Access to Capital and the IPO Decision: An Analysis of US Private Firms*

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Abstract

We analyze firms' IPO decisions using detailed financial data on US private firms. We find that firms with higher external capital needs are more likely to go public. Following the IPO, firms increase their investment and debt issuance, resulting in leverage ratios close to their pre-IPO levels. Finally, newly public firms borrow from an expanded pool of lenders at improved terms, with a decrease in the within-firm dispersion in banks' private risk assessments. Our evidence is consistent with firms going public to improve their access to capital, which is facilitated by a reduction in asymmetric information.

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1 Introduction

Improved access to capital is often cited as a primary motive for firms to go public.[1] Through the IPO process and the ongoing disclosure requirements that follow, public firms become more transparent, reducing asymmetric information, which allows them to raise capital more easily and at lower cost.[2]

Despite the intuitive appeal of this mechanism, direct empirical evidence for it remains limited for three main reasons.[3] First, testing the access-to-capital motive requires detailed data on private firms, which are difficult to obtain, particularly in the US – the world's largest IPO market. Second, identifying changes in firms' access to external capital around the IPO is confounded by changes in firms' business models and risk profiles. Third, linking such improvements in financing conditions to reductions in asymmetric information requires direct measures of private information, which are typically unavailable.[4] Beyond these direct empirical challenges, the rapid growth of private capital markets in recent years raises a more fundamental question: is this presumed advantage of public markets still relevant, and if so, is it an important driver of IPO behavior? Answering these questions is important not only for understanding why firms go public, but also for evaluating the extent to which public markets allocate capital more efficiently than private markets.[5]

In this paper, we provide evidence that improved access to capital, driven by reductions in asymmetric information, is a key motive for firms going public. Our analysis uses the Federal Reserve Y-14Q data, which includes all corporate loans over one million dollars extended by large US bank holding companies from 2012 onward. This data is uniquely suited to examine the access-to-capital motive for two reasons. First, it contains extensive financial information on private firms in the US, including balance sheet and income statement information and granular information on firms' bank loans. Second, the data contains banks' internal risk assessments of borrowers, which, as we describe in more detail below, allow us to examine both how firms' cost of external capital and the degree of asymmetric information change after the IPO.

[1]For example, Christian Weedbrook, CEO of Xanadu, recently stated that "That's really a reason why we're going public, is the access to capital" (see Transcript of Christian Weedbrook's live interview with BNN Bloomberg).

[2]A large theoretical literature shows that reducing information asymmetries can improve a firm's access to capital by lowering adverse selection costs (e.g., Stiglitz and Weiss (1981), Myers and Majluf (1984), Diamond (1985), Sharpe (1990), Rajan (1992), Diamond and Verrecchia (1991) and Easley and O'Hara (2004)). In addition, publicly observable stock prices can reduce asymmetric information and inform firms' investment decisions (e.g., Subrahmanyam and Titman (1999)).

[3]See Lowry et al. (2017) and Bernstein (2022) for excellent discussions of the empirical evidence on the importance of the access-to-capital motive.

[4]See Salanié (2017) for a broader discussion of the difficulties of testing for asymmetric information.

[5]Indeed, one of the express goals of the 2012 JOBS Act was to spur IPO activity with the idea that public markets allocate capital more efficiently than private ones (see The JOBS Act: A Landmark Reform to U.S. Securities Laws).

Using this data, we investigate three related issues: i) Are private firms with greater needs for external capital more likely to go public?, ii) do firms gain improved access to capital and increase their investment expenditures after going public?, and if so, iii) is the improved access to capital after the IPO due to a reduction in information asymmetries?

We first show that firms that are more reliant on external capital, as proxied by their financing deficit, i.e., (capex - EBITDA)/assets, are more likely to go public in the future. Specifically, we find that a one-standard-deviation increase in a firm's financing deficit is associated with 78% higher likelihood of going public. In addition, when we separately analyze the two components of the financing deficit, we find that ex-ante investment, i.e., capex/assets, positively predicts future IPOs, while profitability, i.e., EBITDA/assets, negatively predicts future IPOs, where the relationship between ex-ante investment and going public is stronger for less profitable firms.[6]

We next analyze firms' investment and financing choices before and after they go public by matching IPO firms with comparable firms that remain private. Compared with matched control firms, IPO firms' capex and total assets increase by 40% and 25%, respectively, four years after the IPO. This post-IPO asset growth is not just financed with the influx of equity capital from the IPO, but is largely funded by increases in debt. Moreover, although the leverage ratios of newly public firms initially drop after going public, they are not significantly different than those of control firms four years later.

Why do firms rebalance their capital structure after going public rather than becoming more reliant on equity? One possibility is that going public allows firms to raise debt capital on more favorable terms. Indeed, we find that interest rates drop on firms' bank debt after they go public. However, the drop in interest rates may be purely driven by reductions in risk.[7] To rule out this possibility, we exploit banks' private assessments of each loan's probability of default (PD) and loss given default (LGD), which are available in the Y-14Q data.[8] We find that after controlling for these risk assessments, firms' borrowing costs drop by 32bps after going public. These results suggest that the lower interest rates firms receive on their loans after going public are not solely due to reduced risk, but also reflect more favorable terms.

Our explanation for the improvement in bank loan terms is that the reduction in information asymmetries following the IPO reduces the information rents informed financiers can extract from the firm.[9] Given that firms often borrow from multiple banks at the

[6]The link between capital needs and going public was articulated by John Collison, the Stripe Co-founder and President, who recently stated that more profitable firms have less of a need to go public because internally generated cash flows can fund their investments (Stripe in 'no rush' to go public as cash flow turns positive).

[7]For example, if firms' business models and capital structures are changing around the IPO, the lower interest rates may simply reflect the fact that the firm is less risky after going public.

