201	0.172	0.515	0.435	0.372	0.464	0.379
	(1.05)	(0.73)	(1.44)	(1.27)	(1.70)	(3.18)	(2.77)	(1.81)	(1.46)	(1.84)
$Size$	0.648	0.644	0.631	0.93	0.643	0.468	0.45	0.636	0.868	0.642
	(9.43)	(8.68)	(7.10)	(6.76)	(6.94)	(4.83)	(4.93)	(2.68)	(2.13)	(2.65)
Age	0.016	0.017	0.119	0.642	0.181	0.02	0.02	0.167	0.186	0.173
	(5.96)	(6.94)	(0.80)	(1.94)	(1.26)	(4.33)	(4.14)	(2.76)	(2.06)	(2.69)
Lev	1.364	1.197	0.956	1.074	0.982	2.016	1.845	1.09	1.287	1.133
	(6.98)	(6.40)	(4.45)	(3.09)	(3.72)	(4.67)	(4.58)	(1.62)	(1.15)	(1.65)
Tan	0.577	0.748	0.592	1.131	0.627	0.04	0.442	-0.268	0.4	-0.307
	(2.94)	(2.52)	(1.39)	(1.81)	(1.53)	(0.14)	(0.93)	(-0.32)	(0.35)	(-0.36)
$Prof$	-0.586	-0.593	-0.276	-0.037	-0.264	-1.305	-0.891	-0.077	-0.082	-0.072
	(-2.04)	(-1.88)	(-1.04)	(-0.07)	(-0.89)	(-1.89)	(-1.85)	(-0.30)	(-0.17)	(-0.28)
$NBond$	0.08	0.08	0.063	0.054	0.059	0.129	0.128	0.107	0.097	0.108
	(5.40)	(5.38)	(3.94)	(3.72)	(3.76)	(3.65)	(3.50)	(1.37)	(1.26)	(1.36)
Mat	0.054	0.053	0.032	0.045	0.031	0.049	0.049	-0.016	-0.022	-0.015
	(6.45)	(6.26)	(5.72)	(4.18)	(4.95)	(3.82)	(3.67)	(-0.92)	(-0.81)	(-0.92)
$Cash$	-0.052	0.209	0.062	-0.023	0.083	0.171	0.069	1.175	1.196	1.15
	(-0.31)	(1.09)	(0.29)	(-0.05)	(0.43)	(0.41)	(0.13)	(1.38)	(1.03)	(1.35)
$Rating$	0.007	0.011	0.133	0.135	0.109	0.015	0.003	0.02	-0.01	0.016
	(0.11)	(0.19)	(1.34)	(1.17)	(1.02)	(0.12)	(0.02)	(0.09)	(-0.04)	(0.07)
$Rating^2$	0	0	-0.004	-0.004	-0.003	-0.004	-0.004	-0.001	0	-0.001
	(-0.18)	(-0.17)	(-1.18)	(-1.05)	(-0.93)	(-0.77)	(-0.65)	(-0.16)	(-0.05)	(-0.14)
$Obs.$	12746	12746	12746	7716	12095	1338	1338	1338	952	1332
R^2	0.607	0.614	0.806	0.772	0.798	0.615	0.624	0.956	0.945	0.954
Year FE	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	No	No	Yes	No	No	No
Firm FE	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
$NBond \geq 2$	No	No	No	Yes	No	No	No	No	Yes	No
Straight Bonds Only	No	No	No	No	Yes	No	No	No	No	Yes

