**Determinants of Corporate Debt Specialization: Insights from Private Firms**[*]

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**Abstract**

This study provides the first evidence on private firms' debt specialization. Contrary to existing evidence that firms with higher expected bankruptcy costs, constrained access to capital, and higher information asymmetry specialize in their debt borrowing, we find that private firms adopt more diversified debt portfolios than public firms. We show that private firms' debt diversification is mainly driven by the need to mitigate lender holdup costs arising from high information asymmetry. We also find that the concentration of equity ownership is negatively related to debt specialization, suggesting private firms have less motivation to use specialized debt as a governance mechanism. Our findings highlight the roles of financial flexibility and reduced monitoring in shaping private firms' debt structure decisions.

*Keywords:* debt specialization, debt structure, stock market listing, private firms, holdup cost.

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## 1. Introduction

The choice of debt structure is a critical corporate finance decision. Corporate preferences along debt characteristics such as maturity, priority, and instruments have been the focus of a large and growing literature.[1] The strand of this literature that focuses on debt instruments has documented significant heterogeneity in the mix of debt types that firms use. Rauh and Sufi (2010) and Colla, Ippolito, and Li, (2013, 2020), for example, show that many firms rely on multiple types of debt simultaneously, and the degree of debt specialization—the extent to which firms rely on only a few types of debt (or even a single debt type)—varies widely across firms.

There exists some evidence on why debt specialization takes place (e.g., Colla et al., 2013). However, the debt specialization decisions of privately held firms remain largely unexplored, and as Colla et al. (2020) acknowledge, our understanding of private firms' debt structure is relatively limited. We take a step towards filling this gap by investigating the empirical determinants of private firms' debt specialization. Particularly, our research addresses two questions: (1) Do private firms' debt specialization decisions differ from those of their public counterparts? and (2) Do existing debt financing theories explain private firms' debt specialization choices? Focusing on private firms is important because they constitute a significant portion of the economy. Also, evidence on private firms' debt structure further advances our understanding of the existing stylized facts and evidence about the firm.

We construct a sample of U.S. private and public firms from Capital IQ, specifically focusing on those with financial data during our sample period, 2002–2021.[2] Because Capital IQ only reports the most recent stock market listing status of firms, we capture firms' historical listing status using a detailed list of IPO and going private (GoP) transactions collected from multiple sources. Our data construction process yields a final sample of 54,341 firm-year observations, involving 4,493 private firms and 5,686 public firms. We employ a second sample in which the private and public firms are matched based on firm characteristics. Further, our empirical analyses involve a third sample that focuses on a difference-in-differences (DiD) design based on private firms transitioning through IPOs compared to non-transitioning private firms.

[1] See Colla, Ippolito, and Li (2020) for an extensive review of this literature.
[2] The Online Appendix Table OA1 compares our initial sample with those of previous literature.

To address endogeneity concerns, we employ a DiD design that compares firms with successful IPOs to those that withdrew IPO filings. Across all specifications, we find that private firms use more diversified debt structures than public firms. More specifically, private firms are up to about 18.6% more likely to diversify their debt structure relative to publicly traded firms, depending on the specification. Colla et al. (2013, 2020) suggest that firms with constrained access to external capital, opaque firms facing high information collection and monitoring costs, and firms with higher expected bankruptcy costs should have a more concentrated debt structure. Given that private firms are more likely to possess these characteristics compared to public firms (Pagano, Panetta, and Zingales, 1998; Brav, 2009; Saunders and Steffen, 2011), our finding that they diversify their debt borrowing more than public firms is surprising.

We propose two mechanisms to explain this divergence. First, we conjecture that private firms diversify their borrowing to mitigate holdup costs and maintain financial flexibility. Rajan (1992) propounds that firms choose their optimal debt structure with the aim of reducing lenders' ability to appropriate rents. Particularly, firms optimally borrow from multiple sources to limit the power of lenders to extract surplus. Consistent with Rajan (1992), Houston and James (1996) find that utilizing multiple debt sources lowers the dominant lender's information rents and mitigates holdup problems.[3] Given that private firms are more exposed to holdup exploitation compared to public firms (Santos and Winton, 2008; Schenone, 2010; Saunders and Steffen, 2011), it follows that private firms would be more incentivized to diversify their borrowing. This prediction is consistent with the capital structure theories that emphasize financial flexibility. Firms achieve a flexible capital structure by preserving access to low-cost sources of external capital (e.g., Denis, 2011; DeAngelo, Gonçalves, and Stulz, 2018; Graham, 2022).[4] If flexibility is expected to be more valuable to private firms (Faulkender and Wang, 2006; Gamba and Triantis, 2008)[5], then they should be more motivated to pursue low-cost external capital, including lower holdup costs, which could be achieved by borrowing from multiple sources. We test our hypothesis using the Uniform Fraudulent Transfer Act (UFTA) and an SEC equity issuance deregulation as shocks that widened the difference in holdup costs between private and public firms. In support of our predictions, we find that these shocks significantly amplified the debt diversification among private firms.

[3] Diamond (1993) also show that using different types of debt can limit lenders' bargaining power.
[4] Additionally, multiple debt sources enhance financial flexibility (Detragiache, Garella, and Guiso, 2000).
[5] These studies find that firms with high external capital costs value financial flexibility more.

Second, we hypothesize that ownership concentration in private firms reduces agency costs, decreasing the need for specialized debt as a governance mechanism. Private firms usually have more concentrated ownership and control (Brav, 2009; Bharath and Dittmar, 2010). Public firms, however, have a more diversified ownership structure and, as such, face higher manager-shareholder agency costs (Gao, Harford, and Li, 2013; Asker, Farre-Mensa, and Ljungqvist, 2015). Jensen and Meckling (1976) suggest that creditor monitoring can serve as a mechanism to alleviate the agency cost of equity, and to ensure effective creditor monitoring, a concentrated debt structure is preferred (Park, 2000). Thus, public firms, compared with their private counterparts, might prefer a concentrated debt structure for effective creditor monitoring that serves as a substitute corporate governance mechanism. Using multiple measures that capture the level of concentration in firms' ownership and control, we document a negative relationship between ownership concentration and debt specialization.[6]

While we document holdup problems and ownership concentration as the underlying mechanisms, we also examine whether other determinants of debt specialization in the existing literature explain why private firms undertake more debt diversification. More specifically, Colla et al. (2013) suggest constrained access to capital as a reason for debt specialization. Accordingly, we test the potential role of capital access in our baseline results using the WW index (Whited and Wu, 2006), SA index (Hadlock and Pierce, 2010), and credit rating as our proxies. Given the strong link between access to capital, default risk, and bankruptcy probabilities (e.g., Leland, 1994; Shumway, 2001; Vassalou and Xing, 2004; Da and Gao, 2010; Graham et al., 2023), our proxies also largely capture another determinant of debt specialization suggested by Colla et al. (2013)—expected bankruptcy costs. Our findings imply that constrained access to financial markets and expected bankruptcy costs do not significantly influence private firms' preference for a highly diversified debt structure.

Next, we conduct various additional tests to further paint a more complete picture of private firms' debt specialization. For example, if our conjecture about holdup is true, we expect the diversification to be evident in firms' creditor relationships. Using 205,451 syndicated loans by U.S. private and public firms from the Loan Pricing Corporation's DealScan database, we find that loans borrowed by privately held firms are associated with a more diversified lender structure.

[6] Since we do not have ownership data for private firms, we rely on public firms' data for this test.

Building on a similar argument, we also document diversification in other debt structure dimensions, including maturity and security. Mainly, our findings indicate that private firms prefer to spread their debt maturity more than public firms do. In addition, private firms are more likely to simultaneously use a debt structure with multiple types of security status relative to publicly traded firms. Overall, the evidence corroborates the idea that private firms borrow from diversified sources to reduce exploitation by dominant lenders.

Our contributions are twofold. First, we provide the first evidence on private firms' debt specialization, filling a critical gap in the literature, especially the one that investigates the fundamental differences between private and public firms and how these differences drive corporate policies. For example, Brav (2009) finds that privately owned firms, compared to their public counterparts, maintain higher leverage ratios. Saunders and Steffen (2011) document a considerable loan cost disadvantage incurred by privately held firms. Michaely and Roberts (2012) find lower dividend smoothing among private firms than public firms. Stock marketing listing also has economic implications for corporate investment, mergers and acquisitions, and labor (Asker et al., 2012; Sheen, 2020; Borisov et al., 2021; Liang et al., 2022).

Second, we contribute to the debt specialization literature by identifying holdup cost mitigation and ownership structure as key drivers of debt specialization. Notable research in this area includes Colla et al. (2013, 2020), who stress the importance of debt specialization, highlighting how it varies across firms. Focusing on lenders, the theoretical models of Green and Liu (2021) and Zhong (2021) suggest that maintaining a highly dispersed debt structure exposes firms to high debtholder coordination problems. Li et al. (2021) show that accounting quality affects the tendency for firms to specialize in their debt borrowing. A striking feature of this literature is that the empirical studies focus on public firms. Hence, aside from documenting new determinants of debt specialization, our research offers valuable insights beyond public firms' debt specialization. Further, the results that private firms prefer a more diversified debt structure relative to publicly traded firms allow us to better understand the documented stylized facts in the debt specialization literature. For instance, Colla et al. (2013) show that close to 90 percent of public companies employ one type of debt instrument. Our channel tests suggest that public firms' relatively more dispersed ownership structure and lower level of holdup problems could explain why they are not as motivated as private firms to use a diversified debt structure.

The rest of the paper is organized as follows. Section 2 details our data sources, sample construction, and key variable definitions. Section 3 presents the univariate analyses of the relationship between stock market listing status and debt specialization. In Section 4, we provide empirical evidence using multivariate regressions. Section 5 explores the potential mechanisms underlying our results. Section 6 provides additional analyses, and in Section 7, we conclude.