[8]Beyhaghi, Fracassi, and Weitzner (2025) show that 1) these risk assessments strongly predict future loan performance and 2) interest rates no longer predict firm performance after controlling for them.

[9]E.g., Rock (1986), Sharpe (1990) and Rajan (1992). In these models, the adverse selection problem that arises from asymmetric information *across financiers* causes the increase in firms' cost of capital.

same time, we can construct a proxy for the degree of asymmetric information based on the within-firm dispersion in banks' PD assessments. Consistent with a reduction in asymmetric information, we find that PD dispersion drops after the IPO.[10]

Our final set of tests examines whether the reduction in asymmetric information after the IPO allows firms to borrow from a broader pool of lenders. First, we document an increase in the number of banks from which IPO firms borrow after going public. Second, we find that IPO firms increase their use of syndicated loans and bonds dramatically after going public.[11] These results suggest that going public not only provides firms with additional equity but also facilitates access to syndicated loan and public bond markets.[12]

The analysis in this paper builds on the literature that uses data on private firms to examine the ex-ante determinants and the ex-post outcomes following firms' IPO decisions (e.g., Pagano, Panetta, and Zingales (1996), Pagano, Panetta, and Zingales (1998), Fischer (2000), Chemmanur, He, and Nandy (2010), Aslan and Kumar (2011), Gopalan and Gormley (2013), Maksimovic, Phillips, and Yang (2020) and Bias et al. (2025)).[13] The seminal paper in this literature, Pagano, Panetta, and Zingales (1998), analyzes a sample of private Italian firms from 1982 to 1992 and documents several pieces of evidence inconsistent with the access to capital channel. In particular, they find that more profitable firms are more likely to go public and show that investment, profitability, and leverage drop after the IPO. More recently, Chemmanur, He, and Nandy (2010) and Aslan and Kumar (2011) find a positive relationship between both ex-ante and ex-post investment among samples of private US manufacturing firms and UK firms, respectively.[14]

[10]Differences of opinion, such as in bond ratings and analyst forecasts, are a common proxy for asymmetric information (e.g., Morgan (2002), Flannery and Kwan (2004), Iannotta (2006) and Livingston and Zhou (2010)). PD dispersion may also arise from differences in subjective beliefs (e.g., Diether, Malloy, and Scherbina (2002)). However, as we argue in further detail below, if differences in subjective beliefs were the sole driver of PD dispersion, there would be little reason for this disagreement to systematically decrease following an IPO unless asymmetric information is reduced.

[11]Syndicated loans involve elements of both traditional, private relationship bank lending and public bond offerings, given that the loans are often widely held by dispersed investors (Dennis and Mullineaux (2000) and Gadanecz (2004)).

[12]Our result on syndicated loans is consistent with anecdotal evidence that IPO activity is an important determinant of aggregate bank lending (Reuters (2019)). This complementarity between equity and debt financing is also consistent with Hartman-Glaser, Mayer, and Milbradt (2024), who show that improved access to equity markets increases firms' debt capacity.

[13]A related literature compares the behavior and outcomes of public and private firms (e.g., Brav (2009), Saunders and Steffen (2011), Kovner and Wei (2014), Asker, Farre-Mensa, and Ljungqvist (2015), Gilje and Taillard (2016), Acharya and Xu (2017), Phillips and Sertsios (2017), Maksimovic, Phillips, and Yang (2017), Sheen (2020), Dambra and Gustafson (2021) and Sanati and Spyridopoulos (2023)). Bernstein (2022) and Ewens and Farre-Mensa (2022) survey this literature. Some papers also analyze a small set of private firms in which pre-IPO data is more prevalent (e.g., Lerner (1994), Helwege and Packer (2003), and Aghamolla and Thakor (2022b)).

[14]In addition, Jain and Kini (1994) document an increase in capital expenditures following IPOs using other public firms as a control group. Kim and Weisbach (2008) show that a large portion of IPO proceeds are used for capex and R&D, and Mikkelson, Partch, and Shah (1997) show that 64% of firms include new investments as a use of proceeds in the IPO prospectus. Lowry (2003) shows that proxies for demand for capital are important determinants of IPO volume at the aggregate level.

Our paper makes a number of contributions to this literature: First, our analysis uses the most detailed data on US private firms in the literature.[15] In comparison, many papers use the Census Longitudinal Business Database (LBD), which contains incomplete income statement and balance sheet information, and no information on firms' financing or borrowing terms.[16] Second, we provide evidence that private firms' expected external capital needs predict them going public and access to capital improves after the IPO, the latter of which we link to reductions in asymmetric information. Third, we introduce several new results to the literature. Specifically, our paper is the first to use banks' private risk assessments to show that after going public, firms' borrowing costs drop *conditional on the borrower's risk* and this coincides with a decrease in the dispersion of banks' private credit assessments. Our results that 1) ex-ante profitability *negatively predicts going public* and 2) that this effect is stronger when ex-ante investment is high, are also new and differ from studies using European data (e.g., Pagano, Panetta, and Zingales (1998) and Aslan and Kumar (2011)).[17] Finally, our paper is the first to show that firms increase their use of syndicated loans and bonds after going public.[18]

The ex-post part of our analysis relates to the more recent literature that focuses on the causal impact of IPOs on subsequent outcomes. This literature, starting with Bernstein (2015), uses data on firms that file to go public but may ultimately withdraw, instrumenting for the completion decision with market-wide returns (e.g., Babina, Ouimet, and Zarutskie (2020), Borisov, Ellul, and Sevilir (2021), Cornaggia et al. (2021), Cornaggia et al. (2022) and Larrain et al. (2025)). The closest paper to ours in this literature is Larrain et al. (2025), which shows that European firms' sales and profitability increase after going public, which they argue is facilitated by reductions in financial constraints. Our evidence is complementary to theirs in that we 1) show that firms with

[15]Our data is also more detailed than most foreign data used in this literature. For example, we are not aware of any paper using banks' internal risk assessments in the IPO literature. Beyond studies focused on banking, the Y-14Q data have been increasingly used to analyze private firm behavior (e.g., Ivanov, Pettit, and Whited (2025) and Beyhaghi et al. (2024)).