Panel B: $GRAN2$										
	Pre-Crisis					Crisis				
Q	0.39	0.341	0.331	0.169	0.386	1.024	0.986	0.606	0.491	0.618
	(3.84)	(3.64)	(4.46)	(1.98)	(5.91)	(5.66)	(5.40)	(1.37)	(0.98)	(1.40)
$Size$	0.795	0.793	0.769	0.599	0.797	0.651	0.683	0.997	1.113	0.999
	(18.95)	(17.05)	(10.56)	(9.29)	(11.19)	(9.53)	(9.02)	(3.38)	(3.32)	(3.38)
Age	0.026	0.025	-0.278	0.471	-0.157	0.029	0.026	0.204	0.085	0.209
	(9.13)	(9.49)	(-1.31)	(1.92)	(-0.76)	(6.27)	(5.48)	(2.72)	(1.09)	(2.71)
Lev	2.132	1.966	2.192	0.897	2.273	3.18	3.402	2.027	2.004	2.081
	(8.47)	(7.34)	(9.20)	(4.10)	(9.25)	(5.96)	(5.76)	(1.70)	(1.39)	(1.73)
Tan	0.547	0.627	0.41	0.52	0.375	-0.136	-0.101	-0.872	0.748	-0.887
	(2.77)	(2.90)	(1.11)	(1.79)	(1.16)	(-0.45)	(-0.23)	(-0.51)	(0.41)	(-0.51)
$Prof$	-0.918	-0.856	-0.705	-0.162	-0.502	-1.279	-0.692	0.687	0.734	0.655
	(-2.62)	(-2.71)	(-2.32)	(-0.48)	(-1.60)	(-1.78)	(-1.25)	(1.39)	(1.63)	(1.33)
$NBond$	0.032	0.033	0.032	0.018	0.031	0.057	0.059	0.071	0.032	0.071
	(3.40)	(3.75)	(3.48)	(3.49)	(3.37)	(3.18)	(3.00)	(1.12)	(0.91)	(1.11)
Mat	0.063	0.063	0.044	0.06	0.045	0.059	0.058	-0.019	-0.034	-0.019
	(8.87)	(8.68)	(6.98)	(19.26)	(6.56)	(3.40)	(3.11)	(-0.43)	(-0.64)	(-0.43)
$Cash$	-0.249	0.19	0.331	0.206	0.432	-0.088	0.256	1.619	0.419	1.578
	(-0.94)	(0.81)	(1.06)	(0.67)	(1.41)	(-0.19)	(0.42)	(1.07)	(0.42)	(1.04)
$Rating$	0.05	0.063	0.086	0.068	0.054	0.073	0.063	-0.141	-0.106	-0.144
	(1.13)	(1.56)	(1.34)	(1.77)	(0.77)	(0.95)	(0.75)	(-0.66)	(-0.64)	(-0.67)
$Rating^2$	-0.003	-0.004	-0.002	-0.002	-0.001	-0.006	-0.006	0.005	0.004	0.005
	(-1.73)	(-2.13)	(-1.07)	(-1.52)	(-0.58)	(-1.97)	(-1.71)	(0.71)	(0.69)	(0.73)
$Obs.$	12746	12746	12746	7716	12095	1338	1338	1338	952	1332
R^2	0.522	0.534	0.761	0.767	0.763	0.51	0.519	0.907	0.915	0.906
Year FE	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	No	No	Yes	No	No	No
Firm FE	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
$NBond \geq 2$	No	No	No	Yes	No	No	No	No	Yes	No
Straight Bonds Only	No	No	No	No	Yes	No	No	No	No	Yes

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

This table provides results for the following panel regression equation:

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

for the low and the high bank loan subsamples. $X_{i,t}$ is a vector of explanatory variables, α_i is a firm or industry level fixed effect, and y_t is a year fixed effect. Firms are categorized as low bank loan firms if more than 50% of debt (long-term debt plus debt in current liabilities) is corporate bonds and are categorized as high bank loan firms otherwise. Panel A and Panel B report results based on $GRAN1$ and $GRAN2$, respectively. In columns named All Firms, the entire sample of firms is considered in the regressions. In the next two columns, only firms with at least two bonds outstanding are included in the regressions. The last two columns reports results from the sample without bonds with sinking fund provisions. $GRAN1$ and $GRAN2$ are the inverse of Herfindahl index and the negative value of the log of the Atkinson index of bond fractions, respectively. To obtain bond fractions, we group bond maturities into the nearest integer years and compute their fractions out of the total amount of bonds outstanding. $Size$ is the total assets in million dollars. Age is the number of years in the COMPUSTAT file prior to observations. Q is the market-to-book ratio and Lev is the market value of leverage. Tan and $Prof$ are tangibility and profitability. $NBond$ is the number of bonds outstanding and Mat is the average of firms' bond maturities. $Cash$ is the cash holdings of firms, and $Rating$ is the issuer-level S&P rating, where smaller values of $Rating$ represent higher ratings. Numbers in parentheses are t-statistics for which standard errors are clustered at the Fama-French 48 industry level. The sample period is from 1991 to 2009.