## 2. Data and Methodology

### 2.1. Data Sources and Sample Construction

We collect firm-level debt structure data from Capital IQ, loan structure data from DealScan, and ownership data from Thomson Reuters Ownership Structure database. Following studies such as Gao et al. (2013), we also extract a sample of U.S. private and public firms from Capital IQ. While Capital IQ's financial data starts from 1994, debt structure data becomes comprehensive from 2002. Thus, our sample period starts from 2002 and ends in 2021. We begin with all U.S. firms in Capital IQ that have financial data during our sample period. Our initial sample includes 698,932 firm-year observations corresponding to 96,894 private firms and 8,515 public firms. We drop financial firms (SIC codes 6000-6999), utility firms (SIC codes 4900-4999), government entities (SIC codes starting with 9), and firms without SIC information. We also remove observations with zero, missing, or apparently incorrect values of debt and total assets. The final sample, 54,341 firm-year observations, involves 4,493 private firms (16,966 observations) and 5,686 public firms (37,375 observations).

Capital IQ only reports the most recent stock market listing status of firms. To determine the historical ownership type, we track the IPO and GoP transactions of our sample firms. We identify 7,239 IPOs from Capital IQ, Compustat, and Jay Ritter's IPO database, and 1,249 GoP transactions using Intelligize.[7] Firms are classified as public or private based on fiscal year-end dates relative to IPO or GoP events, with a six-month lag to account for transition periods; firms

[7] It is more complex to identify GoP dates since firms could go private either from being delisted from the trading exchange(s) or from being acquired through "going-private" M&As. To circumvent this problem, we rely on the legal definition of going private outlined by the SEC: a transaction "by which an individual or a group of individuals controlling a public corporation... undertakes a corporate transaction in order to acquire... the entire equity interest in the corporation" (Bharath and Dittmar, 2010).

with no IPO or GoP transaction during our sample period retain their Capital IQ status, while those with multiple or unidentified transactions are excluded to ensure data accuracy.[8]

We check the accuracy of our samples by comparing them with those of prior literature. In the Online Appendix, Table OA1, we report the summary statistics of our initial and final samples alongside those of two prior works that also study private vs. public U.S. firms. Gao et al. (2013) obtain a sample of private firms from Capital IQ and public firms from Compustat. Notably, they focus on private firms that have SEC Form 10-K, 10-Q, and S-1 filings. Since we focus on all private firms with financial data, the number of observations for our initial (552,262) and final (16,966) samples is more than the corresponding sample size of 10,595 reported by Gao et al. Consequently, the mean of total assets for our initial sample's private firms is considerably smaller than theirs (223.2 vs 1493). The other firm characteristics are comparable. Asker et al. (2012) use the Sagework database to collect a large sample of U.S. private firms and obtain public firm data from Compustat. Their 409,762 private firm-year observations are more than those of Gao et al. (2013) but less than ours. However, their average value of total assets for private firms, 13.5, is smaller than both ours and Gao et al.'s. Statistics of variables such as cash holding, sales growth, leverage, and age are similar across samples.

### 2.2. Matched Sample

Our analysis also incorporates a matched sample. We match each private firm from the beginning of the sample period to a public firm that has the closest propensity score within the same two-digit SIC classification. Propensity scores are constructed based on all firm characteristics employed in our baseline regression.[9] If no match forms, we discard the firm-year observation and search for a match in the following year. Once a matched pair forms, the subsequent time-series observations for the pair are reserved in order to preserve the panel structure of the data. If a matched private or public firm exits the panel, a new match is reformed. Most importantly, if a firm's private/public status changes due to IPO or GoP, the matching panel ends in the year prior to the year of status change. The matching procedure generates a propensity score matched (PSM) sample of 16,360 private firm-year observations and an equal number of public

[8] Excluding the status-changing firms from our analyses does not change our findings.
[9] We estimate propensity scores using a Probit regression model in which the indicator for private vs public status is regressed on a number of observed firm characteristics.

observations. This corresponds to 4,397 distinct privately owned firms and 4,328 publicly owned firms. As a robustness test, we further perform a nearest-neighbor matching based on firm size and industry as well as book leverage and industry. Similar matching techniques have been used in existing studies such as Sunders and Steffen (2011), Gao et al. (2013), and Asker et al. (2015). Using these alternative matching approaches does not significantly change our conclusions.

**2.3. Debt Structure Measures**

We use four measures of debt specialization in our analyses. We follow Colla et al (2013) to calculate the normalized Herfindahl-Hirschman Index (HHI) as our first measure of the extent to which firms specialize in a single or few types of debt. Particularly, firm *i*'s debt specialization in period *t* is measured as follows:

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

where *SS* is the sum of the squared ratios of each type of debt instrument captured in Capital IQ (i.e., commercial paper (CP), drawn credit lines (DC), term loans (TL), senior bonds and notes (SBN), subordinated bonds and notes (SUB), capital leases (CL), and other debt (Other)) to total debt (TD).[10] That is

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

The lower and upper bounds of *HHI* by construction are 0 and 1, respectively. An *HHI* of 0 indicates the least level of debt specialization, while 1 signifies the highest degree of specialization.

Our second measure of debt specialization, also adopted from Colla et al. (2013), is a dummy variable that takes the value of one if a firm has at least 90% of its total debt in one type of debt instrument, and zero otherwise. Particularly, we define for firm *i* in year *t* the dummy variable *Excl90* as follows:

$Excl90_{i,t}$ = 1 if a firm obtains at least 90% of its debt from one debt type

[10] Capital IQ decomposes each firm's total debt into seven mutually exclusive debt types: commercial paper, drawn credit lines, term loans, senior bonds and notes, subordinated bonds and notes, capital leases, and other debt.

$= 0$ otherwise. (3)

Like Equation (3), we construct our third and fourth debt specialization measures as binary variables equal to one if a firm has at least 80% and 70% of its total debt in one debt type, respectively, and zero otherwise.

### 2.4. Summary Statistics of Firm Characteristics

Panel B of Table 1 reports the mean values of the relevant variables employed in our study for both private and public firms.[11] We also provide differences in the mean values between private and public firms in our final sample.[12] Public firms tend to hold more cash than private firms (Gao et al., 2013). The average cash holding of 0.176 for public firms significantly exceeds the 0.13 for private firms. Similarly, public firms are larger than private firms, as evidenced by the mean total assets of $3,548 for public firms and $1,754 for private firms. Relative to public firms, private firms tend to be more leveraged (Brav, 2009), spend more on R&D, have higher sales growth rates, and have larger capital expenditures. We also observe that private firms are younger and less profitable. More especially, the average private firm is around 26 years, while the mean age of public firms is approximately 42 years. Privately owned firms pay significantly lower dividends compared to publicly traded firms. This observation is consistent with the findings of Michaely and Roberts (2012). The observed differences in characteristics between private and public firms underlie our decision to incorporate a matched sample in our analysis. It is worth highlighting that the magnitude and significance of these differences generally decrease in our matched samples.

[Insert Table 1 about here]

## 3. Univariate Analyses

### 3.1. Summary Statistics of Debt Structure

We begin our analyses with a univariate test that compares the mean values of debt specialization between private and public firms. Panel A of Table 1 reports such comparisons. On average, *HHI*, *Excl90*, *Excl80*, and *Excl70* for private firms are 0.671, 0.403, 0.520, and 0.641. Meanwhile, the corresponding mean values for public firms are 0.702, 0.450, 0.578, and 0.695.

[11] We winsorize all continuous variables at the 1st and 99th percentiles. Appendix A displays detailed variable definitions and data sources.
[12] Additionally, we report similar statistics for the alternatively matched samples.

The differences suggest that privately owned firms employ a significantly more diversified debt structure compared to their public counterparts. Moreover, Panel A of Table 1 shows similar statistics for the other matched samples.[13]

### 3.2. Reliance on One Debt Type Considering Credit Ratings

An alternative way to compare debt specialization between private and public firms is to compute the fraction of firm-year observations between two samples that obtain a significant amount of a certain debt type usage (Colla et al., 2013). To identify the significant usage, we employ a wide spectrum of thresholds ranging from 10% to 99%. We also separate our private and public firms into rated and unrated subsamples so that they are comparable with the findings in Rauh and Sufi (2010) as well as Colla et al. (2013). A firm-year is classified as rated if it has an S&P long-term issuer credit rating and unrated otherwise. The proportion of public firms that are rated exceeds that of privately held firms. There are more than 12,500 firm-year observations without ratings and around 4,400 observations with ratings for private firms. In the case of public firms, there are over 12,400 rated and 24,000 unrated observations.

[Insert Table 2 about here]

In Table 2, we calculate the proportion of firms that use a particular debt type at or above the specified level of threshold (referred to as "significant users") for each debt type and threshold. From Panels A to D, we present the results of four subsamples. The total across all debt types of significant users is also reported. If firms were to split their debt equally into 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 firms were to specialize in only one debt type, then the total for all thresholds would be one instead. As shown in Panel A, 27.9% of rated public firms rely exclusively on one debt type (at a 99% threshold). Around 44.9% (66.9%) of rated public firms obtain more than 90% (70%) of their debt from one debt type. These figures are comparable to Colla et al. (2013), who report that around 17.2%, 36.6%, and 64.9% of firms borrow more than 99%, 90%, and 70% of their debt using one type of debt instrument, respectively.

[13] We also observe the usage of specific debt types between public and private firms, which for brevity, are not presented. For instance, the most common debt types for both private and public firms are term loans and senior bonds and notes, while the least employed debt instruments are commercial paper and other debt.

Consistent with the summary statistics reported in Panel A of Table 1, the statistics provided in Table 2 suggest that private firms tend to borrow debt using more diversified instruments than public firms. For example, around 21.8% of rated private firms borrow more than 99% of their debt using one instrument, compared with 27.9% for rated public firms. 59.9% of rated private firms borrow more than 70% of debt using one instrument compared with 66.9% for rated public firms. Panels C and D, which present values for unrated firms, conform with Panels A and B. That is, public unrated firms use a more concentrated debt structure compared with private unrated firms. The statistics also indicate that credit rating does not alter our conclusion about the relationship between stock market listing and debt specialization.[14] Further, a comparison of Panels A and C, as well as B and D, shows that unrated firms, both private and public, employ more concentrated debt than rated firms do (Rauh and Sufi, 2010).