[16]Among these papers, several use the Census of Manufacturers and the Annual Survey of Manufacturers data, which contains sales and capital expenditures at the plant-level for firms in the manufacturing industry (e.g., Chemmanur, He, and Nandy (2010), Chemmanur and He (2011), Chemmanur et al. (2018), and Chemmanur et al. (2022)). However, the data, which is collected every five years for all firms and annually for plants with more than 250 employees, does not contain any information about firms' balance sheets or income statements beyond sales and capital expenditures/stock. In contrast, our data contains a quarterly panel of detailed firm financials for an extremely broad set of private firms.

[17]Relatedly, to our knowledge our paper is the first documenting a positive relationship between financing deficits and firms' subsequent IPO decisions. Our results may differ from Pagano, Panetta, and Zingales (1998) for two reasons. First, as Pagano, Panetta, and Zingales (1998) note, firms that go public in Italy are much older and more profitable than in the US, suggesting that the capital markets are fundamentally different than those in the US. Second, because our sample is more recent, the reason firms go public could have fundamentally changed. However, given the recent rise of private capital markets, we would think that, if anything, access to capital would be less important for public firms than it was 30 years ago.

[18]While some papers analyze firms' first bond issuances (e.g., Datta, Iskandar-Datta, and Patel (2000) and Hale and Santos (2008)), we are the first to analyze how bond issuance evolves after the IPO using a set of control firms that remain private.

higher ex-ante external capital needs are more likely to go public, 2) provide direct evidence of access to capital improving after the IPO, and 3) show that this improved access to capital can be attributed to a reduction in information asymmetries.

As we discuss below in more detail, for several reasons, the Bernstein (2015) instrument has limited power during our sample period, precluding us from taking this approach.[19] However, while it is clearly important to isolate the treatment effects of IPOs, selection effects, i.e., which types of firms *choose to IPO*, are also interesting and important. For example, if the IPO results in a reduction in the cost of external capital, which we find support for in our analysis, firms will invest more as a result of going public, but also will be more likely to go public when they expect to invest more in the future. As a result, our results capture both of these important effects. Nonetheless, several of our findings regarding the access to capital channel are difficult to explain through selection alone. For example, if the convergence in bank risk assessments induces firms to go public, we would expect this to occur before the IPO; however, the convergence only occurs after the IPO. Similarly, we find that firms receive improved terms on their bank debt after going public; however, selection effects would predict that firms should be less likely to go public if they anticipate an improvement in terms in the future, regardless of their listing status.[20]

Finally, a few other studies find evidence that public firms obtain lower interest rates on bank debt than private firms (e.g., Pagano, Panetta, and Zingales (1998), Schenone (2010), and Saunders and Steffen (2011)). Schenone (2010) finds that firms' borrowing costs decrease after they go public[21] and Saunders and Steffen (2011) show that public firms borrow at lower average interest rates than private firms in the UK. While some of our evidence is consistent with these studies, our analysis differs in several key respects. First, by controlling for firms' underlying risk, as perceived by their lenders, we show that the decrease in borrowing costs is not simply due to a reduction in firm risk. Second, we document a drop in the dispersion in banks' risk assessments after the IPO, providing evidence for a reduction in asymmetric information as a potential mechanism for the improvement in borrowing terms. Third, we show that firms increase their usage of bonds and syndicated loans after the IPO.[22]

[19]For example, our sample period occurs after the 2012 JOBS Act, which allowed firms to file and withdraw the IPO confidentially, potentially reducing the number of withdrawn IPOs observable to researchers (Dambra, Field, and Gustafson (2015), Boeh and Dunbar (2021) and Bias (2021)).

[20]We also find that firms increase their use of syndicated loans and bonds after the IPO, but not before.

[21]Due to a lack of data on private firms, this study does not compare borrowing costs to control firms, but rather analyzes how borrowing costs change among IPO firms only.

[22]Additionally, in contrast to Schenone (2010) and Saunders and Steffen (2011), our data allows us to analyze how firms' financing structure changes after firms go public, relative to similar control firms that remain private.

2 Data

In this section, we describe our data sources for private firms and IPOs and explain how we construct our firm-level and loan-level samples.

2.1 Sample of Private Firms

Our main source of data is Schedule H.1 of the Federal Reserve's Y-14Q data. The Federal Reserve began collecting the Y-14 data in 2011 to support the Dodd-Frank-mandated stress tests and the Comprehensive Capital Analysis and Review (CCAR). The sample includes corporate loans from all bank holding companies (BHCs) with $50bn or more in total assets, accounting for 85.9% of all assets in the US banking sector as of 2018:Q4 (Frame, McLemore, and Mihov (2020)). Qualified BHCs are required to report detailed quarterly loan-level data on all corporate loans that exceed one million dollars in size. These loans constitute over 97% of these BHCs' corporate exposure (Beyhaghi (2022)) and represent about 70% of all commercial and industrial loan volume in the US extended by BHCs that file a FR Y-9C report (Bidder, Krainer, and Shapiro (2020)). Our sample of private firms starts in 2012, when borrower financial data became fully populated.