Panel A: $GRAN1$

	Low Bank Loan					High Bank Loan				
Q	0.062	0.066	0.232	0.285	0.238	0.333	0.275	0.153	0.374	0.252
	(0.62)	(0.68)	(2.49)	(1.82)	(2.33)	(2.83)	(2.28)	(1.06)	(1.39)	(1.63)
$Size$	0.907	0.911	0.795	1.103	0.792	0.527	0.543	0.581	1.005	0.616
	(9.10)	(8.58)	(7.33)	(7.21)	(6.89)	(7.83)	(7.31)	(5.27)	(5.37)	(6.25)
Age	0.017	0.018	0.256	1.165	0.341	0.014	0.013	-0.118	0.071	-0.1
	(5.02)	(5.26)	(1.12)	(3.20)	(1.53)	(3.80)	(4.55)	(-0.64)	(0.21)	(-0.60)
Lev	2.532	2.324	1.6	1.793	1.556	1.304	1.287	0.903	1.49	1.052
	(7.28)	(6.87)	(5.36)	(4.21)	(4.80)	(4.78)	(4.46)	(2.95)	(2.72)	(2.69)
Tan	0.601	0.627	0.269	0.842	0.49	0.2	0.304	0.015	-0.16	0.136
	(1.98)	(1.69)	(0.61)	(1.21)	(1.00)	(0.99)	(1.14)	(0.03)	(-0.19)	(0.31)
$Prof$	-0.676	-0.737	-0.17	-0.037	-0.2	-0.476	-0.376	-0.185	0.567	0.041
	(-1.89)	(-1.91)	(-0.68)	(-0.09)	(-0.76)	(-1.00)	(-0.82)	(-0.34)	(0.39)	(0.07)
$NBond$	0.065	0.062	0.039	0.033	0.037	0.1	0.099	0.106	0.104	0.104
	(5.52)	(4.82)	(2.41)	(2.25)	(2.36)	(3.22)	(3.20)	(4.13)	(4.82)	(3.91)
Mat	0.045	0.045	0.019	0.034	0.021	0.05	0.047	0.029	0.049	0.029
	(4.49)	(4.46)	(2.24)	(2.59)	(2.34)	(4.88)	(4.65)	(3.18)	(3.45)	(2.78)
$Cash$	-0.025	0.154	0.01	0.17	0.11	-1.842	-1.451	-0.225	0.764	0.12
	(-0.10)	(0.66)	(0.04)	(0.44)	(0.54)	(-3.32)	(-2.82)	(-0.35)	(0.60)	(0.21)
$Rating$	-0.066	-0.049	0.075	0.09	0.067	0.033	0.022	0.043	0.029	-0.012
	(-0.91)	(-0.70)	(0.65)	(0.69)	(0.55)	(0.65)	(0.42)	(0.50)	(0.16)	(-0.13)
$Rating^2$	0.002	0.002	-0.001	-0.002	-0.001	-0.001	-0.001	-0.002	-0.001	0
	(0.77)	(0.68)	(-0.45)	(-0.57)	(-0.36)	(-0.60)	(-0.24)	(-0.46)	(-0.14)	(-0.02)
$Obs.$	9270	9270	9270	6067	8959	4814	4814	4814	2601	4468
R^2	0.672	0.683	0.856	0.827	0.845	0.582	0.595	0.81	0.773	0.808
Year FE	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	No	No	Yes	No	No	No
Firm FE	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
$NBond \geq 2$	No	No	No	Yes	No	No	No	No	Yes	No
Straight Bonds Only	No	No	No	No	Yes	No	No	No	No	Yes