## 4. Multivariate Analyses

In this section, we conduct various multivariate tests that incorporate common determinants of debt structure and reduce potential selection bias. Particularly, we first examine how annual private-public ownership status affects firms' debt specialization decisions. Next, we study the effect of IPOs on debt specialization using a DiD framework. Finally, we implement a DiD design that compares the debt specialization of firms that successfully complete IPO transactions (treatment) and those that withdraw their IPO application (control).

### 4.1. Private Firms and Debt Specialization

Having shown in our univariate tests that private firms prefer a more diversified debt structure relative to public firms, we test whether this result holds in a regression of debt specialization on firms' annual stock market listing status and other determinants of corporate debt choices. Specifically, we estimate the following baseline regression model:

$$Debt\ Spec_{i,t} = \alpha + \beta_1 Private_{i,t} + \beta_2 X_{i,t-1} + \ Industry\ FE_i + Year\ FE_t + \varepsilon_{i,t} \qquad (4)$$

In Equation (4), *i* and *t* denote firm and year, respectively. *Debt Spec* represents the four measures of debt specialization, including *HHI*, *Excl90*, *Excl80*, and *Excl70*. Our independent variable of interest, *Private*, is a dummy variable that equals one if the ownership status of a firm-

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[14] In Section 4, we also provide a multivariate test on the effect of credit rating on private firms' tendency to use a more dispersed debt structure for which we show that credit quality indeed does not drive our results.

year observation is private and zero otherwise. In line with prior literature (e.g., Li et al., 2021), we control for firm size (natural logarithm of total assets), book leverage (total debt/total assets), sales growth (annual percentage change in sales), profitability (operating income before depreciation/total assets), tangible assets (net PPE/total assets), cash holding (cash and short-term investments/total assets), CAPEX (capital expenditure/total assets), R&D expenses scaled by total assets, dividend-paying status, rating history and firm age. Control variables are one period lagged relative to the dependent variable to mitigate reverse causality problems (Leary and Roberts, 2014).

[Insert Table 3 about here]

Table 3 presents the results of our baseline multivariate regressions. Columns (1) to (4) present results from using our final sample, and Columns (5) to (8) present those of our matched sample. The estimates across all columns consistently demonstrate that private firms employ a more diversified debt structure relative to publicly traded firms. For our final sample, being a private firm reduces debt concentration by 0.022, 0.152, 0.182, and 0.183, according to Columns (1) to (4), respectively. Similar results can be observed in the other matched sample. In Table 4, we show that employing alternative matching variables or methods does not significantly affect our baseline findings. Aside from being statistically significant at the 1 percent level, the magnitudes are also economically significant, especially when they are compared with their respective means. Additionally, the coefficients of the control variables are consistent with the literature. For example, large, low-leveraged, and rated firms are likely to use a diversified debt structure due to their superior debt capacity. On the contrary, firms that hold more cash or pay dividends tend to use a concentrated debt structure.

[Insert Table 4 about here]

### 4.2. Difference-in-Differences Analysis Using IPOs

Next, we perform a DiD analysis in which the treatment group includes IPO firms, and the control group includes matched private firms that never changed status.[15] We employ a one-to-one nearest-neighbor matching based on firm size and two-digit SIC classification to generate the matched sample.[16] Our design helps to control for time-invariant unobserved differences between

[15] In untabulated results, we conduct a similar DiD test where the control group involves matched public firms that never changed status. Our baseline conclusions remain unchanged.
[16] Our results are not significantly affected when we use different matching variables and approaches.

the treatment and control groups. In line with studies such as Bertrand and Mullainathan (2003), Imbens and Wooldridge (2009), and Atanassov (2013), we examine the before-and-after effect of IPOs on debt specialization using the following DiD regression model:

$$HHI_{i,t} = \alpha + \beta_1 IPO\ Firm_i \times\ Post\ IPO_t + \beta_2 X_{i,t-1} +\ Industry\ FE_i + Year\ FE_t + \varepsilon_{i,t} \qquad (5)$$

where *IPO Firm* is one if the firm made an IPO during our sample period, and zero otherwise. *Post IPO* is an indicator variable that takes the value of one after an IPO and zero otherwise. $X_{i,t}$ is a set of observable firm characteristics. We also include industry and year-fixed effects, and cluster standard errors at the firm level. The coefficient of interest, $\beta_1$, is the estimate of the within-firm difference between the periods before and after IPO issuance relative to a similar before-after difference in private firms with non-changing stock market listing status. The definition of the other variables remains unchanged.

[Insert Table 5 about here]

In Table 5, the coefficient of interest is significantly positive irrespective of the debt specialization measure. In the first column, for example, debt specialization increases by 0.037 when a firm's stock market listing status changes from private to public. Figure 1 graphically depicts the effect by showing the trend of debt specialization around IPOs for the transition sample and the control sample. For both *HHI* and *Excl90*, we observe a sharp rise in debt specialization after IPOs for the treated firms and not the control group.

[Insert Figure 1 about here]

### 4.3. Difference-in-Differences Analysis Using IPO Success and Withdrawal

Firms choose to go public at a particular stage in their life cycle, and as such, our empirical approach in Section 4.2. may produce biased estimates of the IPO effect (Bernstein, 2015). For example, extant studies find that debt specialization is associated with several firm factors, including growth opportunities, R&D, age, size, cash holdings, profitability, asset tangibility, leverage, cash flow volatility, advertising expenses, and credit rating. If a firm chooses to go public following an R&D breakthrough (Pastor, Taylor, and Veronesi, 2009), then the firm's post-IPO debt specialization decisions may reflect reversion to the mean, consequently mixing life cycle effects with the IPO effect.

To overcome this selection bias, we set up our second DiD test such that the treatment sample includes firms that completed an IPO (IPO success sample), and the control sample includes firms that filed for an IPO but did not complete the transaction (IPO withdrawal sample) (Bernstein, 2015). These two samples are similar regarding the timing and decision to go public. We re-estimate Equation (5), where *Post IPO* incorporates the redefined control sample. Our IPO success group includes 2,613 firms (14,548 observations), and the IPO withdrawal sample involves 981 firms (6,366 observations). In the Online Appendix, Table OA3, we show a time series distribution of these two samples. Generally, the number of observations for both samples gradually increased throughout our sample period.

In Table 6, we present estimates from our DiD regression of debt specialization on an interaction term between *IPO success* and *Post IPO*. The first three columns show results from using *HHI* as our dependent variable, and in the last three columns, *Excl90* is the dependent variable. We find a positive relationship between a successful IPO and debt specialization. This result is observable with and without the inclusion of control variables. The trend analysis in Columns (3) and (6) further shows that there is no significant difference in debt specialization between private and public firms before an IPO. After an IPO, however, the degree of debt specialization significantly increases for the IPO success sample relative to the IPO withdrawal group. The magnitudes of the increase, which persist over the post-IPO period, are both statistically and economically significant. Taken together, the evidence suggests that private firms use a less concentrated debt structure than public firms do and that the endogeneity of IPO timing and decisions does not significantly impact our results.

[Insert Table 6 about here]

## 5. Why Do Private Firms Employ a More Diversified Debt Structure?

The literature suggests some explanations for why firms specialize in their borrowing. Rauh and Sufi (2010), for example, stress the importance of credit quality in debt heterogeneity decisions. According to Colla et al. (2013), access to capital, information asymmetry, and bankruptcy costs explain corporate debt specialization decisions. These studies, however, focus on public firms. Our empirical predictions about private firms' debt specialization build on the fundamental differences between private and public firms regarding holdup costs and ownership concentration. Before testing these two mechanisms, however, we first investigate whether private firms' debt specialization could be explained by certain determinants in the existing literature, particularly focusing on access to capital and expected bankruptcy costs (Colla et al, 2013).

### 5.1. Access to Capital and Bankruptcy Costs

In this section, we examine the role that the difference in capital access and bankruptcy costs between private and public firms plays in our baseline findings. This test is motivated by the conflicting predictions about how access to capital could impact debt specialization. According to Rauh and Sufi (2010), low-credit-quality firms are more likely to have a multi-tiered capital structure, suggesting that firms with constrained access to capital maintain a diversified debt structure. On the contrary, Colla et al. (2013, 2020) suggest that firms with limited access to capital should employ a more concentrated debt structure.

To test the role of limited access to capital in our baseline findings, we employ three measures, including the *WW Index* (Whited and Wu, 2006), the *SA Index* (Hadlock and Pierce, 2010), and *Credit Rating* (S&P long-term issuer credit rating). Access to capital and default risk are strongly linked with bankruptcy probabilities (e.g., Leland, 1994; Shumway, 2001; Vassalou and Xing, 2004; Da and Gao, 2010; Graham et al., 2023). As such, our proxies also give indications about expected bankruptcy costs, which is another determinant of debt specialization suggested by Colla et al. (2013). In Panel A of Table 7, we adapt Equation (4) to include an interaction term between *Private* and the proxies of constrained capital access and bankruptcy costs. Using our matched sample, the results indicate that the interaction terms are not significant. In Panel B of Table 7, we perform a similar analysis with our IPO success and withdrawal sample. The interaction terms remain insignificant. We conduct a third test in which we match private and public firms based on the capital access measures and re-estimate Equation (4). As shown in Table 7, Panel C, *Private* is significantly negative under all three columns. Taken as a whole, the results suggest that our baseline finding is not driven by differences in capital access and bankruptcy costs between the two firm types.