We apply several filters consistent with other papers using the Y-14 data (e.g., Gustafson, Ivanov, and Meisenzahl (2020) and Beyhaghi, Fracassi, and Weitzner (2025)). Specifically, we drop firms with missing taxpayer identification numbers (TINs), firms headquartered outside the US, firms with loans denominated in foreign currencies, borrowers that appear to be high-net-worth individuals, financial firms (NAICS code 52), real estate firms (NAICS code 53), and public administration and government entities (NAICS code 92).[23] We also drop firms with less than $10mm in assets because these firms are unlikely to go public. Additionally, because we are interested in comparing private firms that go public with those that remain private, we exclude all public firms that never appear as private during our sample period. We identify public firms, as well as their subsidiaries, in the Y-14 data using a multi-step process similar to that of Beyhaghi et al. (2024), which we discuss in detail in Appendix A.2.

Each loan record includes the period-end date of the borrower's latest financial statements; we use this date to define firm-quarters (and, when financials are annual, we carry them forward within the year up to three quarters). Many firms in the Y-14 data borrow from multiple banks. In these cases, different loans may contain different financial information for the same borrower.[24] Hence, we take the median financial record across each loan within each firm-quarter. After we aggregate the loan-level data to the firm-level,

[23] See Appendix A for additional details. We also make several minor adjustments to the firm's financial data, as described in Appendix A.1.

[24] Reported financials can differ across banks because there are no standard reporting requirements for private firms.

we have a quarterly panel with over one million firm/quarter observations with just over 100,000 unique private firms.

2.2 IPO Firms

We use SDC Platinum (from LSEG Data and Analytics) to obtain US IPO data. Following Bernstein (2015), we exclude financial firms (SIC codes between 6000 and 6999), unit trusts, closed-end funds, real estate investment trusts (REITs), American depositary receipts (ADRs), limited partnerships, "blank check" special purpose acquisition vehicles (SPACs), and spin-offs. These filters result in 1,390 unique firms in the SDC data that go public between 2012 and 2023.

To merge the IPO data into the Y-14 dataset, we use a multi-step matching process, which is described in further detail in Appendix A.3. Using this process, we identify 425 unique IPOs (a 31% match rate) in the Y-14 data within a three-year window prior to the IPO.[25]

Our data does not include the entire universe of IPOs. Some IPO firms are not in our data because 1) they do not have bank debt, 2) if they have bank debt, it is not from one of the BHCs in the Y-14, or 3) the size of the loan is below $1mm.[26] Although our match rate is less than half on an absolute basis, we match the majority of the larger IPOs. Specifically, Appendix Table C1 shows that the IPOs that we do match account for 61% of the aggregate IPO proceeds, suggesting that our sample of IPOs tends to be larger private firms.[27] Appendix Table C2 compares the distribution of total assets prior to the IPO and IPO proceeds for our sample of IPO firms in the Y-14 data with IPO firms in SDC that are not in our sample. Appendix Table C3 compares IPO firm-quarters for IPOs in our sample to those only in SDC, using pre-IPO financial data from Compustat. IPOs in our sample are indeed much larger in terms of sales and assets.

Table C1 also shows that our sample of IPOs is not fully representative of all IPOs over this period in terms of industries. For example, there are 518 pharma and biotech IPOs over this period, but only 106 in our sample. However, this industry effect appears to be entirely explained by firm size. Appendix Table C4 includes regressions in

[25]For comparison, Maksimovic, Phillips, and Yang (2020) identify 48% of the firms from Jay Ritter's IPO data in the US Census data. This is likely due to the Census data containing more small firms than the Y-14 data. We choose a three-year window, given that our ex-ante tests examine which characteristics predict firms going public over a three-year window.

[26]Some firms borrow through subsidiaries prior to going public. In these cases, the borrowing entity may have a different name and taxpayer identification number than the parent company conducting the IPO. As a result, these firms may not be matched to our Y-14 sample. Additionally, many firms that we do not match prior to the IPO enter our dataset *after* they go public. Indeed, we show below that firms increase the number of lenders from whom they borrow after going public, thereby increasing the likelihood that they are present in the Y-14 data. Consistent with this, Beyhaghi, Howes, and Weitzner (2022) show that over half of publicly traded firms are in the Y-14 data.

[27]Our sample includes 63% of IPOs larger than $250mm and 74% of IPOs larger than $500mm in proceeds.

which the dependent variable is a dummy equal to 1 if the IPO firm is in our sample. Column (1) includes dummy variables for the ten largest industries in the overall IPO sample. Consistent with Table C1, the coefficients for pharma and biotech are negative and statistically significant, and the F-stat suggests that the industry dummies are jointly significant. However, in column (2), when we include Log(1+Sales) to control for firm size, the pharma and biotech coefficients are much smaller in magnitude and no longer statistically significant. Moreover, the F-stat is below one, suggesting that the difference in industry composition in our sample can be fully explained by firm size.

That our sample consists of relatively large private firms that borrow from large banks suggests that these firms already have relatively good access to capital and thus lower needs to go public. In this respect, this sample selection likely works against the access to capital hypothesis we explore in our analysis. That said, most firms that go public have some debt prior to going public.[28] For example, Barry and Mihov (2015) use pre-IPO financials from Compustat and find that only 11% of firms that go public report zero debt prior to the IPO. Similarly, in the sample of IPOs reported in SDC, only 13% of firms report zero debt and 19% debt less than one million prior to the IPO. Moreover, this measure likely overstates the prevalence of debt-free firms, as it excludes debt-like instruments such as convertible bonds and preferred stock, which are common financing instruments for VC-backed firms (Metrick and Yasuda (2021)), as well as firms with undrawn credit lines that appear in our Y-14 sample.

