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Debt Specialization

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ABSTRACT

This paper examines debt structure using a new and comprehensive database on types of debt employed by public U.S. firms. We find that 85% of the sample firms borrow predominantly with one type of debt, and the degree of debt specialization varies widely across different subsamples—large rated firms tend to diversify across multiple debt types, while small unrated firms specialize in fewer types. We suggest several explanations for why debt specialization takes place, and show that firms employing few types of debt have higher bankruptcy costs, are more opaque, and lack access to some segments of the debt markets.

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Much attention has been devoted to the questions of why firms choose to issue debt over equity, and how optimal capital structure is designed to minimize a firm's cost of financing (see the survey by Graham and Leary (2011) of the voluminous literature on capital structure). In this paper, we focus on a related, but much less studied topic in corporate finance, namely debt structure. Our goals are to explore the types of debt commonly employed by publicly listed U.S. firms, and to understand why some firms tend to use relatively few debt types, while others display a more diversified debt structure. To our knowledge, our paper is one of the first to provide large sample evidence on the subject.

Our paper is closely related to Rauh and Sufi (2010), who examine types, sources, and priorities of debt using a sample of 305 randomly selected non-financial rated public U.S. firms for the period 1996 to 2006. They show that almost three quarters of their firm-year observations employ more than two different debt instruments, and that a quarter of the firms has no significant year-to-year change in debt level, but experiences a significant change in debt composition. Further, they find that high-credit-quality firms (BBB and higher) primarily use two tiers of capital: equity and senior unsecured debt. Low-credit-quality firms (BB and lower) tend to use several tiers of debt including secured, senior unsecured, and subordinated issues.

The work of Rauh and Sufi suggests a number of important and as of yet unanswered questions concerning debt structure: Do unrated firms tend to borrow simultaneously from a variety of sources, as rated firms do? Or do they specialize in fewer debt types? What are the economic factors that explain the cross-sectional heterogeneity in debt structure?

To answer these questions, we take advantage of a new database available through Capital IQ, an affiliate of the Standard and Poor's, to examine debt structure of public U.S. firms including both unrated (about 60% of our firm-year observations and representing 9% of the total

assets of our firms) and rated firms—an important distinction from Rauh and Sufi (2010), who look at rated firms only. Within what is generally referred to as debt financing, we are able to distinguish between commercial paper, drawn credit lines (also known as revolving credit facilities), term loans, senior and subordinated bonds and notes, and capital leases. After merging the Capital IQ database with the Compustat database, we end up with a large panel data set that comprises 16,115 firm-year observations involving 3,296 unique firms for the period 2002 to 2009.

Our main finding is that most firms—85% of the sample—borrow predominantly with one type of debt, thus showing a remarkable tendency towards specialization. Furthermore, the degree of specialization varies widely across different subsamples: Large rated firms simultaneously employ multiple types of debt, similar to what is shown in Rauh and Sufi (2010), while all other firms, which comprise the majority of listed firms in the U.S., make use of only one type of debt. Rauh and Sufi (2010) is the first to identify debt structure as an important dimension of the overall capital structure choice. However, their conclusion that firms use different debt types is not representative of the population of firms.

We then show that firms with high growth opportunities, cash holdings, cash flow volatility, R&D expenses, and advertising expenses, and firms with unique products and a strong board specialize in few types of debt; while large, mature, profitable firms with more tangible assets, high leverage, and a credit rating use multiple sources. These cross-sectional correlations suggest several possible explanations for the observed pattern of debt specialization. We focus on the potential economic benefits associated with the usage of few debt types, such as lower bankruptcy costs, and economies in information collection costs and enhanced incentives to monitor. While we do not have any instrumental variables or natural experiments to cleanly

distinguish among these hypotheses and/or establish causality, we find some evidence of lower bankruptcy costs in a positive relation between the degree of debt specialization and measures of expected bankruptcy costs, and of lower information collection costs in a positive relation between the degree of debt specialization and measures of firm opaqueness. Finally, we provide suggestive evidence that firms specialize in few debt types because they lack access to some segments of the debt markets.

The findings of our paper have the following important implications for the capital structure literature. First, since the seminal work by Jensen and Meckling (1976) and Myers (1977), research has focused on conflicts of interest between shareholders and debt holders and their implications on capital structure choices. Our work extends this literature by highlighting the importance of considering potential conflicts of interest among different groups of debt holders, and how these conflicts may shape debt structure choices. Second, given the recent attention to applications of the optimal contracting literature to better understand capital structure (e.g., Sufi (2009a), Roberts and Sufi (2009a, 2009b), and surveys by Roberts and Sufi (2009c) and Graham and Leary (2011)), our evidence on the composition of debt and the heterogeneity in debt structure has important implications on the design of optimal debt contracts. Finally, we show that firms' differential access to debt markets may potentially affect debt structure, adding to the existing work of Graham and Harvey (2001), Faulkender and Petersen (2006), Leary (2009), Sufi (2009b), and Lemmon and Roberts (2010).

The outline for the rest of the paper is as follows. Section I describes our data and provides an overview of debt structure in publicly listed U.S. firms. Section II provides evidence on debt specialization and illustrates the prevalence of this phenomenon. Section III first documents which types of firms specialize in few types of debt and which types use multiple

sources, then discusses potential explanations for firms concentrating or diversifying their lender base, and finally provides some suggestive evidence for each explanation. Finally, Section IV summarizes our findings and suggests potential areas of future research in debt structure.

I. Data Overview

A. Sample Description

We start with U.S. firms traded on the AMEX, NASDAQ, and NYSE, and covered by Compustat from 2002 to 2009. We remove utilities (SIC codes 4900-4949) and financials (SIC codes 6000-6999) and end up with 29,138 firm-year observations. We further remove 1) firm-years with missing or zero values for total assets (27,885 observations remaining); 2) firm-years with missing or zero total debt (19,969 observations remaining); and 3) firm-years with market or book leverage outside the unit interval (as in Lemmon, Roberts and Zender (2008), 18,164 observations remaining). We then merge the resulting sample of the Compustat leveraged firms with Capital IQ,[1] and remove 4) firm-years for which the difference between total debt as reported in Compustat and the sum of debt types as reported in Capital IQ exceeds 10% of total debt. Our final sample comprises 16,115 firm-year observations involving 3,296 unique firms.

In constructing firm characteristics we use the same definitions as in Lemmon et al. (2008). Firm-level characteristic variables are from Compustat and CRSP. Firm-level debt structure variables are from Capital IQ. All continuous firm characteristic variables are winsorized at the 1st and 99th percentiles. Table AI in the Appendix provides a detailed description of the variables used in our analysis. Table 1 presents descriptive statistics.

TABLE 1

Columns (1) and (2) report means and medians of firm characteristics aggregated over the sample period for the firms in our sample. As a comparison, Columns (3) and (4) present means and medians for the Compustat leveraged firms. Our sample covers approximately 90% of the Compustat leveraged firms. Columns (5) and (6) provide tests of differences between the two samples. From these tests we observe that the firms in our sample are not significantly different from those in the Compustat sample along most dimensions except dividend payout. We conclude that our sample is representative of the Compustat leveraged firms.

B. Overview of Debt Structure in Public U.S. Firms

Capital IQ decomposes total debt into seven mutually exclusive debt types: commercial paper (*CP*), drawn credit lines (*DC*),[2] term loans (*TL*), senior bonds and notes (*SBN*), subordinated bonds and notes (*SUB*), capital leases (*CL*),[3] and other debt (*Other*).[4] Table AII in the Appendix provides an example of how Capital IQ classifies debt types and calculates the amount of each debt type for AMR Corporation. Table 2 Panel A provides detailed summary statistics of U.S. firms' usage of different debt types.

TABLE 2

First, we find that about two thirds of firms rely on senior bonds and notes for financing. The sample mean (median) ratio of senior bonds and notes to total debt is 0.382 (0.208). Second, about half of firms use either drawn credit lines or term loans for financing. Third, more than 40% of the firms employ capital leases, though they are much less important on average than each component of bank debt: The sample mean ratio of capital leases to total debt is 0.054, while that of drawn credit lines (term loans) is 0.220 (0.212). Fourth, about one fifth of the firms

use subordinated bonds and notes. Lastly, very few firms—about 5% of our sample—use commercial paper for financing.

Total adjustment is the difference between total debt obtained from Compustat and the sum of seven debt types from Capital IQ. We show that both the mean and median ratios of total adjustment to total debt are zero, and the 1st and 99th percentiles are -0.029 and 0.038, respectively. This small residual error and the ample coverage of the Compustat leveraged firms are reassuring about the quality of our data.

Table 2 Panel B presents the time series evidence on U.S. firms' usage of various debt types. Over the sample period we find that firms appear to rely more on term loans and less on commercial paper, subordinated bonds and notes, and capital leases. The use of senior bonds and notes and other debt remains stable over time.

In summary, although there are seven different debt types, we conclude that senior bonds and notes are the most commonly employed debt type, followed by drawn credit lines and term loans.