[Insert Table 7 about here]

### 5.2. Mechanism: Holdup Costs

Next, we test whether the difference in lender holdup costs between public and private firms explains private firms' preference for a diversified debt structure. Rajan (1992) argues that firms optimize debt structure to reduce lenders' rent appropriation by borrowing from multiple sources, limiting any single lender's ability to extract surplus. Houston and James (1996) support this, finding that multiple debt sources lower the dominant lender's information rents and mitigate holdup issues. We argue that private firms, more vulnerable to holdup than public firms (Santos and Winton, 2008; Schenone, 2010; Saunders and Steffen, 2011), should be more incentivized to diversify borrowing. This aligns with the capital structure theories suggesting that firms achieve a flexible capital structure by preserving access to low-cost sources of external capital (e.g., Denis, 2011; DeAngelo, Gonçalves, and Stulz, 2018; Graham, 2022). As flexibility is likely to be more valuable for private firms (Faulkender and Wang, 2006; Gamba and Triantis, 2008), we expect privately held firms to be more motivated to pursue low-cost capital, including by diversifying debt sources to reduce holdup costs. To the extent that this argument is valid, our documented results should be increasing in holdup cost exposure.

We perform DiD analysis around two events that potentially widened the difference in holdup costs between private and public firms. The staggered adoption of Universal Fraudulent Transfer Acts (UFTAs) in the U.S. strengthened creditors' rights and effectively gave lenders more power in creditor-borrower relationships (Ersahin et al., 2021). By increasing lenders' power, including the capacity to hold up borrowers, UFTAs widened the holdup exposure gap between private and public firms because private firms are more dependent on lenders than public firms. The second shock is a deregulation by the SEC in 2008 that allowed some public firms to accelerate their public equity issuance. The existing requirements before this deregulation prevented roughly one-quarter of U.S. public firms from conducting shelf-registered SEOs (Gustafson and Iliev, 2017). By making it easier for public firms to access another source of finance, the deregulation reduced creditors' capacity to hold publicly traded firms, which in turn increased the holdup problem gap between the two types of firms. Consistent with our prediction, we expect the documented results to be more pronounced after the events than before. In Table 8, we demonstrate that these shocks significantly heightened the debt diversification among private firms.

[Insert Table 8 about here]

### 5.3. Mechanism: Ownership Concentration

The significant difference in ownership concentration between private and public firms could also explain why private firms are more likely to diversify their debt compared to public firms. Private firms usually have more concentrated ownership and control. As Brav (2009) and Bharath and Dittmar (2010) argue, maintaining concentrated control is probably one of the main reasons why private firms are private. Public firms, however, have a more diversified ownership structure and, as such, face higher manager-shareholder agency costs (Gao et al., 2013; Asker et al., 2015). Jensen and Meckling (1976) suggest that creditor monitoring can serve as a mechanism to alleviate the agency costs of equity. Given that concentrated debt, relative to dispersed debt, offers better creditor monitoring (Park, 2000), we conjecture that firms with dispersed ownership, i.e., public firms, might use concentrated debt to alleviate agency costs. This line of argument predicts a negative relationship between ownership concentration and debt specialization.

To test our hypothesis, we employ three measures of firms' ownership concentration: HHI of institutional ownership (*Inst. Ownership HHI*), percentage of shares held by the highest institutional holder (*Top1 Inst. Owner*), and that held by the highest 5 institutional holders (*Top5 Inst. Owners*). Ownership data is obtained from the Thomson Reuters Stock Ownership database. Because this database collects details of institutional investors' stock ownership reported in 13F filings, the ownership concentration variables employed in this study focus on only public firms. Table 9 presents our multivariate evidence on how ownership concentration affects debt specialization. We find a significant negative association between debt specialization and ownership concentration. The results support the conjecture that public firms, which normally have dispersed ownership compared to private firms, maintain a higher debt specialization.

[Insert Table 9 about here]

## 6. Private Firms and the Diversification of Other Debt Characteristics

Our final set of analyses aims to further support our arguments and documented evidence about why private firms prefer a diversified debt structure. This section also paints a more complete picture of the relationship between private ownership status and debt specialization. We first investigate the concentration of the creditors from whom firms borrow. We then study how firms diversify other aspects of their debt structure, including maturity and security.

### 6.1. Creditor Concentration

Different types of debt generally have different characteristics, including lenders (Lou and Otto, 2020). Therefore, to the extent that our hypothesis about holdup is true, we expect the diversification to be evident in firms' creditor relationships. From LPC's DealScan database, we collect a sample of 205,451 syndicated loans borrowed by private and public borrowers during our sample period. Next, we construct a set of variables that measure the concentration of loan lenders. The first group of variables centers around relationship lending. A bank is classified as a relationship bank if it served as the lead arranger for the borrower in the past five years. *RltBank Dummy* equals one if a loan is borrowed from a relationship bank and zero otherwise. *RltBank Amount* is the ratio of the dollar amount borrowed from the relationship bank to the total value of loans in the past five years. *RltBank Number* is the number of loans from a relationship bank scaled by the total number of loans in the past five years.

The second group of variables is based on portfolio concentration. *Port Top1*, *Port Top3*, and *Port Top10* are the proportions of loans borrowed from top 1, top 3, and top 10 lenders in the past five years. The last group of variables is the HHI of lenders' loan share. There are many missing values of lenders' loan shares in DealScan. We, therefore, create two indices to handle the missing value issue. First, we calculate a lender's share as the lender's allocation divided by the total loan. Second, we estimate a lender's share as the lender's allocation divided by the sum of bank allocations of all available lenders' shares. We then use these proxies to calculate the lender concentration measures, which are named *HHI Loan1* and *HHI Loan2,* respectively. Panel A of the Online Appendix, Table OA2, presents loan-level summary statistics, highlighting the difference in loan structure between private and public borrowers.

To conduct firm-level analysis, we merge the loan-level data with our final sample through fuzzy name matching between firms in Capital IQ and borrowers in DealScan. We manually check the matched firm names to verify the quality of the merge. We take a simple average of multiple loans in a firm year to construct a firm-level lender structure. Panel B of the Online Appendix, Table OA2, reports firm-level descriptive statistics of our sample firms' loan structure.

In Table 10, we present the results of multivariate regressions at the loan level (Panel A) and the firm level (Panel B). In Panel A, we control for loan characteristics, while in Panel B, we control for the firm characteristics in our baseline regression model. In all columns of Panel A, we observe significant negative coefficients of the private dummy. In Panel B, two out of three columns indicate a negative association between *Private* and lender concentration. The evidence suggests that private firms maintain a more diversified lender structure.

[Insert Table 10 about here]

### 6.2. Debt Maturity and Security

Similar to our arguments about creditor concentration, we analyze the effect of stock market listing on the degree to which firms diversify their debt maturity dates and security. Particularly, we compute *Debt Granularity* as the HHI of debt within different maturity groups (Choi, Hackbarth, and Zechner, 2021). *Security Spec* is a binary variable that equals one if a firm has both secured and unsecured debt in a particular year. We rerun our baseline model by replacing the independent variables with the new specialization measures. Our regression estimates are presented in Table 11. We find a strong negative relationship between *Private* and the measures of maturity and security concentration. The results are consistent with the evidence that privately owned firms rely more on a dispersed debt structure compared to public firms.

[Insert Table 11 about here]

## 7. Conclusion

This study examines the debt specialization decisions of private firms, addressing a critical gap in the corporate finance literature. We demonstrate that private firms maintain significantly more diversified debt structures than their public counterparts—a finding that is contrary to existing evidence that constrained capital access, information asymmetry, and higher bankruptcy costs should lead private firms to favor a concentrated debt structure. Particularly, our results reveal that private firms are up to 18.6% more likely to diversify in their debt borrowing compared to publicly traded firms. The documented evidence persists across rigorous identification strategies, including matched samples and DiD designs.

The mechanisms driving our results are equally striking. First, we show that private firms diversify debt to mitigate holdup costs imposed by dominant creditors, a strategic response to their heightened vulnerability to lender exploitation. Second, concentrated ownership in private firms reduces agency conflicts, diminishing the need for specialized debt as a governance mechanism. Constrained access to capital and expected bankruptcy costs, however, do not have a significant influence on private firms' preference for a highly diversified debt structure.

Our research contributes to the literature by documenting holdup cost mitigation and ownership concentration as novel determinants of debt specialization, offering new insights into the mechanisms driving firms' debt structure choices. We also extend the debt specialization literature by providing the first comprehensive evidence on private firms, which are economically significant yet underexplored. Taken together, by shedding light on private firms' debt specialization, this study paves the way for a deeper understanding of corporate finance decisions across the spectrum of firm ownership.

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**Appendix A: Variable definitions**

This table provides the definition and data sources of the study's variables.

| Variable | Definition | Source |
|---|---|---|
| ***Debt Specialization*** | | |
| *HHI* | Herfindahl-Hirschman Index of Capital IQ's seven types of debt instruments $\{[[CP/(\text{Total debt})]^2 + [DC/(\text{Total debt})]^2 + [TL/(\text{Total debt})]^2 + [SBN/(\text{Total debt})]^2 + [SUB/(\text{Total debt})]^2 + [CL/(\text{Total debt})]^2 + [(\text{Other})/(\text{Total debt})]^2] - (1/7)\}/(1 - (1/7))$, where CP, DC, TL, SBN, SUB, CL, and Other are commercial paper, drawn credit lines, term loans, senior bonds and notes, subordinated bonds and notes, capital leases, and other debt, respectively. | Capital IQ |
| *Excl90* | Dummy variable that equals one if a firm has more than 90% of its total debt in one debt type, and zero otherwise. | Capital IQ |
| *Excl80* | Dummy variable that equals one if a firm has more than 80% of its total debt in one debt type, and zero otherwise. | Capital IQ |
| *Excl70* | Dummy variable that equals one if a firm has more than 70% of its total debt in one debt type, and zero otherwise. | Capital IQ |
| ***Stock Market Listing*** | | |
| *Private* | Dummy variable that equals one if a firm is private at the end of the fiscal year, and zero otherwise. | Capital IQ |
| *IPO Firm* | Dummy variable that equals one if a firm made an IPO, and zero otherwise. | Capital IQ |
| *Post IPO* | Dummy variable that equals one for years after IPO, and zero otherwise. | Capital IQ |
| *IPO Success* | Dummy variable that equals one if a firm successfully completed an IPO, and zero otherwise. | Capital IQ |
| *IPO Withdrawal* | Dummy variable that equals one if a firm withdrew its IPO after initial filing, and zero otherwise. | Capital IQ |
| ***Control Variables*** | | |
| *Cash Holding* | Cash and short-term investments divided by total assets | Capita IQ |
| *Firm Size* | Natural logarithm of total assets. | Capita IQ |
| *Book Leverage* | Long-term debt plus in current liabilities divided by total assets. | Capita IQ |