2.3 Firm-Level Panel

We use the Y-14 data to construct a quarterly panel of private firms from 2012 to 2023, supplementing it with VC financing data from the Preqin VC funding database.[29] We merge the Preqin data with the Y-14 data using industry, location, and firm name, as further detailed in Appendix A.3.[30] We use similar matching methods to identify private firms that are acquired based on the SDC Platinum mergers and acquisitions dataset.[31]

Appendix Tables C5 and C6 display the industry and location composition of the IPO firms in our sample, and Appendix Tables C7 and C8 display the industry and location composition of the other private firms in our sample. While the firms that go public represent a variety of industries and are located in many different cities, they are

[28]Bank debt is also quite common among private firms that do not go public (e.g., Robb and Robinson (2014)).

[29]For some empirical tests, we include post-IPO observations of recently private firms that have gone public during our sample period.

[30]The Preqin VC funding database includes many types of private equity investments (e.g., angel investments, seed financing, series A, etc). To be defined as a VC investment in Preqin, the investment firm must take a minority stake in the target firm. We refer to all of these deals as VC investments.

[31]We also identify the amount of bonds outstanding each firm has using the LSEG Mergent Fixed Income Securities Database (FISD) dataset. We describe the details of the Preqin, SDC, and FISD merges in Appendix A.3.

clustered in technology-related industries, and many are located in the San Francisco-Oakland-Hayward and Palo Alto-San Jose core-based statistical areas (CBSAs), which include Silicon Valley. By contrast, the top industries for the entire sample of private firms tend to be consumer retail-related, such as auto dealers and restaurants, with locations more aligned with the overall US population distribution.

We define a firm's IPO quarter as the latest quarter in which we observe Y-14 data within the three-year window preceding the IPO. We also create the dummy variable IPO, which equals one if the firm goes public in the next three years. We construct several standard corporate finance variables (e.g., investment and profitability).[32] To minimize the impact of outliers, we winsorize variables that are ratios at the 1% and 99%. Appendix B contains detailed definitions of the variables used throughout the paper.

Table 1 provides summary statistics comparing financial information for IPO firm-quarters to non-IPO firm-quarters. Unsurprisingly, IPO firms have greater assets and sales than the broader sample of private firms. Moreover, IPO firms invest more (0.08 versus 0.05 Capex/Assets) and are less profitable (0.08 versus 0.16 EBITDA/Assets).[33] As we discuss later, an important variable in our analysis is the financing deficit, which is defined as (Capex-EBITDA)/Assets, and measures the amount of external financing a firm needs beyond what it generates internally.[34] This variable is standard in the literature (e.g., Frank and Goyal (2003)); however, we exclude some smaller components that are not available or as well populated in the Y-14 data, such as changes in net working capital. On average, IPO firms have a financing deficit close to zero, whereas the average financing deficit of non-IPO firms is significantly negative (-0.12), implying that the average firm that stays private internally generates more cash flows than it needs to fund its investment. IPO firms are also more likely to be VC-backed than non-IPO firms (29% versus 2%) and are much more likely to be located in Silicon Valley (14% versus 2%) and operate in technology and life sciences industries (23% versus 6%).[35]

2.4 Loan-Level Sample

We also construct a loan-level sample for our tests that examine changes in bank lending terms.

In addition to basic information about the loan, such as its size, interest rate, maturity and syndication status, the data contains each bank's private assessments of the

[32]The latest instructions detailing what qualifying banks are required to report can be found here: FR Y-14 Instructions.

[33]As is standard in the literature, for all ratios involving assets, we use the prior year's assets.

[34]One benefit of this measure is that, to the extent firms make investments that are not capitalized, e.g., R&D, this is still captured in the variable through its effect on profitability.

[35]See Appendix B for the list of NAICS codes we consider technology and life science firms, which closely follows Chemmanur et al. (2022).

borrower's probability of default (PD) and the loan's expected loss given default (LGD). More specifically, PD is a long-run, borrower-level annual default rate, and LGD is a long-run expected loss per dollar of exposure in default. According to the Basel Committee on Banking Supervision, internal estimates of PD and LGD "*must incorporate all relevant, material and available data, information and methods. A bank may utilize internal data and data from external sources (including pooled data).*"[36] Moreover, banks must update these estimates regularly and immediately after any material changes: "*Borrowers and facilities must have their ratings refreshed at least on an annual basis... In addition, banks must initiate a new rating if material information on the borrower or facility comes to light.*[37]"

Following Beyhaghi, Fracassi, and Weitzner (2025), we apply a few additional filters to the loan-level data. Specifically, we exclude observations with a zero or negative interest rate. We also drop observations in which the PD or LGD is missing, zero, or greater than or equal to one.

3 Empirical Analysis

Our empirical analysis is divided into five parts. In Section 3.1, we test which characteristics predict the decision to IPO in the cross-section of private firms. In Section 3.2, we examine the dynamics of firm outcomes before and after the IPO based on a matched sample of firms that remain private. In Section 3.3, we examine the change in firms' borrowing costs after the IPO. In Section 3.4, we examine changes in asymmetric information after the IPO. In Section 3.5, we explore changes in the composition of firms' debt after they go public. Finally, in Section 3.6, we discuss the extent to which our findings capture both treatment and selection effects.

3.1 Which Firm Characteristics Predict IPOs?

We first examine which ex-ante characteristics predict whether firms go public. To do this, we estimate the following linear probability model:

$$IPO_{i,t+1:t+12} = \Gamma X_{i,t} + \beta MTB_{j,t} + \delta_t + u_{i,t+1:t+12}, \tag{1}$$

where i, j, and t index firm, industry, and quarterly date, respectively. The dependent variable $IPO_{i,t+1:t+12}$ is a dummy variable that equals one if the firm goes public within the next twelve quarters, which we multiply by 100, and $X_{i,t}$ is a vector of

[36]The most recent instructions for calculating these risk assessments are available at Calculation of RWA for credit risk.