II. Evidence on Debt Specialization

A. Measures of Specialization

To measure the different degree of debt specialization across firms, we compute a normalized Herfindahl-Hirschman Index (henceforth referred to as *HHI*) of debt type usage as follows. First, we calculate

$$SS_{i,t} = \left(\frac{CP_{i,t}}{TD_{i,t}}\right)^2 + \left(\frac{DC_{i,t}}{TD_{i,t}}\right)^2 + \left(\frac{TL_{i,t}}{TD_{i,t}}\right)^2 + \left(\frac{SBN_{i,t}}{TD_{i,t}}\right)^2 + \left(\frac{SUB_{i,t}}{TD_{i,t}}\right)^2 + \left(\frac{CL_{i,t}}{TD_{i,t}}\right)^2 + \left(\frac{Other_{i,t}}{TD_{i,t}}\right)^2 \quad (1)$$

where $SS_{i,t}$ is the sum of the squared seven debt type ratios for firm *i* in year *t*; *CP*, *DC*, *TL*, *SBN*, *SUB*, *CL*, and *Other* refer to commercial paper, drawn credit lines, term loans, senior bonds and notes, subordinated bonds and notes, capital leases, and other debt, respectively; while *TD* refers to total debt. Then, we obtain

$$HHI_{i,t} = \frac{SS_{i,t} - 1/7}{1 - 1/7}. \tag{2}$$

If a firm employs exclusively one single debt type, *HHI* equals one, while if a firm simultaneously employs all seven debt types in equal proportions, *HHI* equals zero. Higher *HHI* values indicate firms' tendency to specialize in fewer debt types.

As an alternative debt specialization measure to *HHI*, we define for firm *i* in year *t*, a dummy variable, *Excl90*, as follows:

$$\begin{aligned} Excl90_{i,t} &= 1 \quad if \quad a\ firm\ obtains\ at\ least\ 90\%\ of\ its\ debt\ from\ one\ debt\ type, \\ &= 0 \quad otherwise \end{aligned} \tag{3}$$

Table 2 Panel B presents the time series pattern of our two specialization measures.

B. Cluster Analysis

Our first piece of evidence on debt specialization comes from cluster analysis. This technique, commonly used to discover unknown structure in data, relies on the minimization of the variance within clusters (in terms of the Euclidian distance of a firm-year observation from the center of its own cluster) and the maximization of the variance between clusters (in terms of

the Euclidian distance of a firm-year observation from the center of other clusters).[5] We end up with six clusters for our sample firms.

FIGURE 1

Figure 1 presents the distribution of different debt types within each cluster using mean ratios. We find that five clusters of firms specialize in only one type of debt, while only one cluster of firms diversifies in their debt usage.

Table 3 presents the mean and median values for different debt types and key firm characteristics across the identified clusters, sorted in ascending order by the cluster mean firm size.[6] We find that the firms in Cluster 1 predominantly rely on drawn credit lines, with a cluster mean (median) drawn credit to total debt ratio of 0.84 (0.90). Cluster 2 includes a set of firms that has very similar size to those in Cluster 1, but much lower leverage. These firms use predominantly capital leases for financing, and have a cluster mean (median) capital leases to total debt ratio of 0.88 (1.00). Firms in Cluster 3 use predominantly term loans for financing. The cluster mean (median) term loans to total debt ratio is 0.82 (0.88). Firms in Cluster 4 use primarily subordinated bonds and notes with a cluster mean (median) subordinated bonds and notes to total debt ratio of 0.79 (0.83). Firms in Cluster 5 are considerably larger than those in Cluster 4, and use predominantly senior bonds and notes with a cluster mean (median) senior bonds and notes to total debt ratio equal to 0.91 (0.95). Finally, Cluster 6, representing 15% of the firm-year observations in the sample, includes some of the largest firms in the sample. These firms use a mix of senior bonds and notes, drawn credit lines, and term loans. The cluster mean (median) senior bonds and notes, drawn credit lines, and term loans to total debt ratio is 0.48

(0.52), 0.17 (0.10), and 0.14 (0.02), respectively. It is worth noting that this cluster includes the most highly levered firms with the lowest *M/B* ratios in our sample.

TABLE 3

In summary, the evidence from our cluster analysis shows that 85% of the sample firms borrow predominantly with one type of debt, and that only the largest firms simultaneously employ multiple types of debt. Our evidence thus far highlights that debt specialization is an important phenomenon for listed firms. Our findings also confirm the results of Rauh and Sufi (2010), who show that debt heterogeneity is the norm for their sample of large, rated firms.

C. Reliance on One Debt Type

An alternative way to investigate debt specialization is to compute the fraction of firm-year observations in the sample that obtain a significant amount of their debt from one single type of debt.[7] We employ a wide spectrum of thresholds ranging from 10% to 99% to identify significant usage. To compare with the findings in Rauh and Sufi (2010), for this and the next analyses, we separate our firms into rated and unrated subsamples. We consider a firm-year to be rated if it has at least one monthly Standard & Poor's long-term issuer rating, as recorded in Compustat (data item 280). There are 9,968 firm-year observations with ratings and 6,147 firm-year observations without; corresponding to about 60% and 40% of the observations in the sample, respectively.[8]

TABLE 4

Table 4 presents the results. For each debt type and threshold we compute the share of firms that use this particular debt type at or above the level of a particular threshold ("significant users"). In row "*Total*" we report the sum across all debt types of significant users. If firms were to split their debt equally into all seven debt types, then the total in the 10% column would be seven, while in the 30% (or any other) column the total would be zero. If instead firms were to specialize in only one debt type, then the total for all thresholds would be one.

The evidence provided in Table 4 lies somewhere between these two extreme cases, showing a general tendency towards specialization. Within the rated firm subsample, we show that less than a fifth of our firm-year observations relies exclusively on one debt type, and 37% (65%) obtain more than 90% (70%) of their debt from one debt type. Within the unrated firm subsample, we show that more than a third of our firm-year observations relies exclusively on one debt type, and over half (close to three quarters) obtain more than 90% (70%) of their debt from one debt type. The evidence in Table 4 suggests that the degree of debt specialization is clearly more pronounced among the unrated firms than among the rated firms in our sample.

Our third piece of evidence on debt specialization comes from examining conditional debt structure. Specifically, we first impose the condition that the usage of a particular debt type must exceed 30% of total debt. Then, for the subset of observations that satisfy this condition—which we call the significant users of a particular debt type—we compute mean and median ratios of each debt type to total debt. Table 5 presents the results of this analysis.

TABLE 5

In Panel A, using only rated firms, the values along the main diagonal show that the conditional mean usage for the debt type upon which we condition is between 51% and 78%. Off

the main diagonal, the conditional mean usage for debt types other than the one upon which we condition is generally small, with the following exceptions: Significant users of commercial paper also use senior bonds and notes (38.3%); significant users of drawn credit lines also use senior bonds and notes (25.5%); and significant users of other debt also use senior bonds and notes (28.1%). In Panel B we repeat the analysis for unrated firms. Along the main diagonal, the conditional mean usage for the debt type upon which we condition is between 66% and 78%, again showing a stronger tendency towards specialization among unrated firms. This result is further confirmed by the much smaller values off the main diagonal for unrated firms as compared to those for rated firms.[9]

The results in Table 5 highlight the general phenomenon that not many firms use other debt types beyond the one upon which we condition, and reaffirm the idea that there is a higher degree of debt specialization among unrated firms than among rated firms.

Our results are new and different from the existing literature. Using LPC's Dealscan database, Carey, Post, and Sharpe (1998) present evidence on specialization by different types of lenders within the private debt markets, with finance companies lending to borrowers with higher observable risk, and especially those with higher leverage. Different from Carey et al. (1998), we focus on types of debt, not types of lenders in the private debt markets. Closer to our analysis but with coarser classifications of debt types are Barclay and Smith (1995) and Johnson (1997). Barclay and Smith (1995) use the Compustat data over the sample period 1981 to 1992, covering 4,995 industrial firms. They show that on average, firms issue claims in 2.4 of the following classes: capital leases, secured debt, ordinary debt, subordinated debt, and preferred stock. Moreover, 26% of the firms issue claims in a single priority class, while only 3% of the firms issue claims in all five classes. Johnson (1997) finds that 73% of his sample firms with positive

long-term debt borrow simultaneously from at least two of the following sources: bank debt, non-bank private debt, and public debt.

D. Credit Quality and Debt Structure

Rauh and Sufi (2010) show that investment grade firms (BBB and higher) primarily use senior unsecured debt, while speculative grade firms (BB and lower) tend to use several tiers of debt, including secured, senior unsecured, and subordinated issues. They further show that the increase in secured debt for low-credit-quality firms is driven by secured bank debt, and the increase in subordinated debt is driven by subordinated bonds and convertible debt. The findings of Rauh and Sufi lend broad support to the predictions of Diamond (1991), Chemmanur and Fulghieri (1994), and Bolton and Freixas (2000) regarding the role of credit quality in driving a firm's choice between bank debt and arm's length debt: High credit quality firms rely on arm's length financing, while low credit quality firms rely on bank debt. We also explore the relation between credit quality and debt structure among rated firms. Table 6 presents our results.

TABLE 6

We find that the degree of debt specialization varies with credit quality, revealing a non-monotonic pattern. Excluding firms with the lowest ratings (i.e., lower than CCC+), the degree of debt specialization is highest for firms in the middle of the rating spectrum (A and BBB)—*HHI* at about 0.70 and *Excl90* at about 0.40—and decreases for higher and lower ratings outside this range.

We also show that as firms move from investment grade to speculative grade, they rely more on term loans and subordinated bonds and notes, and rely less on senior bonds and notes.