| | | |
|---|---|---|
| *Tangible Assets* | Net property, plant, and equipment divided by total assets | Capita IQ |
| *Profitability* | Operating income before depreciation divided by total assets. | Capita IQ |
| *Dividend Payer* | Dummy variable that equals one if a firm pays dividends, and zero otherwise. | Capita IQ |
| *CAPEX* | Capital expenditures divided by total assets. | Capita IQ |
| *R&D* | Research and development expenses divided by total assets. Missing values of R&D are replaced with zeros. | Capita IQ |
| *Sales Growth* | The annual percentage change in sales. | Capita IQ |
| *Unrated* | Dummy variable that equals one if a firm is not rated by Standard & Poor, and zero otherwise. | Capital IQ |
| *Firm Age* | Number of years since the firm was founded. | Capita IQ |
| ***Loan Structure*** | | |
| *RLTBank Dummy* | A dummy variable that equals one if the loan is borrowed from a relationship bank (i.e., a bank from which the firm had borrowed in the past five years). | DealScan |
| *RLTBank Amount* | Ratio of amount borrowed from relationship bank to total loans in the past five years. | DealScan |
| *RLTBank Number* | Number of borrowings from relationship banks scaled by total number of borrowings in the past five years. | DealScan |
| *Port Top1* | Percentage of debt held by the highest lender in the past five years. | DealScan |
| *Port Top3* | Percentage of debt held by the top 3 lenders in the past five years. | DealScan |
| *Port Top10* | Percentage of debt held by the top 10 lenders in the past five years. | DealScan |
| *HHI Loan1* | Herfindahl-Hirschman Index of lender's share. Lender's share is calculated as the lender's allocation divided by total dollar size of loan. | DealScan |
| *HHI Loan2* | Herfindahl-Hirschman Index of lender's share where lender's share is lender's allocation divided by the sum of bank allocations of all available lender's shares. With many missing data on lender's share, we use only available data for this measure. | DealScan |
| *No. of Lenders* | Number of lenders. | DealScan |
| *Secured Dummy* | Binary variable that takes the value of one if the loan is secured, and zero otherwise. | DealScan |

| | | |
|---|---|---|
| *Seniority Dummy* | Dummy variable that equals one if the loan is a senior loan, and zero otherwise. | DealScan |
| *Average Life* | Average life of loans borrowed by the firm. | DealScan |
| *Facility Amount* | Dollar amount of loans borrowed by the firm. | DealScan |
| *Debt Granularity* | Herfindahl-Hirschman Index of debt maturity dates. | DealScan |
| *Security Spec* | Indicator variable that takes the value of one if all loans borrowed by the firm in a given year have a same security status, and zero otherwise. | DealScan |
| ***Other Variables*** | | |
| *WW Index* | Whited and Wu's (2006) index of financial constraint calculated as – 0.091×Cash Flow – 0.062×Dividend Payer + 0.021×(Long Term Debt/Total Assets) – 0.044×Firm Size + 0.102×Industry Sales Growth – 0.035×Sales Growth. | Capital IQ |
| *SA Index* | Hadlock and Pierce's (2010) financial constraint index computed as – 0.737×Firm Size + 0.043×Firm Size$^2$ – 0.040×Age. | Capital IQ |
| *Credit Rating* | Capital IQ's long-term issuer credit rating. | Capital IQ |
| *UFTA* | Dummy variable that equals to one after the adoption of Uniform Fraudulent Transfer Act (UFTA) in a state, and zero otherwise. | Constructed |
| *Deregulation* | Dummy variable that is one after the SEC deregulation in 2008, and zero otherwise. | Constructed |
| *Inst. Owners HHI* | HHI of institutional ownership. | Thomson Reuters |
| *Top1 Inst. Owner* | Percentage of the top 1 institutional owner's shares scaled by shares held by all institutional owners. | Thomson Reuters |
| *Top5 Inst. Owners* | Percentage of the top 5 institutional owners' shares scaled by shares held by all institutional owners. | Thomson Reuters |

**Table 1: Summary Statistics and Univariate Analysis**

This table presents the descriptive statistics of our main study variables, decomposed by private vs public firms. In Panel A, we show the differences in debt specialization between the private and public firms in our samples. Panel B compares the other fundamental characteristics of the private and public firms. Columns (1) and (2) focus on our final sample, Columns (3) and (4) focus on a matched sample based on size and industry, and Columns (5) and (6) focus on a propensity score matching (PSM) sample based on all the covariates in our baseline regression model. Both panels also present differences between private and public firms. Detailed variable definitions are provided in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Panel A: Differences in Debt Specialization Between Private and Public Firms**

| | Final sample | | | Matched sample – Size and Industry | | | PSM sample – All covariates | | |
|---|---|---|---|---|---|---|---|---|---|
| | Private (1) | Public (2) | Difference (1) – (2) | Private (3) | Public (4) | Difference (3) – (4) | Private (5) | Public (6) | Difference (5) – (6) |
| HHI | 0.671 | 0.702 | -0.031*** | 0.677 | 0.721 | -0.044*** | 0.673 | 0.703 | -0.030*** |
| Excl90 | 0.403 | 0.450 | -0.047*** | 0.413 | 0.484 | -0.071*** | 0.406 | 0.451 | -0.045*** |
| Excl80 | 0.520 | 0.578 | -0.058*** | 0.527 | 0.602 | -0.075*** | 0.523 | 0.579 | -0.056*** |
| Excl70 | 0.641 | 0.695 | -0.054*** | 0.646 | 0.710 | -0.064*** | 0.643 | 0.694 | -0.051*** |
| No. of Obs. | 16,966 | 37,375 | | 15,367 | 15,367 | | 16,360 | 16,360 | |
| No. of Firms | 4,493 | 5,686 | | 4,353 | 4,244 | | 4,397 | 4,328 | |

**Panel B: Differences in Firm Characteristics Between Private and Public Firms**

| | Final Sample | | | Matched sample – Size and Industry | | | PSM sample – All covariates | | |
|---|---|---|---|---|---|---|---|---|---|
| | Private (1) | Public (2) | Difference (1) – (2) | Private (3) | Public (4) | Difference (3) – (4) | Private (5) | Public (6) | Difference (5) – (6) |
| Cash Holding | 0.130 | 0.176 | -0.046*** | 0.135 | 0.175 | -0.040*** | 0.132 | 0.150 | -0.018*** |
| Total Assets | 1753.5 | 3548 | -1,794*** | 1174.2 | 1199.6 | -25.40 | 1766.3 | 2500.7 | -734.4*** |
| Book Leverage | 0.465 | 0.379 | 0.086*** | 0.468 | 0.385 | 0.083*** | 0.459 | 0.414 | 0.045*** |
| Tangible Assets | 0.256 | 0.255 | 0.178 | 0.251 | 0.250 | 0.001 | 0.253 | 0.255 | -0.002 |
| Profitability | -0.036 | 0.014 | -0.050*** | -0.047 | 0.005 | -0.052*** | -0.035 | 0.005 | -0.040*** |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Dividend Payer | 0.200 | 0.345 | -0.145*** | 0.191 | 0.269 | -0.078*** | 0.202 | 0.240 | -0.038*** |
| CAPEX | 0.051 | 0.047 | 0.004*** | 0.051 | 0.050 | 0.001** | 0.051 | 0.050 | 0.001 |
| R&D | 0.056 | 0.049 | 0.007*** | 0.060 | 0.054 | 0.006*** | 0.057 | 0.050 | 0.007*** |
| Ln(Total Sales) | 5.124 | 5.627 | -0.503*** | 4.941 | 4.889 | 0.052* | 5.125 | 5.178 | -0.053* |
| Sales Growth | 0.204 | 0.160 | 0.044*** | 0.212 | 0.177 | 0.035*** | 0.201 | 0.179 | 0.022*** |
| Unrated | 0.740 | 0.667 | 0.073*** | 0.761 | 0.763 | -0.002 | 0.740 | 0.734 | 0.006 |
| Total Debt | 701.98 | 1129.24 | -427.3*** | 499.12 | 414.77 | 84.35*** | 705.07 | 827.20 | -122.1*** |
| Firm Age | 25.73 | 41.79 | -16.06*** | 25.22 | 35.12 | -9.90*** | 26.01 | 31.69 | -5.68*** |
| No. of Obs. | 16,966 | 37,375 | | 15,367 | 15,367 | | 16,360 | 16,360 | |
| No. of Firms. | 4,493 | 5,686 | | 4,353 | 4,244 | | 4,397 | 4,328 | |

**Table 2: Reliance on One Debt Type**

This table reports the shares of firm-year observations that use one debt type above a given threshold. For example, column "30%" presents the share of observations that employ more than 30% of debt from one debt type. "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 one debt type. Panels A and B focus on public firms, while Panels C and D focus on private firms. We also present corresponding figures reported in Colla et al. (2013).

| | Threshold | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 10% | 30% | 50% | 60% | 70% | 80% | 90% | 95% | 99% |
| **Panel A: Public Rated Firms** | | | | | | | | | |
| Total | 1.610 | 1.235 | 0.963 | 0.835 | 0.669 | 0.555 | 0.449 | 0.408 | 0.279 |
| *Colla et al.'s (2013) Total* | *1.746* | *1.233* | *0.915* | *0.782* | *0.649* | *0.510* | *0.366* | *0.278* | *0.172* |
| **Panel B: Public Unrated Firms** | | | | | | | | | |
| Total | 1.566 | 1.201 | 0.949 | 0.841 | 0.735 | 0.634 | 0.522 | 0.458 | 0.377 |
| *Colla et al.'s (2013) Total* | *1.564* | *1.205* | *0.944* | *0.835* | *0.727* | *0.626* | *0.513* | *0.442* | *0.355* |
| **Panel C: Private Rated Firms** | | | | | | | | | |
| Total | 1.739 | 1.310 | 0.915 | 0.746 | 0.599 | 0.486 | 0.366 | 0.289 | 0.218 |
| **Panel D: Private Unrated Firms** | | | | | | | | | |
| Total | 1.668 | 1.249 | 0.936 | 0.795 | 0.668 | 0.553 | 0.436 | 0.371 | 0.289 |