[37]Recent work has also shown that these risk assessments strongly predict future realized default (Beyhaghi, Fracassi, and Weitzner (2025) and Howes and Weitzner (2025)) and public equity and bond returns (Beyhaghi, Howes, and Weitzner (2022)).

firm-level predictors. The primary variable of interest is the financing deficit ((Capex-EBITDA)/Assets), which proxies for the firms' expected external financing needs. Under the access to capital channel, we expect that firms with higher financing deficits are more likely to go public.

Our other predictors, which closely follow those in Pagano, Panetta, and Zingales (1998), include: 1) sales (log(1+Sales)), as there are likely large fixed costs associated with going public, making the IPO more attractive for larger firms (Ritter (1987)); 2) sales growth, because faster growing firms have higher market valuations; 3) debt/assets, as firms with higher leverage may have less financial flexibility and find it more difficult to raise external capital; and 4) the industry-level market-to-book ratio, which, as Pagano, Panetta, and Zingales (1998) discuss, can proxy for either better investment opportunities or mispricing in the industry. To control for time-specific shocks, we also include date fixed effects (δ_t); however, in some specifications, we also include date by industry, date by CBSA, and date by industry by CBSA fixed effects. We cluster our standard errors by firm.[38]

Column (1) of Table 3 displays the estimated coefficients of (1) with date fixed effects. First, we find a statistically significant relationship between firms' propensity to IPO and their size. Specifically, a 10% increase in sales increases the likelihood of a firm going public by 12% from its base rate of 0.20%. Second, firms with higher trailing one-year sales growth are also more likely to IPO. A one-standard-deviation increase in sales growth (0.41) is associated with a just over 100% increase in the likelihood that a firm goes public. These effects are consistent with larger, faster-growing firms being more likely to go public. Third, firms with higher leverage are more likely to go public; however, the coefficient is statistically significant only in specifications with more saturated fixed effects.

Fourth, firms with higher financing deficits are more likely to go public. Specifically, a one-standard-deviation increase in Financing Deficit (0.23) is associated with a 78% increase in the likelihood that a firm goes public. This result suggests that firms with higher external capital needs are more likely to go public. Moreover, after controlling for Financing Deficit, the coefficient on investment (Capex/Assets) is not significant. This implies that in an equivalent regression in which investment and profitability are treated as separate predictors, 1) investment positively predicts IPOs and profitability negatively predicts IPOs, and 2) we cannot reject the null hypothesis that the coefficients on profitability and investment are equal in magnitude.[39]

The fact that profitability negatively predicts firms going public is the opposite of Pagano, Panetta, and Zingales (1998), who estimate similar regressions on a sample of

[38]The standard errors are very similar throughout the entire analysis if we double cluster by firm and date.

[39]Since Financing Deficit is equal to Capex/Assets - EBITDA/Assets, the coefficient for Capex/Assets tests whether Capex/Assets and EBITDA/Assets are different in magnitude.

private Italian firms,[40] and is consistent with recent evidence that firms delay going public when their profits increase, allowing them to generate cash flows internally. For example, the Stripe Co-founder and President, John Collison, recently stated that more profitable firms do not need to go public because internally generated cash flows can fund their investments.[41] This also mirrors evidence from LBOs, where firms that go private tend to generate higher cash flows internally and have lower investment needs (e.g., Opler and Titman (1993)).

Finally, we find that the industry-level market-to-book ratio is positively associated with the propensity to go public, consistent with firms with greater investment opportunities being more likely to go public.

In columns (2), (3), and (4) of Table 3, we estimate the same regressions but include industry by date fixed effects, CBSA by date fixed effects, and industry by CBSA by date fixed effects, respectively.[42] Across these alternative specifications with more restrictive fixed effects, the coefficients remain fairly similar except for the coefficient of leverage, which becomes about four times as large and statistically significant once we control for industry effects.[43] Taken together, our initial results suggest that firms with higher external capital needs and better investment opportunities are more likely to go public.

If less profitable firms go public due to a lack of internal funds to finance investment, we expect this effect to be stronger for firms with more investment needs. Intuitively, under the access to capital motive, internally generated cash flows should only matter to the extent that firms have substantive investment needs to begin with. To test this hypothesis, we re-estimate a similar regression as Table 3, but include EBITDA/Assets and Capex/Assets separately, as well as an additional interaction term between them. As shown in Table 4, the interaction coefficient is negative and statistically significant across all specifications. These results suggest that the relationship between ex-ante investment and going public is even stronger for firms that generate fewer internal cash flows, and are thus more reliant on external capital. Hence, these results provide further evidence that firms are more likely to go public when they have higher external capital needs.

3.1.1 Technology and Life Science Subsample Analysis

We next analyze the subsample of technology and life science firms, which, as mentioned earlier, represent a substantial share of IPO activity.[44] On the one hand, these firms may invest more in intangible assets such as R&D rather than capital expenditures,

[40] Aslan and Kumar (2011) also find the same result in a sample of private firms in the UK.

[41] See Stripe in 'no rush' to go public as cash flow turns positive.

[42] Column (2) has more observations than column (1) because it does not include the industry-level market-to-book ratio, which is not available for a few industries in the Y-14 data.

[43] In unreported results, we also find qualitatively similar results if we estimate a probit regression with date fixed effects.

[44] Specifically, these firms represent 48% of the SDC IPOs and 23% of the IPOs in the subsample in the Y-14 data.

so our financing deficit measure may not accurately capture their external capital needs. Moreover, technology-related firms tend to have proprietary technologies, which can more easily be expropriated when these firms are public.[45] On the other hand, asymmetric information is likely especially severe for technology and life science firms, suggesting that access to capital may be a particularly important consideration in their decision to go public.