For firms with a rating of BBB (A), the mean ratio of senior bonds and notes to total debt is 72.7% (76.9%), while term loans and subordinated bonds and notes together represent less than 10% of total debt. For firms with a rating of BB (B), the mean ratio of term loans to total debt is 22.3% (25.2%), subordinated bonds and notes to total debt is 21.4% (21.1%), and senior bonds and notes to total debt is 40.3% (43.4%). The pattern documented here is consistent with Rauh and Sufi's (2010) finding that low-credit-quality firms have a multi-tiered debt structure.

III. Which Firms Specialize?

A. Cross-Sectional Variations

The previous section has established that although the degree of debt specialization varies across different subsamples, debt specialization is a widespread phenomenon. In this section, we first provide a comprehensive view of the cross-sectional differences in specialization before offering some explanations.

Table 7 presents summary statistics and correlations for *HHI* with a set of firm characteristics (Table IA.3 in the Internet Appendix provides similar statistics for *Excl90*). The first column gives the correlation of each of these characteristics with *HHI*, the next four columns give the mean and median values for firms within the first quartile and the fourth quartile of *HHI*, and the last two columns give tests of differences between the two quartiles.

TABLE 7

We show that growth opportunities, cash holdings, cash flow volatility, R&D expenses, advertising expenses, and firms with unique products and a strong board are positively and significantly associated with the degree of debt specialization; while firm size, firm age,

profitability, asset tangibility, leverage, and firms with a credit rating are negatively and significantly associated with the degree of debt specialization. These large cross-sectional variations in the degree of debt specialization beg the question of why debt specialization takes place.[10]

B. Possible Explanations for Debt Specialization

We offer three possible explanations for the observed pattern of debt specialization: lowering expected bankruptcy costs, economizing on information collection and monitoring costs,[11] and firms' constrained access to capital.

B.1. Conflicts of Interest among Debt Holders and Bankruptcy Costs

The idea that optimal capital structure trades off the benefits of debt and bankruptcy costs goes back to the seminal work of Modigliani and Miller (1963). Bankruptcy costs arise in part from conflicts of interest among different claim holders. In addition to the conflicts between shareholders and debt holders (Jensen and Meckling (1976), and Myers (1977)), conflicts among different groups of debt holders may also affect capital structure (Welch (1997), and Bris and Welch (2005)). Bolton and Scharfstein (1996) formalize the idea that an optimal debt structure should minimize expected bankruptcy costs. They predict that firms with low credit-quality maximize liquidation value by borrowing from just one creditor, while firms with high credit-quality minimize the likelihood of default by borrowing from multiple creditors. Consistent with their idea that debt concentration lowers negotiation costs, Ivashina, Iverson, and Smith (2011) show that higher creditor concentration increases the speed of restructuring under Chapter 11 and lowers the likelihood of liquidation. Furthermore, Bolton and Scharfstein (1996) show that firms

with easily redeployable assets—defined as assets with a higher value to another firm in the industry or some other investor who can manage the asset—will borrow from only one creditor because a concentrated creditor structure facilitates easy bargaining with an outside buyer and because the single creditor benefits more from the high liquidation value.

Following this line of research, we conjecture that firms with higher expected bankruptcy costs should be more specialized in their borrowing to reduce renegotiation costs associated with multiple lenders, while firms with lower expected bankruptcy costs should diversify across different debt types.

Our measures of expected bankruptcy costs are tangibility[12] and cash flow volatility following Titman and Wessels (1988), and Rajan and Zingales (1995). The expected bankruptcy costs are decreasing in tangibility, and increasing in cash flow volatility.

B.2. Information Collection Costs and Incentives to Monitor

In the presence of asymmetric information, investors face information collection costs and lack incentives to monitor. As a result, ownership and debt structure are chosen to alleviate the information problems and to provide incentives to monitor. On the equity side, there is a large literature showing that shareholders with concentrated ownership are effective monitors (see for example, Shleifer and Vishny (1986), Burkart, Gromb, and Panunzi (1997), Chen, Harford, and Li (2007), and Cronqvist and Fahlenbrach (2009)).

On the debt side, relational lenders are generally perceived to be monitors of corporate borrowers (see for example, Diamond (1991) and Park (2000)). Park (2000) shows that an optimal debt structure maximizes the incentives for lenders to monitor when there is a single senior lender. Employing data on syndicated loans and on the composition of lending syndicates,

Sufi (2007) shows that the lead bank in a lending syndicate retains a larger share of the loan and forms a more concentrated syndicate when the borrowing firm requires more intense monitoring and due diligence. However, there is a growing literature on creditor governance which shows that bond holders can also be influential on corporate decisions when there is violation of covenants or when a firm enters Chapter 11 (see for example, Nini, Smith, and Sufi (2009), Roberts and Sufi (2009a), Ivashina et al. (2011), and Jiang, Li, and Wang (2012)).

The main message from the prior literature is that any investor in equity or debt has incentives to monitor as long as she has a sufficiently large claim in the firm. We therefore conjecture that opaque firms facing high information collection and monitoring costs should have a more concentrated debt structure. On the other hand, when borrowing firms are relatively transparent, information collection and monitoring costs are lower, and diversification across different types of debt should be more likely. Given our lack of data on individual debt holders and the amount of their claims, in this paper we use our specialization measures to proxy for concentrated debt claims.[13]

Our main measure of information collection and monitoring costs is R&D expenses following Sufi (2007). In firms with high R&D investment, earnings depend on the realization of future investment opportunities, thus making these firms harder to evaluate. Aboody and Lev (2000) show that insider trading gains in R&D-intensive firms are larger than in firms without R&D investment, suggesting that R&D is a major contributor to information asymmetry.

B.3. Access to Capital

Finally, we turn our attention to the source of capital, which might also explain the observed pattern of debt specialization by U.S. firms. Market frictions that make debt structure

choices relevant (such as bankruptcy costs and information asymmetry) may also lead lenders to ration certain firms (see the empirical evidence in Faulkender and Petersen (2006), and Rauh and Sufi (2010)), thus preventing those firms from reaching their desired debt structure. This mechanism may act directly through a quantity channel, i.e., some lenders are not willing to lend to certain types of firms, or indirectly through a price channel, i.e., some firms may find certain types of debt prohibitively expensive, and end up specializing in debt types that are not as expensive. Therefore, when examining a firm's debt structure, it is important to consider not only the determinants of its preferred degree of debt specialization, but also the constraints on the firm's ability to reach its desired debt structure.

Our measure of firms' constrained access to capital is a dummy for not being rated. A firm is unlikely to pay for a credit rating unless it plans to access public bond markets (Hale and Santos (2009)). *A priori*, having a credit rating may decrease debt specialization if public debt is added to the types of debt employed, or increase it if public debt totally replaces the types of debt employed. Johnson (1997) finds evidence of a systematic use of bank debt by firms with access to public debt, and Hale and Santos (2009) show that access to public bond markets is associated with reduced costs of bank loans. We thus conjecture that firms with easy access to capital should exhibit a lower degree of debt specialization, while firms with constrained access to capital should have a more concentrated debt structure.

C. Empirical Tests on Debt Specialization

We have identified three possible explanations for debt specialization: reducing expected bankruptcy costs, economizing on information collection and monitoring costs, and lacking access to some segments of the debt markets. Ideally, one should employ instrumental variables

(e.g., Faulkender and Petersen (2006)) or natural experiments (e.g., Leary (2009), Sufi (2009b), and Lemmon and Roberts (2010)) to distinguish among the possible explanations and/or to establish causality. However, as discussed below, it is difficult to deal with endogeneity in our setting. Thus, one should regard the evidence presented below as merely suggestive in support of each explanation.

TABLE 8

Table 8 presents the regression results where our two measures of debt specialization are the dependent variable.[14] The first specification in Columns (1) and (5) includes those variables used in many capital structure studies (see for example, Titman and Wessels (1988), and Rajan and Zingales (1995)). The second specification in Columns (2) and (6) adds cash flow volatility and R&D expenses. The third specification in Columns (3) and (7) adds the unrated dummy. The final specification in Columns (4) and (8) further include book leverage. We show that there is a positive and significant association between growth opportunities and our measures of debt specialization. Importantly, there are positive and significant associations between our measures of expected bankruptcy costs—tangibility and cash flow volatility—and measures of debt specialization, and between opaqueness—R&D expenses—and measures of debt specialization. Further, there is a positive and significant association between the unrated dummy—our measure of firms' constrained access to capital—and measures of debt specialization. Tables 4 and 5 show that there is a strong and negative association between firms having a credit rating and their degrees of debt specialization. Columns (3) and (7) confirm that after controlling for firm characteristics, which we conjecture to matter in debt structure decisions, firms with access to public debt are associated with a lower degree of debt specialization. Columns (4) and (8)

highlight that our proxies for expected bankruptcy costs, opaqueness, and access to capital remain significantly associated with debt specialization after controlling for leverage.

Our evidence in Table 8 is consistent with our three hypotheses that a high degree of debt specialization helps minimize expected bankruptcy costs, economizes on information collection and monitoring costs, and is associated with firms' lack of access to some segments of the debt markets. We acknowledge that our test does not allow us to cleanly distinguish among these hypotheses. For example, asset tangibility—our proxy for bankruptcy costs—may reduce information asymmetries because tangible assets are more easily evaluated by corporate outsiders than R&D expenses. Also, the existence of a credit rating—our measure of firms' constrained access to capital—is clearly correlated with many firm characteristics—firms with more tangible assets and stable cash flows, for example, are more likely to be rated (Faulkender and Petersen (2006), and Lemmon and Zender (2010)). Further, a credit rating itself might alleviate information asymmetries because firms with credit ratings are scrutinized by rating agencies and covered by bond market analysts, who then disseminate the information to capital markets (Hale and Santos (2009)). Therefore, rather than evidence in favor of a specific mechanism through which debt specialization takes place, our findings should be broadly regarded as consistent with all three hypotheses. We look forward to future research to help discriminate among these hypotheses.