Panel B: $GRAN2$										
	Low Bank Loan					High Bank Loan				
Q	0.436	0.446	0.501	0.21	0.519	0.617	0.474	0.282	0.471	0.398
	(4.62)	(4.80)	(5.81)	(2.55)	(6.34)	(3.85)	(3.05)	(1.39)	(2.18)	(1.96)
$Size$	1.06	1.081	0.958	0.67	0.972	0.738	0.753	0.754	0.73	0.805
	(20.44)	(20.49)	(12.33)	(12.89)	(12.29)	(14.72)	(12.84)	(6.32)	(6.16)	(6.31)
Age	0.025	0.024	-0.058	0.746	0.149	0.023	0.023	-0.457	-0.004	-0.486
	(9.26)	(8.34)	(-0.17)	(2.53)	(0.46)	(5.48)	(6.17)	(-1.31)	(-0.01)	(-1.48)
Lev	3.568	3.446	3.114	1.485	3.106	2.12	2.016	2.036	1.083	2.276
	(15.25)	(15.17)	(8.88)	(4.88)	(8.06)	(7.43)	(6.70)	(4.87)	(2.21)	(5.16)
Tan	0.406	0.305	-0.055	0.383	-0.02	0.43	0.473	0.477	0.37	0.401
	(2.45)	(1.47)	(-0.15)	(1.32)	(-0.06)	(2.05)	(1.67)	(0.95)	(0.90)	(0.73)
$Prof$	-0.786	-0.739	-0.175	0.048	-0.101	-1.093	-0.952	-0.97	-0.288	-0.917
	(-2.58)	(-2.61)	(-0.52)	(0.18)	(-0.30)	(-1.57)	(-1.45)	(-1.47)	(-0.27)	(-1.53)
$NBond$	0.012	0.012	0.015	0.008	0.013	0.063	0.061	0.059	0.037	0.066
	(2.25)	(2.17)	(2.36)	(2.07)	(2.42)	(3.66)	(3.69)	(5.18)	(5.20)	(4.41)
Mat	0.046	0.046	0.028	0.057	0.03	0.067	0.066	0.047	0.055	0.046
	(6.19)	(6.21)	(3.07)	(8.88)	(3.43)	(7.15)	(7.16)	(3.22)	(3.93)	(2.92)
$Cash$	-0.519	-0.11	0.099	0.281	0.242	-2.753	-2.359	-0.84	0.332	-0.305
	(-1.84)	(-0.41)	(0.36)	(1.13)	(0.93)	(-3.83)	(-3.74)	(-0.90)	(0.57)	(-0.43)
$Rating$	0.011	0.021	0.041	0.088	0.002	0.068	0.077	0.092	0.095	0.035
	(0.25)	(0.50)	(0.57)	(1.87)	(0.03)	(1.51)	(2.04)	(1.14)	(0.93)	(0.40)
$Rating^2$	-0.002	-0.002	0	-0.003	0.001	-0.004	-0.004	-0.004	-0.004	-0.002
	(-1.14)	(-1.12)	(-0.09)	(-2.16)	(0.48)	(-1.87)	(-2.16)	(-1.27)	(-0.80)	(-0.61)
$Obs.$	9270	9270	9270	6067	8959	4814	4814	4814	2601	4468
R^2	0.626	0.635	0.83	0.812	0.826	0.528	0.547	0.775	0.794	0.779
Year FE	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	No	No	No	Yes	No	No	No
Firm FE	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
$NBond \geq 2$	No	No	No	Yes	No	No	No	No	Yes	No
Straight Bonds Only	No	No	No	No	Yes	No	No	No	No	Yes

Table 8. Speed-Of-Adjustment Analysis

This table provides results for the following panel regression equation:

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

where $X_{i,t}$ is a vector of explanatory variables. Panel A and Panel B report results based on $GRAN1$ and $GRAN2$, respectively. In columns named All Firms, the entire sample of firms is considered in the regressions. In the next two columns, only firms with at least two bonds outstanding are included in the regressions. The last two columns reports results from the sample without bonds with sinking fund provisions. $GRAN1$ and $GRAN2$ are the inverse of Herfindahl index and the negative value of the log of the Atkinson index of bond fractions, respectively. To obtain bond fractions, we group bond maturities into the nearest integer years and compute their fractions out of the total amount of bonds outstanding. $Size$ is the total assets in million dollars. Age is the number of years in the COMPUSTAT file prior to observations. Q is the market-to-book ratio and Lev is the market value of leverage. Tan and $Prof$ are tangibility and profitability. $NBond$ is the number of bonds outstanding and Mat is the average of firms' bond maturities. $Cash$ is the cash holdings of firms, and $Rating$ is the issuer-level S&P rating, where smaller values of $Rating$ represent higher ratings. Numbers in parentheses are t-statistics for which standard errors are clustered at the Fama-French 48 industry level. The sample period is from 1991 to 2009.