As shown in Online Appendix Table C9, the technology and life science IPO firms in our sample do engage in meaningful capital expenditures: their Capex/Assets ratio is 0.06 compared to 0.08 for non-technology firms. These firms also have a reasonable level of leverage, with a debt-to-assets ratio of 0.26, compared with 0.33 for non-technology firms.

In Table 5, we also re-estimate our baseline regressions while restricting the sample to technology and life science firms. The coefficient estimates on Financing Deficit are larger than the baseline in this subsample, suggesting that technology and life science firms' IPO decisions are *more* sensitive to their financing deficits. This result is consistent with technology and life science firms being particularly subject to asymmetric information.[46]

3.1.2 VC-Backed Subsample Analysis

If firms with higher external capital needs are more likely to go public, one might expect this effect to be weaker for VC-backed firms with access to private capital markets. On the other hand, firms that seek VC financing may require more capital and be more subject to asymmetric information to begin with; hence, when their external capital needs are high, they may find public markets particularly attractive.

In Table 6, we re-estimate the same regressions from Table 3 but only include firms that we identify as VC-backed. Across all specifications, the coefficient estimates for Financing Deficit are larger than our baseline results in Table 3. These results suggest that even firms with access to private equity capital go public when their external capital needs are high. Moreover, the fact that the magnitudes are even larger than those in our baseline tests is consistent with firms that have VC backing being more subject to

[45] E.g., Campbell (1979), Bhattacharya and Ritter (1983), Yosha (1995), Dambra, Field, and Gustafson (2015), Farre-Mensa (2017), Aghamolla and Thakor (2022a), Davydova et al. (2022) and Bennett, Stulz, and Wang (2023).

[46] Although our analysis below suggests that the increased transparency benefits firms in terms of their ability to raise capital, we do not claim that there are no potential costs of increased transparency. To the extent that transparency is costly for certain firms, we would expect those firms to be less likely to go public. Second, not all forms of information disclosure affect asymmetric information and expropriation risk in the same way. For example, public firms are required to report audited financial information regularly. While audited financial information clearly reduces asymmetric information, it is not obvious that it increases the potential of expropriation. Similarly, technology firms may not reveal the exact details of their proprietary algorithms or production methods in an IPO. However, this lack of disclosure need not result in substantial asymmetric information. Relatedly, Boone, Floros, and Johnson (2016) show that firms often redact proprietary information in their IPO prospectuses.

asymmetric information, and hence, the benefit of being public increases more with their external capital needs.[47]

3.1.3 Robustness Tests

In this section, we conduct various robustness tests for our main results in Table 3.

One concern is that some of the smaller private firms in our sample that remain private are acquired or otherwise drop out of the sample much earlier than the firms that IPO. In Appendix Table C11, we show that our results are robust to excluding firms that exit via acquisition. In addition, in Appendix Table C12 we show that our results are robust to excluding all firms that exit the sample for any reason within three years.

Another concern is that linear independent variables and fixed effects are insufficient to control for potentially large differences between IPO and non-IPO firms. In particular, Table 1 shows that IPO firms are, on average, almost ten times as large (in terms of assets) as firms that do not go public. In Appendix Table C13, we estimate the same regressions in Table 3, but interact the existing fixed effects with an additional asset decile fixed effect to compare firms of similar sizes and find very similar qualitative results. In addition, we show that our results are robust to including all firms smaller than $10 million in assets (Appendix Table C14) and excluding all firms smaller than $50 million in assets (Appendix Table C15).

Although we include industry/date fixed effects in our regressions, firms within industries may still not be fully comparable, particularly for high-tech firms, which comprise a large share of the IPO firms in our sample. One concern is that these "high-tech" firms that IPO tend to also have larger financing deficits. For example, many biotech firms that have not had their drugs approved by the FDA have zero revenue before going public. In Appendix Table C16, we show that the main results in Table 3 are robust to excluding all technology and life science firms and firms located in Silicon Valley. Similarly, our results are robust to controlling for firm fixed effects that absorb firm-specific differences not captured by industry (Appendix Table C17).

3.2 How Do Firm Outcomes Evolve after the IPO?

Having analyzed which firm characteristics predict future IPO decisions, we now examine how firm outcomes evolve after the IPO. Specifically, we conduct an analysis that matches IPO firms with control firms from the last quarter of available data in the year prior to the IPO. We form a matched sample by estimating propensity scores using the ex-ante regression (1) with date by industry by CBSA fixed effects, in which, for each IPO firm, we classify its last quarter before the IPO as "treated" and all other observations as

[47]The main results also hold if we reestimate Table 3, but control for whether the firm is VC-backed (Appendix Table C10).

"controls". The matched sample includes the three closest firms by propensity score in the same quarter, with exact matching on their two-digit NAICS industry and VC-backing status.

After identifying cohorts of treated and matched control firms, we employ a cohort generalized difference-in-differences strategy with a 3-year window before the IPO and up to 4 years after the IPO. Specifically, we analyze the difference in outcome $Y_{i,c,t}$ for each treated firm i after the IPO relative to before and compare it with the difference in outcome of its matched control firms within the same cohort c using the following regression:

$$Y_{i,c,t} = \sum_{k=-3}^{4} \beta_k (d_{i,c} \times \lambda_{k,c}) + \alpha_{i,c} + \delta_{t,c} + u_{i,c,t},$$

where $d_{i,c}$ is a dummy that equals one if the firm is treated (i.e., is an IPO firm), $\lambda_{k,c}$ is a dummy for event-year k, where $k = 0$ is the year of the IPO. We include firm cohort fixed effects, $\alpha_{i,c}$, to compare changes in outcomes within the same firm. We also include time-cohort fixed effect, $\delta_{t,c}$, to ensure that the IPO firm is compared only with the matched control firms at each point in time. Standard errors are again clustered by firm.