IV. Conclusion and Areas for Future Research

This paper provides the first large sample evidence on the patterns and determinants of debt structure using a new and comprehensive database of public U.S. firms. Within what is generally referred to as debt financing, we are able to distinguish between commercial paper,

drawn credit lines, term loans, senior and subordinated bonds and notes, and capital leases. We first show that most of the firms concentrate their borrowing in only one of these debt types, and only low risk, large firms with high profitability, low growth opportunities, and high leverage borrow through multiple debt types. We then consider several explanations for the observed pattern of debt specialization. Despite the data and our tests not allowing strong conclusions about causality nor clean separation of the underlying mechanisms, we show that firms employing few types of debt have higher bankruptcy costs, are more opaque, and lack access to some segments of the debt markets. We conclude that debt specialization is a widespread phenomenon among publicly listed firms.

The findings of this paper suggest the following new directions for future research. First, more theoretical work is needed in order to develop models of debt structure that can account for the various types of debt empirically examined in this paper as well as to guide future research to help understand why debt specialization takes place. The development of such theories would complement well the established literature on capital structure.

Second, due to the relatively short time series on debt structure, our analysis focuses on the cross-sectional heterogeneity in specialization, rather than on its dynamic evolution over time. Going forward, as we obtain longer time series, it will be important to examine the persistence of specialization over time, following a similar approach to Lemmon et al.'s (2008) examination of capital structure. Such analysis would also shed light on how debt structure varies with the business cycle and how it moves together with the public and private supply of liquidity (Holmström and Tirole (1998)).

Finally, debt structure choices are not limited to the amount of debt types examined in this paper. Another possible avenue of future research would be to examine the joint

determination of amount, maturity, pricing, and covenants of the various debt types, thanks to the new text search algorithms and other techniques to examine different debt contracts in detail (see for example, Sufi (2009a), and Roberts and Sufi (2009b)).

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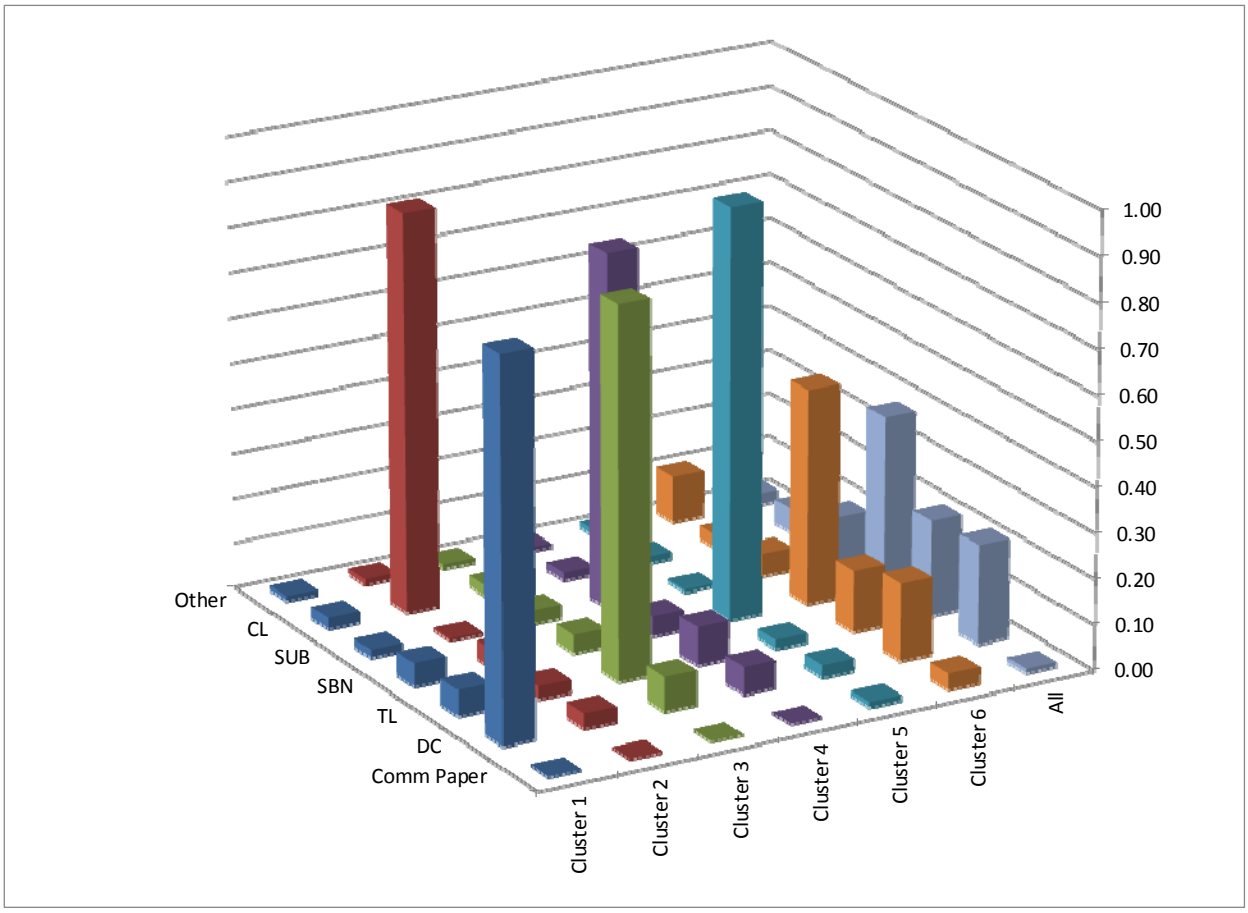

Figure 1 The Distribution of Debt Types within a Cluster This figure plots firm-year observations clustered according to their use of each debt type. For each cluster, the figure shows each debt type, normalized by total debt. For comparison, we also report the debt structure for the entire sample under the "All" column. Definitions of the variables are provided in Table AI.

Table 1
Sample Overview

This table presents means and medians aggregated across all years for our sample and for the sample of Compustat leveraged firms. Our sample consists of non-utility (excluding SIC codes 4900-4949) and non-financial (excluding SIC codes 6000-6999) U.S. firms covered by both Capital IQ and Compustat from 2002 to 2009. We have removed 1) firm-years with missing or zero values for total assets; 2) firm-years with missing or zero total debt; 3) firm-years with market or book leverage outside the unit interval; and 4) firm-years for which the difference between total debt as reported in Compustat and the sum of debt types as reported in Capital IQ exceeds 10% of total debt, to obtain our sample of 16,115 firm-year observations involving 3,296 unique firms. Applying filters 1) -3) to Compustat firms over the same period, we obtain the Compustat leveraged firm sample of 18,164 firm-year observations. Definitions of the variables are provided in Table AI. The last two columns of the table present test statistics of the t-test and the Wilcoxon test of the differences in firm characteristics between the two samples. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Our Sample		Compustat Leveraged Firms		Test of Differences between Samples	
	(1) Mean	(2) Median	(3) Mean	(4) Median	(5) t-test	(6) Wilcoxon test
Size	3,784.9	565.8	3,631.5	532.7	-0.736	-2.039
M/B	1.503	1.148	1.497	1.138	-0.328	-1.464
Profitability	0.086	0.114	0.083	0.113	-1.275	-1.618
Dividend Payer	0.342	0.000	0.330	0.000	-2.227**	-2.227**
Cash Holdings	0.151	0.079	0.154	0.080	1.364	1.138
Tangibility	0.288	0.213	0.286	0.212	-0.909	-0.893
Asset Maturity	4.501	2.767	4.497	2.757	-0.078	-0.427
Market Leverage	0.252	0.195	0.252	0.193	0.301	-0.630
CF Volatility	0.018	0.010	0.018	0.010	0.679	1.541
# Observations	16,115		18,164			

Table 2
Summary Statistics on Debt Structure

This table presents summary statistics on ratios of different debt types to total debt and measures of debt specialization. Definitions of the variables are provided in Table AI. Panel A presents the sample distribution of ratios of debt types to total debt. The last column reports the percentage of firm-year observations using each debt type. Panel B presents annual mean ratios of debt types to total debt and annual mean values of debt specialization measures.