**Table 3: Multivariate Analysis**

This table presents results from estimating our baseline regression model. Columns (1) – (4) are regression estimates for the final sample. Columns (5) – (8) are results for a matched sample using the propensity score matching method based on all covariates in our baseline regression model. Dependent variables are four measures of debt specialization: *HHI*, *Excl90, Excl80, and Excl70*. The independent variable of interest, *Private*, is one if the firm is defined as a private firm at the end of the fiscal year, and zero otherwise. Control variables are one-period lagged to the dependent variable. All regressions include industry-fixed effects and year-fixed effects. Robust standard errors are clustered at the firm level, and t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively. All continuous variables are winsorized at the 1st and 99th percentiles. Detailed variable definitions are provided in Appendix A.

| | Final sample | | | | Matched sample | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | HHI | Excl90 | Excl80 | Excl70 | HHI | Excl90 | Excl80 | Excl70 |
| Private | -0.022*** | -0.152*** | -0.182*** | -0.183*** | -0.022*** | -0.139*** | -0.186*** | -0.184*** |
| | (-4.579) | (-4.045) | (-4.905) | (-4.794) | (-4.374) | (-3.560) | (-4.802) | (-4.601) |
| Firm Size | -0.015*** | -0.114*** | -0.095*** | -0.089*** | -0.016*** | -0.120*** | -0.110*** | -0.110*** |
| | (-13.99) | (-13.16) | (-10.80) | (-9.765) | (-13.45) | (-12.11) | (-11.02) | (-10.46) |
| Sales Growth | -0.007*** | -0.076*** | -0.053*** | -0.052*** | -0.006** | -0.060*** | -0.042** | -0.036* |
| | (-3.664) | (-4.419) | (-3.143) | (-2.969) | (-2.512) | (-2.889) | (-2.051) | (-1.721) |
| Profitability | 0.025*** | 0.248*** | 0.166*** | 0.113** | 0.024*** | 0.218*** | 0.171*** | 0.146*** |
| | (4.386) | (4.845) | (3.334) | (2.211) | (3.921) | (3.941) | (3.116) | (2.585) |
| Tangible Assets | -0.028** | -0.161 | -0.145 | -0.088 | -0.045*** | -0.281** | -0.228** | -0.170 |
| | (-2.115) | (-1.556) | (-1.442) | (-0.867) | (-2.979) | (-2.348) | (-1.982) | (-1.463) |
| Cash Holding | 0.279*** | 2.338*** | 2.221*** | 2.224*** | 0.281*** | 2.240*** | 2.234*** | 2.336*** |
| | (28.72) | (25.27) | (23.07) | (21.23) | (22.65) | (19.13) | (18.05) | (16.72) |
| Dividend Payer | 0.022*** | 0.155*** | 0.210*** | 0.229*** | 0.012* | 0.057 | 0.128*** | 0.168*** |
| | (4.339) | (3.874) | (5.327) | (5.554) | (1.906) | (1.179) | (2.680) | (3.422) |
| CAPEX | 0.018 | -0.154 | 0.246 | 0.266 | 0.029 | -0.115 | 0.273 | 0.330 |
| | (0.681) | (-0.697) | (1.103) | (1.138) | (0.937) | (-0.452) | (1.068) | (1.226) |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Ln(Firm Age) | 0.003 | 0.007 | 0.021 | 0.027 | 0.005* | 0.030 | 0.030 | 0.029 |
| | (1.123) | (0.363) | (1.104) | (1.400) | (1.732) | (1.423) | (1.444) | (1.380) |
| R&D | 0.073*** | 0.607*** | 0.591*** | 0.632*** | 0.089*** | 0.776*** | 0.736*** | 0.717*** |
| | (6.261) | (5.310) | (4.998) | (4.956) | (6.533) | (6.001) | (5.333) | (4.851) |
| Unrated | 0.023*** | 0.137*** | 0.091* | 0.042 | 0.013* | 0.075 | 0.038 | -0.007 |
| | (3.626) | (2.763) | (1.913) | (0.867) | (1.871) | (1.292) | (0.681) | (-0.111) |
| Book Leverage | -0.0615*** | -0.488*** | -0.407*** | -0.351*** | -0.0627*** | -0.487*** | -0.421*** | -0.374*** |
| | (-15.54) | (-13.13) | (-12.49) | (-11.37) | (-13.73) | (-11.62) | (-11.23) | (-10.54) |
| Constant | 0.690*** | -0.175 | 0.129 | 0.798** | 0.670*** | -0.146 | 0.040 | 0.626 |
| | (15.19) | (-0.470) | (0.325) | (2.568) | (9.155) | (-0.253) | (0.0694) | (1.285) |
| Observations | 54,341 | 54,324 | 54,324 | 54,324 | 32,720 | 32,714 | 32,714 | 32,714 |
| Industry Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Model | Tobit | Logit | Logit | Logit | Tobit | Logit | Logit | Logit |
| Pseudo-R-Squared | 0.844 | 0.093 | 0.073 | 0.061 | 0.697 | 0.080 | 0.067 | 0.058 |

**Table 4: Alternative Matching Specifications**

This table reports results from testing the robustness of our matching procedure. The dependent variable in all four columns is *HHI*. *Private* is one if the firm is defined as a private firm at the end of the fiscal year and zero otherwise. Column (1) shows regression estimates for the final sample. Column (2) uses a matched sample based on firm size and a 2-digit SIC code. Column (3) uses a matched sample based on book leverage and a 2-digit SIC code. Column (4) uses a propensity score-matched sample based on all the explanatory variables in our primary model. Control variables are one-period lagged to the dependent variable. All regressions include industry-fixed effects and year-fixed effects. Robust standard errors are clustered at the firm level, and t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively. All continuous variables are winsorized at the 1st and 99th percentiles. Detailed variable definitions are provided in Appendix A.

| | Final | Size-matched | Leverage-matched | PSM |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | HHI | HHI | HHI | HHI |
| Private | -0.022*** | -0.022*** | -0.021*** | -0.022*** |
| | (-4.579) | (-4.423) | (-4.257) | (-4.374) |
| Observations | 54,341 | 30,734 | 32,440 | 32,720 |
| Control Variables | Yes | Yes | Yes | Yes |
| Industry Fixed Effects | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes |
| Model | Tobit | Tobit | Tobit | Tobit |
| Pseudo-R-Squared | 0.844 | 0.710 | 0.766 | 0.697 |

**Figure 1: Debt Specialization Around IPOs**

This figure shows graphs of debt specialization around IPOs. Specifically, we identify a subsample of firms transitioning from private to public during the sample period. For each IPO transition firm, we use nearest-neighbor matching to find a private firm that did not change stock market listing status during our sample period in the same two-digit SIC industry classification and with the nearest firm size. Panels A and B present the mean values of *HHI* and *Excl90*, respectively.