Panel A: $\Delta GRAN1$

	All Firms				Arellano & Bond		Num. Bonds ≥ 2		Straight Bonds	
$GRAN1$	0.107	0.176	0.319	0.363	0.324	0.483	0.354	0.390	0.320	0.363
	(9.32)	(7.72)	(16.45)	(11.99)	(8.89)	(10.28)	(16.43)	(12.87)	(15.45)	(11.55)
Q	0.094	0.094	0.159	0.140	0.256	0.151	0.214	0.172	0.169	0.146
	(7.09)	(4.78)	(3.99)	(3.06)	(4.02)	(2.11)	(2.95)	(2.22)	(4.19)	(2.90)
$Size$	0.128	0.126	0.342	0.326	0.529	0.428	0.514	0.467	0.369	0.349
	(13.21)	(10.51)	(8.91)	(9.22)	(8.73)	(6.44)	(9.06)	(7.98)	(9.25)	(8.76)
Age	0.001	0.000	0.247	0.327	-0.034	-0.023	1.072	1.559	0.251	0.313
	(1.39)	(-0.35)	(0.91)	(0.61)	(-4.63)	(-2.53)	(3.60)	(11.70)	(0.96)	(0.62)
Lev	0.314	0.520	0.797	0.746	0.875	0.634	0.938	0.780	0.826	0.766
	(5.39)	(8.96)	(4.49)	(4.50)	(5.91)	(3.60)	(3.11)	(3.02)	(4.33)	(4.17)
Tan	0.148	0.083	-0.028	0.190	-0.071	0.361	0.064	0.256	0.060	0.295
	(3.79)	(1.72)	(-0.16)	(0.85)	(-0.33)	(1.46)	(0.27)	(0.91)	(0.34)	(1.27)
$Prof$	-0.209	-0.313	-0.223	-0.167	-0.482	-0.489	-0.149	-0.059	-0.219	-0.152
	(-3.88)	(-3.20)	(-1.53)	(-0.90)	(-3.76)	(-3.17)	(-0.59)	(-0.22)	(-1.54)	(-0.78)
$NBond$		0.015		0.027		0.073		0.024		0.025
		(3.44)		(2.99)		(5.11)		(2.85)		(2.96)
Mat		0.018		0.021		0.031		0.030		0.021
		(8.40)		(5.92)		(4.40)		(4.75)		(5.58)
$Cash$		-0.055		0.013		0.594		-0.046		0.076
		(-0.82)		(0.08)		(3.26)		(-0.19)		(0.58)
$Rating$		-0.007		0.013		0.032		0.021		0.015
		(-0.40)		(0.32)		(0.64)		(0.41)		(0.36)
$Rating^2$		0.000		-0.001		-0.001		-0.001		-0.001
		(-0.66)		(-0.53)		(-0.35)		(-0.67)		(-0.57)
$Obs.$	14183	12274	14183	12274	11955	10518	8564	8050	13274	11679
R^2	0.059	0.117	0.097	0.157	–	–	0.149	0.194	0.098	0.155
Year FE	No	No	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	–	–	No	No	No	No
Firm FE	No	No	Yes	Yes	–	–	Yes	Yes	Yes	Yes