Panel A: Sample distribution of debt types

	Debt Types								Obs.
	Mean	1st Perc.	5th Perc.	25th Perc.	Median	75th Perc.	95th Perc.	99th Perc.	with positive usage (%)
Commercial Paper	0.009	0.000	0.000	0.000	0.000	0.000	0.010	0.280	5.24
Drawn Credit Lines	0.220	0.000	0.000	0.000	0.006	0.345	0.999	1.000	51.39
Term Loans	0.212	0.000	0.000	0.000	0.000	0.343	0.999	1.000	46.52
Sen. Bonds and Notes	0.382	0.000	0.000	0.000	0.208	0.806	1.000	1.000	64.65
Sub. Bonds and Notes	0.098	0.000	0.000	0.000	0.000	0.000	0.831	1.000	19.62
Capital Leases	0.054	0.000	0.000	0.000	0.000	0.012	0.308	1.000	42.98
Other Debt	0.025	0.000	0.000	0.000	0.000	0.001	0.118	0.695	28.08
Total Adjustment	0.000	-0.029	-0.001	0.000	0.000	0.000	0.006	0.038	10.52

Panel B: Debt types and debt specialization over time

	2002	2003	2004	2005	2006	2007	2008	2009
Commercial Paper	0.011	0.009	0.010	0.010	0.011	0.011	0.008	0.005
Drawn Credit Lines	0.229	0.204	0.192	0.199	0.221	0.229	0.263	0.221
Term Loans	0.185	0.181	0.186	0.203	0.213	0.237	0.245	0.247
Sen. Bonds and Notes	0.359	0.389	0.406	0.403	0.390	0.374	0.347	0.384
Sub. Bonds and Notes	0.124	0.132	0.117	0.105	0.092	0.079	0.067	0.065
Capital Leases	0.063	0.056	0.059	0.056	0.053	0.050	0.045	0.051
Other Debt	0.030	0.028	0.029	0.025	0.020	0.021	0.023	0.027
HHI	0.676	0.691	0.707	0.706	0.706	0.709	0.670	0.718
Excl90	0.424	0.443	0.459	0.457	0.461	0.467	0.457	0.487

Table 3

Cluster Analysis

This table presents firm-year observations clustered according to their use of each debt type. For cluster analysis, we employ the Stata command cluster *kmeans* with clusters defined over all seven debt types simultaneously and run *kmeans* with up to 15 clusters. Six clusters are obtained using the stopping rule based on the Calinski/Harabasz index that maximizes the ratio of the variance "between clusters" (in terms of the Euclidian distance of a firm-year observation from the center of other clusters) to the variance "within clusters" (in terms of the Euclidian distance of a firm-year observation from the center of its own cluster). The table presents cluster mean and median (in square brackets) ratios of different debt types to total debt, and cluster mean and median values of key firm characteristics for the identified six clusters sorted by ascending cluster mean firm size. For comparison, we also report the debt structure for the entire sample under the "All" row. Definitions of the variables are provided in Table AI.

	Debt Types								Firm Characteristics					
Cluster	CP	DC	TL	SBN	SUB	CL	Other	HHI	Size	M/B	Profit.	Mkt. Lev.	CF Vol.	# Obs.
1	0.00	0.84	0.06	0.05	0.02	0.03	0.01	0.74	594	1.38	0.10	0.22	0.02	3,107
	[0.00]	[0.90]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.79]	[233]	[1.06]	[0.11]	[0.15]	[0.01]	
2	0.00	0.03	0.03	0.04	0.01	0.88	0.01	0.82	595	1.88	0.01	0.09	0.03	617
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[1.00]	[0.00]	[1.00]	[214]	[1.46]	[0.08]	[0.02]	[0.02]	
3	0.00	0.08	0.82	0.04	0.03	0.02	0.01	0.72	810	1.56	0.07	0.25	0.02	3,224
	[0.00]	[0.00]	[0.88]	[0.00]	[0.00]	[0.00]	[0.00]	[0.75]	[226]	[1.16]	[0.11]	[0.18]	[0.01]	
4	0.00	0.06	0.08	0.05	0.79	0.02	0.01	0.67	1,233	1.49	0.08	0.30	0.02	1,611
	[0.00]	[0.00]	[0.00]	[0.00]	[0.83]	[0.00]	[0.00]	[0.67]	[679]	[1.19]	[0.10]	[0.25]	[0.01]	
5	0.01	0.03	0.02	0.91	0.01	0.02	0.01	0.83	6,527	1.58	0.09	0.24	0.02	5,011
	[0.00]	[0.00]	[0.00]	[0.95]	[0.00]	[0.00]	[0.00]	[0.88]	[1,438]	[1.20]	[0.12]	[0.19]	[0.01]	
6	0.04	0.17	0.14	0.48	0.05	0.03	0.10	0.39	8,450	1.34	0.10	0.32	0.01	2,545
	[0.00]	[0.10]	[0.02]	[0.52]	[0.00]	[0.00]	[0.00]	[0.39]	[1,343]	[1.07]	[0.12]	[0.26]	[0.01]	
All	0.01	0.22	0.21	0.38	0.10	0.05	0.03	0.70	3,785	1.50	0.09	0.25	0.02	16,115
	[0.00]	[0.01]	[0.00]	[0.21]	[0.00]	[0.00]	[0.00]	[0.73]	[566]	[1.15]	[0.11]	[0.20]	[0.01]	

Table 4
Reliance on One Debt Type

This table reports the share of firm-year observations that use one debt type above a given threshold. For example, column "10%" presents the share of observations that employ more than 10% of debt from one debt type. Other columns are defined similarly. "Total" is the sum of all share values in a column and represents the share of firm-year observations that employ more than a given threshold level of debt from at least one debt type. Definitions of the variables are provided in Table AI. Panel A employs the rated firm subsample. Panel B employs the unrated firm subsample.

Panel A: Rated firms

	Thresholds								
	10%	30%	50%	60%	70%	80%	90%	95%	99%
Commercial Paper	0.072	0.021	0.009	0.004	0.003	0.002	0.001	0.001	0.001
Drawn Credit Lines	0.245	0.107	0.053	0.037	0.026	0.019	0.014	0.012	0.007
Term Loans	0.316	0.199	0.123	0.095	0.074	0.056	0.044	0.035	0.021
Sen. Bonds and Notes	0.756	0.695	0.600	0.544	0.465	0.370	0.258	0.189	0.113
Sub. Bonds and Notes	0.240	0.182	0.117	0.091	0.072	0.054	0.042	0.036	0.026
Capital Leases	0.041	0.009	0.006	0.005	0.004	0.004	0.002	0.002	0.002
Other Debt	0.075	0.020	0.009	0.007	0.006	0.004	0.004	0.003	0.002
Total	1.746	1.233	0.915	0.782	0.649	0.510	0.366	0.278	0.172

Panel B: Unrated firms

	Thresholds								
	10%	30%	50%	60%	70%	80%	90%	95%	99%
Commercial Paper	0.004	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Drawn Credit Lines	0.465	0.368	0.285	0.252	0.217	0.185	0.147	0.121	0.093
Term Loans	0.381	0.308	0.241	0.211	0.182	0.154	0.125	0.107	0.087
Sen. Bonds and Notes	0.414	0.331	0.270	0.242	0.210	0.181	0.150	0.131	0.105
Sub. Bonds and Notes	0.119	0.095	0.074	0.064	0.058	0.052	0.044	0.039	0.030
Capital Leases	0.138	0.077	0.058	0.051	0.048	0.043	0.039	0.037	0.034
Other Debt	0.044	0.025	0.016	0.014	0.013	0.011	0.009	0.008	0.007
Total	1.564	1.205	0.944	0.835	0.727	0.626	0.513	0.442	0.355

Table 5
Conditional Debt Structure

This table provides evidence on conditional debt structure. We first impose the condition that the usage of a particular debt type exceeds 30% of total debt. We then compute mean and median (in square brackets) ratios of each debt type to total debt for the subset of observations that satisfy this condition. Definitions of the variables are provided in Table AI. Panel A employs the rated firm subsample. Panel B employs the unrated firm subsample.

Panel A: Rated firms

Condition	CP	DC	TL	SBN	SUB	CL	Other
CP>30%	0.513 [0.460]	0.031 [0.000]	0.012 [0.000]	0.383 [0.431]	0.004 [0.000]	0.011 [0.000]	0.046 [0.007]
DC>30%	0.003 [0.000]	0.555 [0.496]	0.061 [0.000]	0.255 [0.206]	0.097 [0.000]	0.012 [0.000]	0.017 [0.000]
TL>30%	0.001 [0.000]	0.050 [0.000]	0.631 [0.573]	0.169 [0.015]	0.126 [0.000]	0.014 [0.000]	0.009 [0.000]
SBN>30%	0.025 [0.000]	0.065 [0.000]	0.065 [0.000]	0.775 [0.822]	0.029 [0.000]	0.014 [0.000]	0.027 [0.000]
SUB>30%	0.001 [0.000]	0.079 [0.000]	0.148 [0.008]	0.100 [0.001]	0.646 [0.604]	0.014 [0.000]	0.011 [0.000]
CL>30%	0.008 [0.000]	0.064 [0.000]	0.058 [0.000]	0.152 [0.000]	0.054 [0.000]	0.646 [0.602]	0.019 [0.000]
Other>30%	0.040 [0.000]	0.045 [0.000]	0.024 [0.000]	0.281 [0.284]	0.028 [0.000]	0.018 [0.000]	0.564 [0.467]

Panel B: Unrated firms

Condition	CP	DC	TL	SBN	SUB	CL	Other
CP>30%	0.663 [0.569]	0.108 [0.012]	0.110 [0.000]	0.115 [0.000]	0.000 [0.000]	0.002 [0.000]	0.002 [0.000]
DC>30%	0.001 [0.000]	0.746 [0.803]	0.100 [0.000]	0.095 [0.000]	0.019 [0.000]	0.028 [0.000]	0.011 [0.000]
TL>30%	0.001 [0.000]	0.122 [0.000]	0.749 [0.800]	0.068 [0.000]	0.023 [0.000]	0.028 [0.000]	0.010 [0.000]
SBN>30%	0.001 [0.000]	0.105 [0.000]	0.058 [0.000]	0.775 [0.852]	0.019 [0.000]	0.030 [0.000]	0.011 [0.000]
SUB>30%	0.000 [0.000]	0.075 [0.000]	0.072 [0.000]	0.069 [0.000]	0.761 [0.859]	0.017 [0.000]	0.006 [0.000]
CL>30%	0.000 [0.000]	0.066 [0.000]	0.068 [0.000]	0.077 [0.000]	0.010 [0.000]	0.766 [0.912]	0.011 [0.000]
Other>30%	0.000 [0.000]	0.089 [0.000]	0.087 [0.000]	0.087 [0.000]	0.012 [0.000]	0.044 [0.000]	0.681 [0.687]

Table 6

Credit Ratings and Debt Structure

This table presents mean and median (in square brackets) values of debt specialization measures and mean and median (in square brackets) ratios of different debt types to total debt across different rating classes. Definitions of the variables are provided in Table AI.