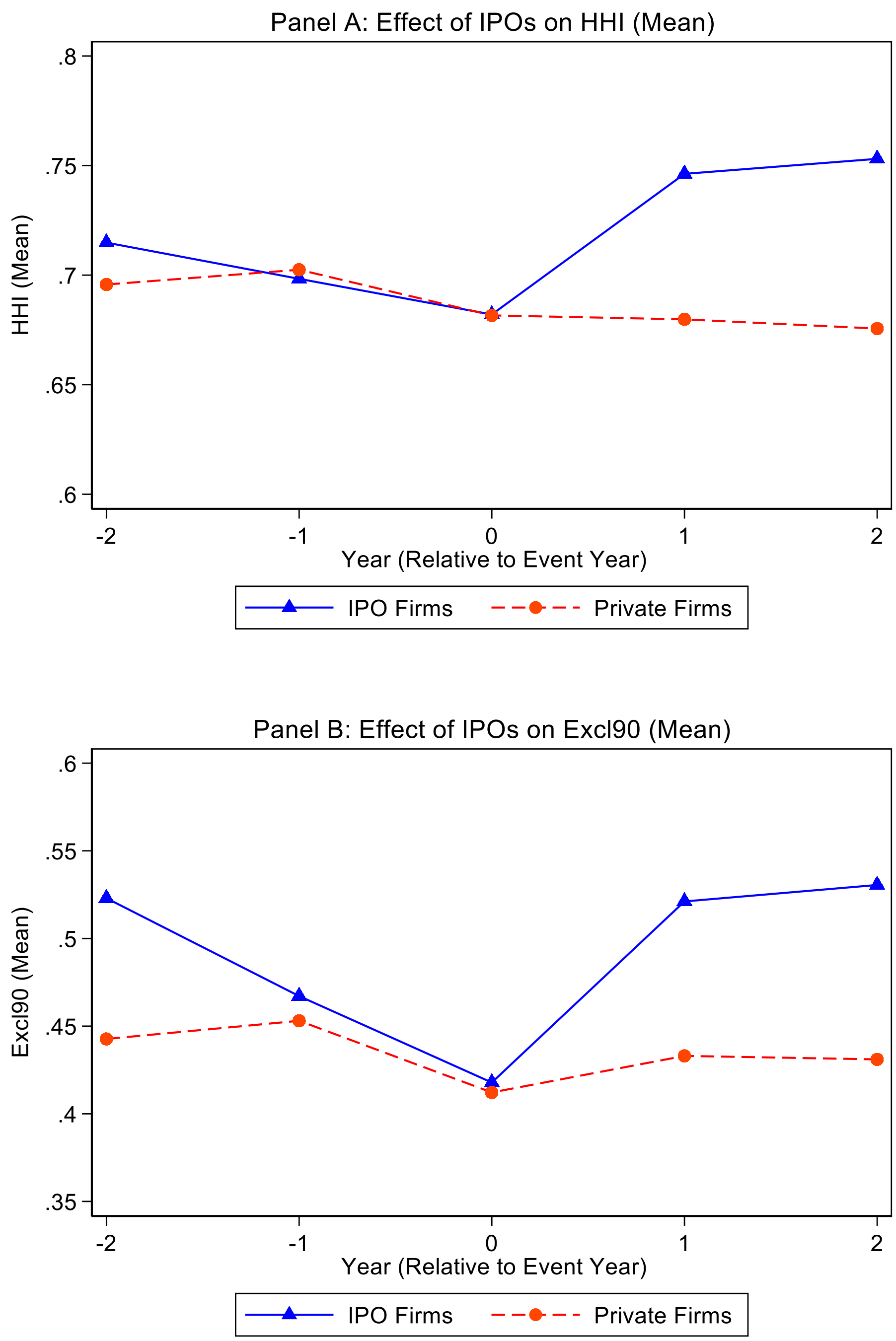

**Table 5: Difference-in-Differences Analysis Using IPOs**

This table reports difference-in-differences (DiD) tests using a treatment sample of firms that changed listing status through IPOs and a control sample of matched private firms that never changed listing status. Dependent variables are four measures of debt specialization: *HHI*, *Excl90, Excl80, and Excl70*. *IPO Firm* is one if the firm made an IPO during our sample period, and zero otherwise. *Post IPO* is one if the year is after IPO, and zero otherwise. Robust standard errors are clustered at the firm level. All continuous variables are winsorized at the 1st and 99th percentiles. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels respectively. Detailed variable definitions are provided in Appendix A.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | HHI | Excl90 | Excl80 | Excl70 |
| IPO Firm × Post IPO | 0.0371*** | 0.233** | 0.304** | 0.313** |
| | (2.898) | (2.066) | (2.541) | (2.469) |
| Observations | 3,224 | 3,192 | 3,201 | 3,202 |
| Control Variables | Yes | Yes | Yes | Yes |
| Industry Fixed Effects | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes |
| Model | Tobit | Logit | Logit | Logit |

**Table 6: Difference-in-Differences Analysis Using IPO Success and Withdrawal**

This table reports difference-in-differences (DiD) tests using a treatment sample of firms that changed listed status through IPOs (IPO Success) and a control sample of firms that withdrew their IPOs after initial filings (IPO Withdrawal). *IPO Success* is one for firms that have completed an IPO transaction and zero otherwise. *Post IPO* is one if the year is after IPO, and zero otherwise. Detailed variable definitions are provided in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels respectively.

| | (1) HHI | (2) HHI | (3) HHI | (4) Excl90 | (5) Excl90 | (6) Excl90 |
|---|---|---|---|---|---|---|
| IPO Success × Post IPO | 0.039*** | 0.030*** | | 0.286*** | 0.242*** | |
| | (4.970) | (4.272) | | (4.859) | (4.048) | |
| IPO Success × t-2 | | | -0.008 | | | 0.002 |
| | | | (-0.647) | | | (0.019) |
| IPO Success × t-1 | | | -0.006 | | | -0.047 |
| | | | (-0.599) | | | (-0.510) |
| IPO Success × t+1 | | | 0.036*** | | | 0.269*** |
| | | | (3.562) | | | (2.962) |
| IPO Success × t+2 | | | 0.033*** | | | 0.193** |
| | | | (3.302) | | | (2.179) |
| IPO Success × $t+3_{more}$ | | | 0.025*** | | | 0.190** |
| | | | (2.675) | | | (2.428) |
| Observations | 17,053 | 17,053 | 17,053 | 17,043 | 17,043 | 17,043 |
| Control Variables | No | Yes | Yes | No | Yes | Yes |
| Industry Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Model | Tobit | Tobit | Tobit | Logit | Logit | Logit |

**Table 7: Does Access to Capital Explain Private Firms' Debt Specialization?**

This table presents regression outputs of the role that constrained capital access plays in the effect of IPOs on debt specialization. In Panel A, we use a PSM sample based on all covariates in our baseline model. Panel B presents results using the IPO success and withdrawal samples. In Panel C, we run our primary regression where private and public firms are matched on the proxies for constrained capital access and bankruptcy costs. *HHI* is the Herfindahl-Hirschman Index of Capital IQ's seven types of debt instruments. Columns (1) – (3) focus on the *WW Index* (Whited and Wu, 2006), the *SA Index* (Hadlock and Pierce, 2010), and *Credit Rating*, respectively. Robust standard errors are clustered at the firm level, and t-values are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively. Detailed variable definitions are provided in Appendix A.

| **Panel A: Matched Sample** | | | |
|---|---|---|---|
| | WW Index | SA Index | Credit Rating |
| | (1) | (2) | (3) |
| | HHI | HHI | HHI |
| Private | -0.0193*** | -0.0368*** | -0.0203*** |
| | (-2.727) | (-3.514) | (-4.040) |
| Private × Financial Const./Renegotiation Cost | 0.0110 | -0.00429 | 0.0146 |
| | (0.361) | (-1.490) | (0.638) |
| Financial Const./Renegotiation Cost | -0.0731** | 0.00515 | 0.0594*** |
| | (-2.268) | (1.566) | (4.180) |
| Observations | 32,720 | 32,720 | 32,720 |
| Control Variables | Yes | Yes | Yes |
| Industry Fixed Effects | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes |
| Model | Tobit | Tobit | Tobit |
| **Panel B: IPO Success and Withdrawal Sample** | | | |
| | WW Index | SA Index | Credit Rating |
| | (1) | (2) | (3) |
| | HHI | HHI | HHI |
| IPO | 0.0353*** | 0.0403*** | 0.0374*** |
| | (3.291) | (2.634) | (5.388) |
| IPO × Financial Const./Renegotiation Cost | 0.0212 | 0.00264 | -0.0629 |
| | (0.447) | (0.667) | (-1.515) |
| Financial Const./Renegotiation Cost | -0.102** | -0.00389 | 0.143*** |
| | (-2.304) | (-0.765) | (5.490) |
| Observations | 17,053 | 17,053 | 17,053 |
| Control Variables | Yes | Yes | Yes |
| Industry Fixed Effects | Yes | Yes | Yes |

| | | | |
|---|---|---|---|
| Year Fixed Effects | Yes | Yes | Yes |
| Model | Tobit | Tobit | Tobit |

**Panel C: Sample Matched Based on Constrained Capital Access and Bankruptcy Costs**

| | WW Index | SA Index | Credit Rating |
|---|---|---|---|
| | (1) | (2) | (3) |
| | HHI | HHI | HHI |
| Private | -0.0203*** | -0.0203*** | -0.0195*** |
| | (-4.024) | (-3.964) | (-3.873) |
| Observations | 31,544 | 31,028 | 31,442 |
| Control Variables | Yes | Yes | Yes |
| Industry Fixed Effects | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes |
| Model | Tobit | Tobit | Tobit |

**Table 8: Mechanism: The Holdup Problem**

In this table, we test the hold-up channel by examining the relationship between stock market listing and debt specialization around two exogenous shocks that amplify the hold-up problem gap between private firms and public firms. In Panel A, *UFTA* is a dummy variable that equals one after the adoption of the Uniform Fraudulent Transfer Act (UFTA) in a state and zero otherwise. The independent variable of interest is *Private × UFTA*, which measures the impact of UFTAs on the relation between stock market listing status and debt specialization. In Panel B, *Deregulation* is a dummy variable that takes the value of one after the 2008 deregulation and zero otherwise. The dependent variable in Columns (1) and (3) is *HHI,* and that of Columns (2) and (4) is *Excl90*. Columns (1) and (2) use our final sample, while Columns (3) and (4) use our matched sample. Robust standard errors are clustered at the firm level, and t-values are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively. Detailed variable definitions are provided in Appendix A.

**Panel A: The Uniform Fraudulent Transfer Acts (UFTAs)**

| | Final sample | | Matched sample | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | HHI | Excl90 | HHI | Excl90 |
| Private | -0.0185*** | -0.105** | -0.0165*** | -0.0846* |
| | (-3.309) | (-2.417) | (-2.880) | (-1.886) |
| Private × UFTA | -0.0543** | -0.377* | -0.0616** | -0.461** |
| | (-2.351) | (-1.883) | (-2.435) | (-2.093) |
| UFTA | 0.0241 | 0.0688 | 0.0314 | 0.134 |
| | (1.412) | (0.458) | (1.615) | (0.779) |
| Observations | 30,134 | 30,124 | 23,198 | 23,194 |
| Control Variables | Yes | Yes | Yes | Yes |
| Industry Fixed Effects | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes |
| Model | Tobit | Logit | Tobit | Logit |

**Panel B: The Stock Issuance Deregulation**

| | Final sample | | Matched sample | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | HHI | Excl90 | HHI | Excl90 |
| Private | -0.0133** | -0.0714 | -0.0151** | -0.0822* |
| | (-2.186) | (-1.504) | (-2.408) | (-1.661) |
| Private × Deregulation | -0.0266*** | -0.227*** | -0.0190** | -0.154** |
| | (-3.416) | (-3.510) | (-2.194) | (-2.145) |
| Deregulation | 0.0234*** | 0.164*** | 0.00947 | 0.00783 |
| | (3.355) | (2.741) | (1.082) | (0.105) |
| Observations | 32,644 | 32,633 | 24,140 | 24,138 |

| | | | | |
|---|---|---|---|---|
| Control Variables | Yes | Yes | Yes | Yes |
| Industry Fixed Effects | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes |
| Model | Tobit | Logit | Tobit | Logit |