Panel B: $\Delta GRAN2$										
	All Firms				Arellano & Bond		Num. Bonds ≥ 2		Straight Bonds	
$GRAN2$	0.208	0.247	0.478	0.499	0.396	0.418	0.724	0.738	0.488	0.508
	(29.97)	(24.26)	(30.09)	(32.46)	(11.49)	(11.52)	(53.59)	(53.28)	(29.13)	(32.81)
Q	0.194	0.234	0.338	0.317	0.458	0.364	0.223	0.157	0.355	0.313
	(10.59)	(7.98)	(7.28)	(6.22)	(6.20)	(4.57)	(3.05)	(1.95)	(8.61)	(6.20)
$Size$	0.215	0.192	0.436	0.404	0.635	0.575	0.456	0.402	0.467	0.426
	(25.09)	(12.44)	(10.19)	(8.39)	(11.00)	(8.62)	(10.19)	(8.52)	(10.47)	(8.40)
Age	0.003	0.002	0.261	-0.112	-0.043	-0.038	0.716	0.901	0.301	-0.093
	(3.16)	(1.96)	(0.47)	(-0.18)	(-7.30)	(-5.10)	(6.05)	(7.64)	(0.51)	(-0.14)
Lev	0.633	1.015	1.652	1.719	1.561	1.44	0.959	0.796	1.712	1.708
	(8.26)	(11.30)	(7.70)	(8.57)	(8.01)	(6.43)	(3.61)	(3.84)	(7.17)	(7.90)
Tan	0.197	0.142	-0.320	-0.092	-1.041	-0.312	-0.125	0.006	-0.262	-0.013
	(3.25)	(1.92)	(-1.43)	(-0.32)	(-3.86)	(-0.93)	(-0.65)	(0.03)	(-1.14)	(-0.05)
$Prof$	-0.272	-0.511	-0.374	-0.413	-0.551	-0.579	-0.169	-0.129	-0.319	-0.318
	(-4.40)	(-3.48)	(-1.69)	(-1.62)	(-2.69)	(-2.45)	(-0.68)	(-0.52)	(-1.63)	(-1.39)
$NBond$		0.007		0.017		0.043		0.012		0.017
		(2.87)		(2.99)		(4.71)		(2.89)		(3.10)
Mat		0.027		0.037		0.048		0.051		0.040
		(9.22)		(7.12)		(5.13)		(14.17)		(6.64)
$Cash$		0.041		0.407		1.421		0.390		0.570
		(0.44)		(1.64)		(5.41)		(1.81)		(2.19)
$Rating$		0.024		0.025		0.022		0.056		0.032
		(1.51)		(0.70)		(0.45)		(1.58)		(0.72)
$Rating^2$		-0.002		-0.002		-0.001		-0.003		-0.002
		(-3.42)		(-1.23)		(-0.50)		(-2.08)		(-1.17)
Obs.	14183	12274	14183	12274	11955	10518	8564	8050	13274	11679
R^2	0.116	0.156	0.223	0.261	–	–	0.596	0.625	0.228	0.267
Year FE	No	No	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	–	–	No	No	No	No
Firm FE	No	No	Yes	Yes	–	–	Yes	Yes	Yes	Yes

Table 9. Time-Series Analysis

Linear probability models are estimated for each maturity bucket:

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

where K_j is five two-year maturity buckets defined as $2j-1$ to $2j$ years for maturities shorter than 10 years ($j \leq 5$), and two maturity buckets (11 to 20 years and 11 years or longer) for maturities longer than 10 ($j = 6$ or $j = 7$). The variable $m_i^{K_j}$ is obtained by subtracting a benchmark from each firm's maturity profile where the maturity profile is defined as fractions of pre-existing bond amounts in each maturity bucket K_j. After firms are sorted into 128 (=2^7) groups based on seven variables (Q, market leverage, age, size, tangibility, profitability, and average maturity), the benchmark is obtained by averaging maturity profiles in each group. Issuance dummy $I_i^{K_j}$ is one if the bond i's maturity falls in K_j, and is zero if the bond has a different maturity than K_j. α_n is a firm fixed effect for the issuing firm n and y_t denotes a year fixed effect. Panel A1 is a sample with bond issues greater than 3% of firms' pre-existing bonds, and Panel A2 is bond issues greater than 5%. Panel B1 and B2 exclude all bonds with option features (callability, convertibility, putability and sinking fund provisions) from the sample. The hypothesis test ($H_0 : a_i - \frac{1}{6}\sum_{n \neq i} a_n = 0$) is also reported. Numbers in parenthesis are t-statistics for which standard errors are clustered at the Fama-French 48 industry level. The sample period is from 1991 to 2009.