	AAA	AA	A	BBB	BB	B	⩽ CCC+	Unrated
HHI	0.409	0.568	0.693	0.686	0.604	0.647	0.712	0.735
	[0.371]	[0.522]	[0.721]	[0.700]	[0.532]	[0.595]	[0.734]	[0.809]
Excl90	0.018	0.176	0.427	0.397	0.314	0.381	0.456	0.513
Commercial Paper	0.190	0.168	0.081	0.022	0.001	0.000	0.001	0.001
	[0.145]	[0.109]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Drawn Credit Lines	0.000	0.011	0.036	0.115	0.118	0.074	0.115	0.297
	[0.000]	[0.000]	[0.000]	[0.007]	[0.012]	[0.000]	[0.000]	[0.047]
Term Loans	0.044	0.046	0.032	0.057	0.223	0.252	0.229	0.248
	[0.003]	[0.001]	[0.000]	[0.000]	[0.031]	[0.069]	[0.010]	[0.000]
Sen. Bonds and Notes	0.538	0.672	0.769	0.727	0.403	0.434	0.440	0.276
	[0.573]	[0.723]	[0.848]	[0.822]	[0.362]	[0.413]	[0.411]	[0.012]
Sub. Bonds and Notes	0.046	0.003	0.015	0.032	0.214	0.211	0.176	0.078
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Capital Leases	0.014	0.021	0.009	0.017	0.022	0.017	0.031	0.076
	[0.000]	[0.003]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Other Debt	0.169	0.079	0.058	0.031	0.019	0.013	0.009	0.023
	[0.113]	[0.027]	[0.006]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]

Table 7

Which Firms Specialize?

This table presents descriptive statistics for the relation between debt specialization (measured by *HHI*) and firm characteristics. The first column gives the correlation for each of these variables with *HHI*. One-way sorting by *HHI* is carried out year by year and then aggregated across years. Columns (2)-(5) presents the mean and median values of firm characteristics in the first and fourth quartiles of *HHI*. The last two columns present test statistics of the t-test and Wilcoxon test of the differences in debt specialization between the first and fourth quartile. Definitions of the variables are provided in Table AI. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Correlation	1st Quartile		4th Quartile		Test of Differences between Quartiles	
	(1)	(2) Mean	(3) Median	(4) Mean	(5) Median	(6) t-test	(7) Wilcoxon test
Ln(Size)	-0.133***	6.551	6.698	5.669	5.723	22.327***	22.041***
Ln(Sales)	-0.155***	6.637	6.754	5.500	5.703	25.410***	23.928***
Ln(Firm Age)	-0.074***	2.610	2.708	2.358	2.485	11.862***	12.828***
M/B	0.114***	1.288	1.035	1.851	1.369	-12.678***	-20.278***
Profitability	-0.089***	0.101	0.114	0.049	0.105	10.891***	6.148***
Dividend Payer	-0.042***	0.341	0.000	0.249	0.000	9.047***	9.014***
Cash Holdings	0.318***	0.090	0.045	0.263	0.189	-40.663***	-40.256***
Tangibility	-0.116***	0.307	0.238	0.240	0.158	13.014***	16.720***
Market Leverage	-0.307***	0.337	0.291	0.155	0.104	40.162***	38.929***
Book Leverage	-0.264***	0.331	0.308	0.189	0.144	34.350***	35.402***
CF Volatility	0.101***	0.015	0.009	0.024	0.013	-12.150***	-22.070***
Asset Maturity	0.012	5.049	2.810	8.025	2.670	-2.221**	2.555**
Capex	-0.009	0.055	0.035	0.056	0.030	-0.160	5.643***
R&D Expenses	0.160***	0.043	0.016	0.119	0.062	-17.121***	-20.633***
Advertising	0.102***	0.242	0.184	0.316	0.250	-12.472***	-13.680***
Product Uniqueness	0.028***	0.265	0.000	0.290	0.000	-2.593***	-2.592***
B-Index	0.113***	1.651	2.000	1.931	2.000	-10.240***	-10.381***
S&P 1500	-0.010	0.388	0.000	0.336	0.000	4.877***	4.870***
Unrated	0.158***	0.541	1.000	0.798	1.000	-25.516***	-24.547***

Table 8

Multivariate Evidence on Debt Specialization

This table presents regression results to examine the relation between firm characteristics and debt specialization. The dependent variables are our two measures of debt specialization: *HHI* and *Excl90*. In Columns (1) and (5) we include common determinants of capital structure choices. In Columns (2) and (6) we add cash flow volatility and R&D expenses. In Columns (3) and (7) we add the unrated dummy. In Columns (4) and (8) we further add book leverage. Definitions of the variables are provided in Table AI. All right-hand-side variables are lagged. All specifications include (Fama-French 48) industry fixed effects and year fixed effects. Robust standard errors are clustered at the firm level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	HHI	HHI	HHI	HHI	Excl90	Excl90	Excl90	Excl90
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Size	-0.012***	-0.009**	0.006	0.004	-0.026*	-0.018	0.025	0.018
	(0.004)	(0.004)	(0.005)	(0.005)	(0.016)	(0.016)	(0.020)	(0.020)
M/B	0.039***	0.027***	0.027***	0.026***	0.128***	0.090***	0.091***	0.089***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.022)	(0.022)	(0.022)	(0.022)
Profitability	-0.105**	0.099*	0.091*	0.066	-0.339**	0.292	0.267	0.190
	(0.046)	(0.053)	(0.053)	(0.053)	(0.164)	(0.197)	(0.197)	(0.201)
Div. Payer	-0.011	-0.011	-0.012	-0.027*	-0.049	-0.050	-0.052	-0.100
	(0.016)	(0.016)	(0.016)	(0.015)	(0.062)	(0.061)	(0.061)	(0.061)
Tangibility	-0.196***	-0.187***	-0.188***	-0.148***	-0.792***	-0.771***	-0.774***	-0.656***
	(0.042)	(0.042)	(0.042)	(0.041)	(0.171)	(0.172)	(0.171)	(0.172)
CF Volatility		0.782**	0.889**	0.924**		3.007**	3.317**	3.449**
		(0.365)	(0.365)	(0.366)		(1.329)	(1.329)	(1.344)
R&D Exp.		0.508***	0.489***	0.456***		1.483***	1.431***	1.339***
		(0.101)	(0.100)	(0.100)		(0.362)	(0.360)	(0.365)
Unrated			0.085***	0.050***			0.240***	0.126*
			(0.018)	(0.018)			(0.070)	(0.072)
Book Lev.				-0.286***				-0.942***
				(0.036)				(0.139)
Industry and Year FEs	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	7,770	7,770	7,770	7,770	7,770	7,770	7,770	7,770
Model	Tobit	Tobit	Tobit	Tobit	Probit	Probit	Probit	Probit
Pseudo R-sq.	0.125	0.138	0.147	0.171	0.056	0.061	0.064	0.073

Appendix

Table AI
Description of Variables

This table provides a detailed description of our variables. Firm characteristics are from Compustat (numbers in parentheses refer to the corresponding Compustat data item). Daily stock returns are from CRSP. Debt structure variables are from Capital IQ. Size and sales are expressed in millions of 2002 dollars.