**Table 9: Ownership Concentration and Debt Specialization**

This table presents the results of testing ownership concentration as a channel through which stock market listing status affects debt specialization. The dependent variables are *HHI* and *Excl90*. We employ three different ownership structure measures as independent variables. In Columns (1) and (2), the independent variable is the HHI of institutional ownership (*Inst. Ownership HHI*). In Columns (3) and (4), the independent variable is the proportional shareholdings of the highest institutional owner (*Top1 Inst. Owner*). In Columns (5) and (6), the independent variable is proportional shareholdings of the top five institutional owners (*Top5 Inst. Owners*). Robust standard errors are clustered at the firm level, and t-values are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively. Detailed variable definitions are provided in Appendix A.

| | Inst. Ownership HHI | | Top1 Inst. Owner | | Top5 Inst. Owners | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | HHI | Excl90 | HHI | Excl90 | HHI | Excl90 |
| Ownership Concentration | -0.049*** | -0.416*** | -0.063*** | -0.522*** | -0.099*** | -0.778*** |
| | (-4.278) | (-4.204) | (-5.202) | (-4.960) | (-6.615) | (-5.931) |
| Observations | 30,843 | 30,826 | 30,843 | 30,826 | 30,843 | 30,826 |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Model | Tobit | Logit | Tobit | Logit | Tobit | Logit |

**Table 10: Private Firms and Loan Structure**

This table presents the results of testing the relation between stock market listing status and bank loan structure. The dependent variables are *RltBank Amount, RltBank Number*, and *HHI Loan1*. We include common controls of loan and firm characteristics for Panels A and B, respectively. Panel B includes industry and year-fixed effects. Robust standard errors are clustered at the loan/firm level, and t-values are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively. Detailed variable definitions are provided in Appendix A.

| **Panel A: Loan Level** | | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| | RltBank Amount | RltBank Number | HHI Loan1 |
| Private | -0.021*** | -0.019*** | -0.060*** |
| | (-9.724) | (-9.162) | (-39.73) |
| Secured Dummy | -0.038*** | -0.039*** | 0.059*** |
| | (-17.58) | (-17.95) | (37.67) |
| Seniority Dummy | 0.092*** | 0.090*** | -0.153*** |
| | (8.581) | (8.385) | (-14.44) |
| Average Life | 0.002*** | 0.002** | 0.005*** |
| | (2.641) | (2.511) | (8.975) |
| Maturity | -0.002*** | -0.002*** | -0.000*** |
| | (-66.65) | (-67.11) | (-4.848) |
| Ln(Facility Amount) | 0.081*** | 0.080*** | -0.031*** |
| | (131.8) | (130.5) | (-69.84) |
| Constant | 0.194*** | 0.197*** | 0.464*** |
| | (17.25) | (17.60) | (42.25) |
| Observations | 205,451 | 205,451 | 205,451 |
| (Pseudo) R-Squared | 0.091 | 0.090 | 0.065 |
| Model | OLS | OLS | Tobit |

| **Panel B: Firm Level** | | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| | RltBank Amount | RltBank Number | HHI Loan1 |
| Private | -0.028** | -0.028** | -0.007 |
| | (-2.306) | (-2.306) | (-0.766) |
| Observations | 8,597 | 8,597 | 8,597 |
| Control Variables | Yes | Yes | Yes |
| Industry Fixed Effects | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes |
| Model | OLS | OLS | Tobit |

**Table 11: The Degree of Specialization in Debt Maturity and Security**

This table presents regression results of examining the effect of stock market listing on the degree of specialization in other debt structure variables, including debt maturity (*Debt Granularity*) and debt security (*Security Spec*). All model specifications include industry and year-fixed effects. Robust standard errors are clustered at the firm level, and t-values are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively. Detailed variable definitions are provided in Appendix A.

| | (1)<br>Debt Granularity | (2)<br>Security Spec |
|---|---|---|
| Private | -0.016** | -0.347*** |
| | (-2.304) | (-2.936) |
| Observations | 8,480 | 8,444 |
| Control Variables | Yes | Yes |
| Industry Fixed Effects | Yes | Yes |
| Year Fixed Effects | Yes | Yes |
| Model | Tobit | Logit |

**Table OA1: Comparison of Our Sample with Those of Previous Papers**

This table compares our sample with those of prior works. Columns (1) and (2) show our initial sample, Columns (3) and (4) report our final sample, Columns (5) and (6) show corresponding statistics for Gao et al. (2013), and Columns (7) and (8) present those of Asker et al. (2015). We also present the differences in characteristics between private and public firms. Detailed variable definitions are provided in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| | Initial sample Capital IQ (2002-2021) | | | Final sample Capital IQ (2002-2021) | | | Gao et al. (2013) Capital IQ (1995-2011) | | | Asker et al. (2015) Sagework (2002-2011) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Private obs. | Public obs. | Difference | Private obs. | Public obs. | Difference | Private obs. | Public obs. | Difference | Private obs. | Public obs. | Difference |
| | (1) | (2) | (1) - (2) | (3) | (4) | (3) - (4) | (5) | (6) | (5) - (6) | (7) | (8) | (7) - (8) |
| Cash Holding | 0.168 | 0.213 | -0.045*** | 0.130 | 0.176 | -0.046*** | 0.009 | 0.172 | -0.163*** | 0.151 | 0.223 | 0.071*** |
| Total Assets | 223.2 | 2243.9 | -2021*** | 1753.5 | 3548.0 | -1795*** | 1493 | 1686 | -193 | 13.50 | 2869.4 | -2856*** |
| Sales Growth | 0.136 | 0.203 | -0.067*** | 0.204 | 0.160 | 0.044*** | 0.192 | 0.194 | -0.002*** | 0.147 | 0.165 | -0.018*** |
| Book Leverage | 0.351 | 0.279 | 0.072*** | 0.465 | 0.379 | 0.086*** | 0.380 | 0.161 | 0.219*** | 0.446 | 0.204 | 0.242*** |
| Firm Age | 26.60 | 38.85 | -12.25*** | 25.73 | 41.79 | -16.06*** | 23.62 | 36.43 | -12.81*** | 26.20 | 40.70 | -14.5*** |
| Profitability | -0.099 | -0.026 | -0.073*** | -0.043 | 0.007 | -0.05*** | | | | -0.118 | 0.064 | -0.182*** |
| CAPEX | 0.061 | 0.046 | 0.015*** | 0.051 | 0.047 | 0.004 | 0.064 | 0.060 | 0.004*** | | | |
| R&D | 0.007 | 0.038 | -0.031*** | 0.056 | 0.049 | 0.007** | 0.015 | 0.036 | -0.021*** | | | |
| Dividend Payer | 0.042 | 0.369 | -0.327*** | 0.200 | 0.345 | -0.145*** | 0.320 | 0.330 | -0.010*** | | | |
| No. of Obs. | 552,262 | 115,971 | | 16,966 | 37,375 | | 10,595 | 54,404 | | 307,803 | 29,718 | |
| No. of Firms | 100,935 | 9756 | | 4,493 | 5,686 | | 3,604 | 7,879 | | 99,040 | 4,360 | |

**Table OA2: Differences in Loan Structure Between Private and Public Firms**

This table compares the mean values of loan structure measures between private firms and their public counterparts. Panel A shows tests of differences between private and public borrowers regarding measures of loan structure at the loan level. Panel B shows similar statistics at the firm level. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Detailed variable definitions are provided in Appendix A.

| **Panel A: Loan level** | | | |
|---|---|---|---|
| | Private | Public | Difference |
| | (1) | (2) | (1) – (2) |
| RltBank Dummy | 0.425 | 0.470 | -0.045*** |
| RltBank Amount | 0.486 | 0.545 | -0.059*** |
| RltBank Number | 0.483 | 0.540 | -0.057*** |
| Port Top1 | 0.471 | 0.492 | -0.021*** |
| Port Top3 | 0.563 | 0.620 | -0.057*** |
| Port Top10 | 0.569 | 0.637 | -0.068*** |
| HHI Loan1 | 0.144 | 0.188 | -0.044*** |
| HHI Loan2 | 0.148 | 0.198 | -0.050*** |
| No. of Lenders | 5.135 | 6.351 | -1.216*** |
| Number of Obs. | 128,397 | 77,054 | |
| **Panel B: Firm level** | | | |
| | Private | Public | Difference |
| | (1) | (2) | (1)-(2) |
| RltBank Dummy | 0.737 | 0.837 | -0.100*** |
| RltBank Amount | 0.668 | 0.794 | -0.126*** |
| RltBank Number | 0.660 | 0.787 | -0.127*** |
| Port Top1 | 0.639 | 0.696 | -0.057*** |
| Port Top3 | 0.830 | 0.889 | -0.059*** |
| Port Top10 | 0.843 | 0.903 | -0.060*** |
| HHI Loan1 | 0.238 | 0.162 | 0.072*** |
| HHI Loan2 | 0.242 | 0.164 | 0.078*** |
| No. of Lenders | 6.512 | 8.283 | -1.771*** |
| Number of Obs. | 2,529 | 6,068 | |

**Table OA3: Time Series Distribution of IPO Success and Withdrawal Samples**

This table shows the time series distribution of IPO success and withdrawal samples from 2002 to 2021.

| Year | IPO Success (Obs.) | IPO Withdrawal (Obs.) |
|---|---|---|
| 2002 | 355 | 198 |
| 2003 | 501 | 301 |
| 2004 | 569 | 301 |
| 2005 | 612 | 329 |
| 2006 | 653 | 347 |
| 2007 | 657 | 331 |
| 2008 | 641 | 327 |
| 2009 | 673 | 337 |
| 2010 | 651 | 335 |
| 2011 | 639 | 320 |
| 2012 | 700 | 321 |
| 2013 | 781 | 328 |
| 2014 | 763 | 323 |
| 2015 | 716 | 303 |
| 2016 | 743 | 292 |
| 2017 | 763 | 291 |
| 2018 | 781 | 284 |
| 2019 | 872 | 308 |
| 2020 | 1,215 | 397 |
| 2021 | 1,263 | 393 |
| Total | 14,548 | 6,366 |
| No. of Firms | 2,613 | 981 |