	Panel A1: Issue Cutoff at 3%, All Bonds						
	K_1: 1-2 Yr	K_2: 3-4 Yr	K_3: 5-6 Yr	K_4: 7-8 Yr	K_5: 9-10 Yr	K_6: 11-20 Yr	K_7 21- Yr
m^{K_1}	**-0.09**	-0.221	-0.452	-0.193	0.191	0.126	0.241
	(-1.87)	(-4.14)	(-6.66)	(-2.98)	(2.52)	(2.02)	(4.40)
m^{K_2}	0.037	**-0.194**	-0.403	-0.158	-0.039	0.178	0.106
	(1.02)	**(-5.01)**	(-6.71)	(-1.98)	(-0.52)	(2.78)	(2.17)
m^{K_3}	0.007	0.022	**-0.423**	-0.178	-0.109	0.099	0.12
	(0.38)	(0.82)	**(-6.16)**	(-2.00)	(-1.31)	(1.84)	(3.35)
m^{K_4}	0.018	0.031	-0.096	**-0.111**	-0.317	0.038	0.016
	(0.66)	(1.05)	(-2.08)	**(-2.16)**	(-4.61)	(0.58)	(0.50)
m^{K_5}	0.013	0.013	-0.001	0.067	**-0.772**	0.249	-0.05
	(0.47)	(0.52)	(-0.01)	(1.48)	**(-8.38)**	(6.80)	(-0.97)
m^{K_6}	0.057	0.062	-0.006	0.047	-0.039	**-0.364**	-0.285
	(1.98)	(1.44)	(-0.11)	(0.88)	(-0.46)	**(-4.38)**	(-3.69)
m^{K_7}	0.107	0.08	0.175	0.15	-0.125	-0.197	**-0.974**
	(3.32)	(2.30)	(2.13)	(1.79)	(-1.19)	(-2.03)	**(-9.91)**
Obs.	6053	6053	6053	6053	6053	6053	6053
H_0	-0.12	-0.19	-0.31	-0.07	-0.71	-0.43	-0.99
	(-2.46)	(-5.04)	(-4.62)	(-1.60)	(-8.00)	(-5.35)	(-10.60)
	Panel A2: Issue Cutoff at 5%, All Bonds						
	K_1: 1-2 Yr	K_2: 3-4 Yr	K_3: 5-6 Yr	K_4: 7-8 Yr	K_5: 9-10 Yr	K_6: 11-20 Yr	K_7 21- Yr
m^{K_1}	**-0.113**	-0.238	-0.467	-0.17	0.261	0.129	0.245
	(-2.36)	(-4.06)	(-6.00)	(-2.41)	(3.34)	(2.44)	(4.45)
m^{K_2}	0.032	**-0.191**	-0.409	-0.163	-0.048	0.184	0.095
	(0.97)	**(-4.92)**	(-6.71)	(-2.00)	(-0.61)	(2.83)	(2.00)
m^{K_3}	0.023	0.008	**-0.415**	-0.177	-0.107	0.084	0.129
	(1.11)	(0.28)	**(-5.97)**	(-2.02)	(-1.27)	(1.54)	(3.79)
m^{K_4}	0.016	0.01	-0.117	**-0.124**	-0.329	0.037	0.041
	(0.60)	(0.35)	(-2.39)	**(-2.41)**	(-5.04)	(0.58)	(1.25)
m^{K_5}	0.019	0.012	0.011	0.067	**-0.763**	0.238	-0.031
	(0.75)	(0.39)	(0.24)	(1.41)	**(-8.19)**	(6.36)	(-0.58)
m^{K_6}	0.051	0.061	0.032	0.064	-0.024	**-0.414**	-0.278
	(2.07)	(1.54)	(0.54)	(1.21)	(-0.30)	**(-4.91)**	(-3.57)
m^{K_7}	0.11	0.079	0.211	0.168	-0.142	-0.192	**-1.009**
	(3.13)	(2.11)	(2.50)	(2.32)	(-1.35)	(-1.85)	**(-10.86)**
Obs.	5732	5732	5732	5732	5732	5732	5732
H_0	-0.148	-0.152	-0.31	-0.094	-0.708	-0.482	-1.04
	(-2.97)	(-4.77)	(-4.62)	(-2.04)	(-8.07)	(-5.82)	(-11.71)