Variable	Definition
	Firm Characteristics
Size	Total assets (6)
Sales	Sales (12)
Firm Age	Firm age since IPO using the first year that a firm appears in CRSP
Total Debt	Debt in current liabilities (34) + Long-term debt (9)
MV Equity	Stock price (199) × Common shares used to calculate earnings per share (54)
M/B	(MV equity + Total debt + Preferred stock liquidating value (10) – Deferred taxes and investment tax credit (35)) / Total assets (6)
Profitability	Operating income before depreciation (13) / Total assets (6)
Dividend Payer	Dummy = 1 if common stock dividends (21) are positive
Cash Holdings	Cash and short-term investments (1) / Total assets (6)
Tangibility	Net property, plant, and equipment (PPENT) (8) / Total assets (6)
Asset Maturity	(Current assets (4)/(Current assets (4) + PPENT)*(Current assets (4)/Cost of goods sold (41)) + (PPENT/(Current assets (4) + PPENT)*(PPENT/Depreciation and amortization (14))
Product Uniqueness	Dummy = 1 if the SIC code of the firm is between 3400 and 4000
Market Leverage	Total debt / (Total debt + MV equity)
Book Leverage	Total debt / Total assets (6)
CF Volatility	Standard deviation of quarterly operating income (13) over previous 12 quarters scaled by total assets (6)
Capex	Capital expenditures (128) / Total assets (6)
Advertising	Selling, general, and administration expenses (189) / Total assets (6)
R&D Expenses	Research and development expenses (46) / Total assets (6)
CEO not COB	Dummy = 1 if the Chief Executive Officer (CEO) is not the Chairman of the Board (COB)
Small Board	Dummy = 1if the board size in year t is less than the median board size for that year
Independent Board	Dummy = 1 if the fraction of independent directors exceeds 50%
B-index	CEO not COB + Small Board + Independent Board
S&P1500	Dummy = 1 if a firm's stock is part of the S&P 1500 index
Unrated	Dummy = 1 if a firm is not rated by the S&P (280)
	Debt Structure
CP	Commercial paper
DC	Drawn credit line
TL	Term loans
SBN	Senior bonds and notes
SUB	Subordinated bonds and notes
CL	Capital leases
Other	Other debt + Total trust-preferred stock
Total Adjustment	Total debt − (CP + DC + TL + SBN + SUB + CL + Other)
HHI	$\{[(CP/(\text{Total debt}))^2 + (DC/(\text{Total debt}))^2 + (TL/(\text{Total debt}))^2 + (SBN/(\text{Total debt}))^2 + (SUB/(\text{Total debt}))^2 + (CL/(\text{Total debt}))^2 + ((\text{Other})/(\text{Total debt}))^2] - (1/7)\}/(1 - (1/7))$
Excl90	Dummy = 1 if a firm has more than 90% of its total debt in one debt type (CP, DC, TL, SBN, SUB, CL or Other), and 0 otherwise

Table AII

An Example of How Capital IQ Classifies Debt Types

This table illustrates how Capital IQ calculates each debt type (in millions of dollars) for AMR Corporation for the fiscal year ended on December 31, 2003. All information is available under Item 8 of Form 10K.

Item		Detailed Calculation
Capital Structure Data		
Total Debt	13,930	Long-term debt, less current maturities (11,901) + Obligations under capital leases, less current obligations (1,225) + Current maturities of long-term debt (603) + Current obligations under capital leases (201) = 13,930
Total Equity	46	Stockholders' equity (46)
Total Capital	13,976	Total debt + Stockholders' equity
Debt Structure Data		
Total Drawn Credit Lines	834	Credit facility agreement due through 2005 (834)
Total Term Loans	0	
Total Senior Bonds and Notes	11,668	Secured variable and fixed rate indebtedness due through 2021 (6,041) + Enhanced equipment trust certificates due through 2011 (3,747) + Special facility revenue bonds due through 2036 (947) + Debentures due through 2021 (330) + Notes due through 2039 (303) + Senior convertible notes due through 2023 (300)
Total Capital Leases	1,426	Obligations under capital leases, less current obligations (1,225) + Current obligations under capital leases (201)
Other Borrowings	2	Other (2)

[1] Regulation S-X of the Securities Act of 1933 requires firms to detail their long-term debt instruments. Regulation S-K of the same act requires firms to discuss their liquidity, capital resources, and operating results. As a result of these regulations, firms provide detailed information on their long-term debt issues and drawn credit lines. Firms often also provide information on notes payable within a year (Rauh and Sufi (2010)). The SEC mandated electronic submission of SEC filings in 1996. Capital IQ has been compiling detailed information on capital structure and debt structure by going through financial footnotes contained in firms' 10K SEC filings since then. However, coverage by Capital IQ is comprehensive only from 2002 onwards.

[2] Our separate treatment of (drawn) credit lines and term loans is motivated by a new and growing line of research that examines the determinants of the presence of credit lines, their amount, and draw-downs (DeMarzo and Sannikov (2006), DeMarzo and Fishman (2007), Jiménez, López, and Saurina (2009), Sufi (2009a), Ivashina and Scharfstein (2010), Campello, Graham, and Harvey (2010), and Campello, Giambona, Graham, and Harvey (2011)). Further, Strahan (1999) shows that there are significant differences between credit lines and term loans in terms of borrower size, pricing, loan size, and maturity.

[3] Capital leases are different from operating leases. While in an operating lease, lease expenses are treated as an operating cost, a capital lease is recognized both as an asset and as a liability on the balance sheet, and is thus subject to depreciation. Typically, firms prefer to keep leases off the books, which gives them the incentive to report all leases as operating leases. As a result, the Financial Accounting Standards Board has outlined the specific conditions under which a lease should be reported as a capital lease. Though often disregarded in the existing literature, the distinction between capital and operating leases is important for our purposes. In our analysis of debt we will only consider capital leases, as operating leases are not reported as debt on the balance sheet.

[4] Other debt mostly consists of unclassified short-term borrowings. Occasionally it takes other forms such as deferred credits, fair value adjustments related to hedging contracts, and trust-preferred securities.

[5] Specifically, to identify the clusters, we employ the Stata command cluster *kmeans* with clusters defined over all seven debt types simultaneously and run *kmeans* for up to 15 clusters. We then apply a stopping rule based on the Calinski/Harabasz index.

[6] Firm characteristics are measured contemporaneously. Using lagged measures gives qualitatively the same results.

[7] We thank an anonymous referee for this suggestion.

[8] Using Compustat firms over the period 1986-2000, Faulkender and Petersen (2006) show that only 19% (21%) of firms (firms with positive debt) have credit ratings. Due to different sample periods and sampling criteria, our sample firms are much larger and have higher leverage than the Faulkender and Petersen sample firms (as shown in Table 1). Faulkender and Petersen (2006) and Lemmon and Zender (2010) have shown that the most important determinants of firms being rated are size and leverage. The large differences in firm size and leverage may explain why we observe a higher fraction of rated firms in our sample than in the Faulkender and Petersen sample. Table IA.1 in the Internet Appendix shows that rated firms in our sample are materially different from unrated firms in all dimensions examined; for example, they are larger and more profitable than unrated firms in our sample.

[9] These findings are robust to different specifications of the conditioning threshold, as shown in Table IA.2 in the Internet Appendix.

[10] The existing theoretical literature has offered several explanations to rationalize the simultaneous usage of different debt types. For example, Diamond (1993) justifies the optimal mix of public debt and bank debt in relation to priority and maturity. Park (2000) derives the optimality of having both bank debt and public debt where bank debt is senior and held by a single lender, while public debt is junior and widely held. DeMarzo and Sannikov (2006) and DeMarzo and Fishman (2007) justify employing both long-term debt and lines of credit in the presence of agency problems.

[11] We thank an anonymous referee for suggesting these possible explanations for why debt specialization takes place.

[12] In this paper, we use asset tangibility to proxy for lower bankruptcy costs, and we show that firms with more tangible assets are more likely to employ different types of debt (see Table 7). To the extent that asset tangibility is positively correlated with asset redeployability as examined by Bolton and Scharfstein (1996), our evidence suggests that asset tangibility mitigates the sensitivity of bankruptcy costs to the need for bargaining among different types of creditors.

[13] In general, behind each type of debt there may be multiple creditors (as examined theoretically by Bolton and Scharfstein (1996) and empirically by Ivashina et al. (2011)), leading to a positive correlation between the degree of debt specialization and the degree of creditor concentration. Our empirical investigation in this section implicitly relies on this positive correlation. However, the extent of this correlation is hard to pin down. For example, there may be firms with only one type of debt, like corporate bonds, held by a large number of investors; there may also be firms borrowing through several types of debt, e.g., capital leases and bank loans, where the number of lenders overall is

very small; and there may be a single lender providing financing through several types of debt. Data limitations prevent us from an in depth examination of this correlation.

[14] Table IA.4 in the Internet Appendix presents the correlation matrix between key firm characteristics that are shown to be important in capital structure decisions (see for example, Lemmon and Zender (2010), and Graham and Leary (2011)) as well as our proxies for the three different hypotheses. We show that there is a strong and negative association between size and the unrated dummy, and between profitability and R&D expenses.

Internet Appendix for "Debt Specialization"*

Table IA.1
Sample Overview: Rated and Unrated Firms

This table presents means and medians aggregated across all years for the sample of rated and unrated firms respectively. Definitions of the variables are provided in Table AI. The last two columns of the table present test statistics of the t-test and the Wilcoxon test of the differences in firm characteristics between the two samples. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Rated Firms		Unrated Firms		Test of Differences across Samples	
	(1) Mean	(2) Median	(3) Mean	(4) Median	(5) t-test	(6) Wilcoxon test
Size	9075.7	2434.6	522.2	215.6	-21.516***	-89.568***
M/B	1.312	1.088	1.621	1.202	13.736***	9.546***
Profitability	0.132	0.128	0.057	0.103	-29.806***	-24.241***
Dividend Payer	0.513	1.000	0.236	0.000	-36.140***	-35.995***
Cash Holdings	0.095	0.059	0.185	0.100	34.736***	-22.503***
Tangibility	0.324	0.259	0.266	0.187	-15.279***	-18.169***
Asset Maturity	6.112	3.342	5.979	2.484	-0.168	-18.844***
*Market Leverage	0.319	0.275	0.210	0.148	-31.850***	-36.526***
CF Volatility	0.012	0.008	0.022	0.012	24.488***	34.487***
# Observations	6,147		9,968			

* Citation format: Colla, Paolo, Filippo Ippolito, and Kai Li, 2012, Internet Appendix to "Debt Specialization," Journal of Finance [vol #], [pages], http://www.afajof.org/IA/[year].asp. Please note: Wiley-Blackwell is not responsible for the content or functionality of any supporting information supplied by the authors. Any queries (other than missing material) should be directed to the authors of the article.