Panel B1: Issue Cutoff at 3%, Straight Bonds Only							
	K_1: 1-2 Yr	K_2: 3-4 Yr	K_3: 5-6 Yr	K_4: 7-8 Yr	K_5: 9-10 Yr	K_6: 11-20 Yr	K_7 21- Yr
m^{K_1}	**-0.063**	-0.095	-0.177	-0.121	-0.388	-0.034	0.145
	(-0.57)	(-1.07)	(-1.25)	(-1.51)	(-3.65)	(-0.45)	(1.58)
m^{K_2}	0.229	**-0.286**	-0.418	-0.03	-0.237	0.009	0.02
	(2.52)	**(-2.64)**	(-5.04)	(-0.32)	(-1.81)	(0.11)	(0.30)
m^{K_3}	0.016	0.096	**-0.505**	-0.038	-0.231	-0.067	0.173
	(0.24)	(1.37)	**(-3.79)**	(-0.34)	(-1.35)	(-0.69)	(1.75)
m^{K_4}	0.075	0.066	-0.002	**-0.062**	-0.389	-0.136	0.012
	(0.94)	(1.06)	(-0.02)	**(-0.78)**	(-2.78)	(-1.17)	(0.15)
m^{K_5}	0.066	0.016	-0.091	0.179	**-1.006**	0.28	-0.024
	(0.95)	(0.30)	(-1.22)	(2.75)	**(-10.45)**	(3.07)	(-0.34)
m^{K_6}	0.034	0.066	-0.219	0.006	-0.33	**-0.144**	-0.106
	(0.40)	(0.75)	(-2.23)	(0.06)	(-2.17)	**(-1.06)**	(-1.05)
m^{K_7}	0.203	0.038	-0.061	0.049	-0.259	0.037	**-0.764**
	(2.80)	(0.50)	(-0.50)	(0.65)	(-2.34)	(0.34)	**(-8.66)**
Obs.	1856	1856	1856	1856	1856	1856	1856
H_0	-0.15	-0.31	-0.37	-0.07	-0.74	-0.16	-0.8
	(-1.32)	(-2.75)	(-3.40)	(-0.85)	(-7.50)	(-1.28)	(-8.23)

Panel B2: Issue Cutoff at 5%, Straight Bonds Only							
	K_1: 1-2 Yr	K_2: 3-4 Yr	K_3: 5-6 Yr	K_4: 7-8 Yr	K_5: 9-10 Yr	K_6: 11-20 Yr	K_7 21- Yr
m^{K_1}	**-0.086**	-0.105	-0.119	-0.068	-0.358	-0.075	0.18
	(-0.75)	(-0.90)	(-0.82)	(-0.69)	(-2.79)	(-0.89)	(1.74)
m^{K_2}	0.265	**-0.281**	-0.403	-0.024	-0.235	0.022	0.019
	(3.03)	**(-2.52)**	(-4.53)	(-0.23)	(-1.71)	(0.26)	(0.27)
m^{K_3}	0.09	0.098	**-0.51**	0.006	-0.26	-0.117	0.213
	(1.23)	(1.16)	**(-3.69)**	(0.05)	(-1.40)	(-1.16)	(2.03)
m^{K_4}	0.096	0.034	-0.041	**-0.101**	-0.41	-0.125	0.028
	(1.22)	(0.47)	(-0.44)	**(-1.29)**	(-2.84)	(-1.04)	(0.42)
m^{K_5}	0.078	0.039	-0.036	0.199	**-0.979**	0.228	-0.005
	(0.99)	(0.58)	(-0.37)	(2.57)	**(-9.70)**	(2.34)	(-0.07)
m^{K_6}	0.068	0.07	-0.19	0.03	-0.379	**-0.221**	-0.137
	(0.82)	(0.81)	(-1.75)	(0.34)	(-2.21)	**(-1.47)**	(-1.22)
m^{K_7}	0.234	0.014	-0.047	0.097	-0.28	0.067	**-0.819**
	(2.63)	(0.19)	(-0.35)	(1.32)	(-2.31)	(0.55)	**(-10.20)**
Obs.	1648	1648	1648	1648	1648	1648	1648
H_0	-0.2	-0.3	-0.39	-0.14	-0.7	-0.22	-0.86
	(-1.76)	(-2.58)	(-3.44)	(-1.90)	(-6.72)	(-1.59)	(-9.16)