Table IA.2
Conditional Debt Structure

This table provides evidence on conditional debt structure. We first impose the condition that the usage of a particular debt type exceeds 10% (50%) of total debt. We then compute mean and median (in square brackets) ratios of each debt type to total debt for the subset of observations that satisfy this condition. Definitions of the variables are provided in Table AI. Panels A and B (C and D) employ the 10% (50%) cut off. Panels A and C (B and D) employ the rated (unrated) firm subsample.

Panel A: Rated firms

Condition	CP	DC	TL	SBN	SUB	CL	Other
CP>10%	0.272 [0.201]	0.028 [0.000]	0.022 [0.000]	0.609 [0.675]	0.008 [0.000]	0.011 [0.000]	0.049 [0.012]
DC>10%	0.008 [0.000]	0.347 [0.263]	0.096 [0.000]	0.396 [0.424]	0.117 [0.000]	0.016 [0.000]	0.020 [0.000]
TL>10%	0.004 [0.000]	0.064 [0.000]	0.468 [0.405]	0.287 [0.205]	0.147 [0.000]	0.015 [0.000]	0.014 [0.000]
SBN>10%	0.026 [0.000]	0.074 [0.000]	0.084 [0.000]	0.728 [0.792]	0.047 [0.000]	0.014 [0.000]	0.028 [0.000]
SUB>10%	0.001 [0.000]	0.090 [0.000]	0.178 [0.036]	0.167 [0.010]	0.539 [0.492]	0.013 [0.000]	0.012 [0.000]
CL>10%	0.009 [0.000]	0.073 [0.000]	0.118 [0.000]	0.420 [0.503]	0.089 [0.000]	0.268 [0.172]	0.023 [0.000]
Other>10%	0.045 [0.000]	0.058 [0.000]	0.056 [0.000]	0.497 [0.569]	0.053 [0.000]	0.015 [0.000]	0.276 [0.196]

Panel B: Unrated firms

Condition	CP	DC	TL	SBN	SUB	CL	Other
CP>10%	0.382 [0.283]	0.181 [0.093]	0.100 [0.000]	0.327 [0.214]	0.009 [0.000]	0.001 [0.000]	0.001 [0.000]
DC>10%	0.001 [0.000]	0.632 [0.653]	0.143 [0.000]	0.147 [0.000]	0.030 [0.000]	0.033 [0.000]	0.013 [0.000]
TL>10%	0.001 [0.000]	0.168 [0.000]	0.642 [0.673]	0.108 [0.000]	0.033 [0.000]	0.035 [0.000]	0.013 [0.000]
SBN>10%	0.001 [0.000]	0.164 [0.000]	0.100 [0.000]	0.658 [0.710]	0.027 [0.000]	0.036 [0.000]	0.013 [0.000]
SUB>10%	0.000 [0.000]	0.116 [0.000]	0.103 [0.000]	0.103 [0.000]	0.647 [0.673]	0.022 [0.000]	0.009 [0.000]
CL>10%	0.000 [0.000]	0.160 [0.000]	0.141 [0.000]	0.151 [0.000]	0.025 [0.000]	0.506 [0.359]	0.018 [0.000]
Other>10%	0.000 [0.000]	0.168 [0.000]	0.123 [0.000]	0.163 [0.000]	0.027 [0.000]	0.053 [0.000]	0.466 [0.353]

Panel C: Rated firms

Condition	CP	DC	TL	SBN	SUB	CL	Other
CP>50%	0.676 [0.595]	0.036 [0.000]	0.004 [0.000]	0.216 [0.279]	0.002 [0.000]	0.006 [0.000]	0.061 [0.000]
DC>50%	0.002 [0.000]	0.737 [0.692]	0.038 [0.000]	0.136 [0.020]	0.062 [0.000]	0.013 [0.000]	0.012 [0.000]
TL>50%	0.000 [0.000]	0.038 [0.000]	0.777 [0.769]	0.085 [0.000]	0.083 [0.000]	0.012 [0.000]	0.006 [0.000]
SBN>50%	0.023 [0.000]	0.049 [0.000]	0.044 [0.000]	0.833 [0.865]	0.015 [0.000]	0.013 [0.000]	0.024 [0.000]
SUB>50%	0.000 [0.000]	0.061 [0.000]	0.087 [0.000]	0.049 [0.000]	0.782 [0.778]	0.013 [0.000]	0.008 [0.000]
CL>50%	0.000 [0.000]	0.040 [0.000]	0.014 [0.000]	0.100 [0.000]	0.013 [0.000]	0.821 [0.864]	0.012 [0.000]
Other>50%	0.011 [0.000]	0.024 [0.000]	0.011 [0.000]	0.134 [0.014]	0.002 [0.000]	0.018 [0.000]	0.800 [0.833]

Panel D: Unrated firms

Condition	CP	DC	TL	SBN	SUB	CL	Other
CP>50%	0.906 [1.000]	0.093 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.001 [0.000]
DC>50%	0.000 [0.000]	0.846 [0.908]	0.054 [0.000]	0.058 [0.000]	0.010 [0.000]	0.024 [0.000]	0.007 [0.000]
TL>50%	0.000 [0.000]	0.075 [0.000]	0.847 [0.913]	0.037 [0.000]	0.010 [0.000]	0.024 [0.000]	0.007 [0.000]
SBN>50%	0.001 [0.000]	0.063 [0.000]	0.035 [0.000]	0.860 [0.939]	0.010 [0.000]	0.022 [0.000]	0.009 [0.000]
SUB>50%	0.000 [0.000]	0.039 [0.000]	0.043 [0.000]	0.032 [0.000]	0.867 [0.959]	0.015 [0.000]	0.005 [0.000]
CL>50%	0.000 [0.000]	0.029 [0.000]	0.026 [0.000]	0.040 [0.000]	0.005 [0.000]	0.891 [1.000]	0.008 [0.000]
Other>50%	0.000 [0.000]	0.041 [0.000]	0.037 [0.000]	0.036 [0.000]	0.005 [0.000]	0.026 [0.000]	0.855 [0.948]

Table IA.3
Which Firms Specialize?

This table presents descriptive statistics for the relation between debt specialization (measured by *Excl90*) and firm characteristics. The first column gives the correlation for each of these variables with Excl90. One-way sorting by *Excl90* is carried out year by year and then aggregated across years. Columns (2)-(3) present the mean values of firm characteristics for firms with *Excl90* = 0 and *Excl90* = 1. The last column presents the t-test of the differences in debt specialization between firms with *Excl90* = 0 and firms with *Excl90* = 1. Definitions of the variables are provided in Table AI. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Correlation	Excl90 = 0	Excl90 = 1	Test of Differences between Excl90 = 0 and Excl90 = 1
	(1)	(2) Mean	(3) Mean	(4) t-test
Ln(Size)	-0.127***	6.538	6.056	16.323***
Ln(Sales)	-0.149***	6.616	5.990	18.950***
Ln(Firm Age)	-0.072***	2.613	2.474	9.136***
M/B	0.103***	1.348	1.688	-12.769***
Profitability	-0.087***	0.101	0.067	10.679***
Dividend Payer	-0.053***	0.365	0.314	6.749***
Cash Holdings	0.305***	0.098	0.213	-39.011***
Tangibility	-0.121***	0.314	0.257	15.525***
Market Leverage	-0.265***	0.304	0.189	35.640***
Book Leverage	-0.230***	0.306	0.218	30.141***
CF Volatility	0.097***	0.015	0.021	-11.895***
Asset Maturity	0.010	5.548	6.591	-1.240
Capex	-0.021**	0.058	0.055	2.595***
R&D Expenses	0.143***	0.049	0.096	-13.995***
Advertising	0.092***	0.247	0.292	-11.145***
Product Uniqueness	0.042***	0.245	0.282	-5.352***
B-Index	0.114***	1.626	1.796	-9.223***
S&P 1500	-0.011	0.405	0.394	1.416
Unrated	0.144***	0.555	0.695	-18.541***

Table IA.4
The Correlation Matrix

This table presents the correlation matrix of firm characteristics included in the regressions of Table 8 (*p*-values are in parentheses).

	Size	M/B	Profitability	Dividend Payer	Tangibility	Cash Flow Volatility	R&D Expenses	Unrated
M/B	-0.107 (0.000)							
Profitability	0.396 (0.000)	-0.114 (0.000)						
Dividend Payer	0.458 (0.000)	-0.088 (0.000)	0.312 (0.000)					
Tangibility	0.124 (0.000)	-0.128 (0.000)	0.221 (0.000)	0.154 (0.000)				
Cash Flow Volatility	-0.412 (0.000)	0.183 (0.000)	-0.473 (0.000)	-0.253 (0.000)	-0.120 (0.000)			
R&D Expenses	-0.306 (0.000)	0.368 (0.000)	-0.700 (0.000)	-0.258 (0.000)	-0.268 (0.000)	0.458 (0.000)		
Unrated	-0.711 (0.000)	0.085 (0.000)	-0.275 (0.000)	-0.346 (0.000)	-0.129 (0.000)	0.260 (0.000)	0.238 (0.000)	
Book leverage	0.128 (0.000)	-0.075 (0.000)	0.013 (0.241)	-0.015 (0.178)	0.198 (0.000)	-0.034 (0.003)	-0.076 (0.000)	-0.273 (0.000)