For each regression, we plot the time series of coefficients, i.e., β_k, with 90% confidence intervals, while omitting the year prior to the IPO, i.e., β_{-1} as the reference point. We estimate annual rather than quarterly coefficients to obtain more precise estimates.

First, we examine the dynamics of firms' capex (in logs) around the IPO. Figure 1 shows that IPO firms' capex increases dramatically after the IPO as compared to matched firms that do not go public. Specifically, capex increases by a statistically significant 40% relative to matched non-IPO firms four years after the IPO. This increase in investment translates into higher total assets. In Figure 2, we plot total assets (in logs) and find that IPO firms' assets increase 25% more than control firms four years after IPO.

Given that firms substantially increase their assets and investment after going public, an obvious question is how firms finance this investment. Is it purely financed through new equity, or do firms use the IPO to facilitate non-equity capital raises? To answer this question, we first analyze how firms' debt levels evolve after the IPO. Figure 3 shows that IPO firms increase their debt after the IPO, whereby year 4, the amount of debt they have increases by about 40% relative to control firms. Moreover, Figure 4 shows that in the first year, there is a statistically significant drop in leverage of about 5 percentage points. However, the point estimate drops to around -2.5 percentage points by year 3 and is not statistically significant.

3.3 Going Public and Bank Borrowing Costs

In Section 3.2, we find that firms do not simply issue equity after they go public. Rather, they also finance their asset growth and investments with debt. In this section, we analyze

how the terms of debt issued by firms change after they go public. In particular, going public may allow firms to raise debt capital on more favorable terms. This can occur if the decrease in information asymmetry following the IPO reduces the amount of information rents informed investors can extract (e.g., Rock (1986), Sharpe (1990), Rajan (1992), Easley and O'Hara (2004) and Beyhaghi, Fracassi, and Weitzner (2025)).

An empirical challenge to testing for such an improvement in borrowing terms is that firms' risk levels also change after the IPO. For example, as we discuss further below, firms' business models may change around IPOs as they move from the innovation to the commercialization stage. Hence, it is not sufficient to simply show that interest rates decline after firms go public. Fortunately, the availability of banks' internal risk assessments (PD and LGD) in the Y-14 data allows us to make this distinction among firms' bank loans. As mentioned earlier, these risk assessments strongly predict future realized default and public equity and bond returns.[48] Moreover, Beyhaghi, Fracassi, and Weitzner (2025) show that after controlling for these risk assessments, interest rates no longer predict default at all, consistent with the risk assessments being sufficient statistics for the underlying risk of the borrower. Hence, we follow their approach and test how interest rates change after controlling for the banks' assessed risk of their underlying loans.

For these tests, we use loan-level data and restrict the sample to newly issued loans. Because we are analyzing new loans, there are not enough observations to do the same matched sample analysis as before; however, as we argue above, the main unobserved confounding variable is the credit risk of the borrower, which our data allows us to observe. To test for an improvement in bank loan terms after the IPO, we estimate the following regression:

$$\begin{aligned} IR_\ell = \beta_0 \left(IPO\ Firm_i \times Post_{i,t}\right) + \Gamma_0 X_{i,t} + \Gamma_1 Z_\ell + \beta_1 PD_\ell + \beta_2 LGD_\ell \\ + \beta_3 \left(PD_\ell \times LGD_\ell\right) + \alpha_{i,b} + \delta_{b,t} + u_\ell, \end{aligned}$$

where IR_ℓ is the interest rate on a new loan ℓ from bank b to firm i in quarter t. $IPO\ Firm_i$ is a dummy variable that equals one if the firm IPOs at any point in the sample, and $Post_{i,t}$ is a dummy variable that equals one if the loan is granted after the IPO. As independent variables, we include the same vector of firm-level controls as in Section 3.1 ($X_{i,t}$), a vector of loan-level controls (Z_ℓ), which include log(maturity), log(amount) and facility type fixed effects,[49] as well as banks' internal risk assessments: probability of default (PD) and loss given default (LGD) and their interaction (expected loss). The variable of interest is $IPO_i \times Post_{i,t}$, which captures the change in firm i's borrowing

[48] E.g., see Howes and Weitzner (2025), Beyhaghi, Howes, and Weitzner (2022), and Beyhaghi, Fracassi, and Weitzner (2025).

[49] See Instructions for the Capital Assessments and Stress Testing Information Collection for the list of facility types in the data.

cost after going public, controlling for bank b's perceived risk of the firm. We also include bank by firm fixed effects ($\alpha_{i,b}$) and bank by year-quarter fixed effects ($\delta_{b,t}$) to control for any time-invariant relationship-specific effects and bank-specific effects on borrowing costs.

The results are displayed in Table 7. In column (1), we estimate the regression without loan-level controls, bank risk assessments, or bank by year-quarter fixed effects. The estimated coefficient -0.389, is statistically significant, showing that credit spreads decrease by 38.9bps after firms go public. We find similar magnitudes when we include loan-level controls in column (2) and add bank by year-quarter fixed effects in column (3). Finally, in column (4), we also include bank risk assessments. The expected loss is positively related to the loan's interest rate; however, the coefficient for $IPO \times Post$ also remains negative and large in magnitude (-0.319). This 32bp drop in borrowing costs compares to an all-in average interest rate of around 415bps and a credit spread of 197bps (compared to the average 10-year treasury rate) for IPO firms prior to going public. Hence, credit spreads drop by 16%, even after *controlling for the underlying risk* of the firm, as perceived by the bank.[50]

These results suggest that borrowing from banks becomes more attractive after firms go public. The most plausible mechanism behind this channel is that by increasing their transparency after going public, information asymmetry drops. This reduction in asymmetric information allows firms to borrow from more banks at lower costs, as banks can extract fewer information rents from public firms.[51]

3.4 Going Public and Asymmetric Information

Our next set of tests examines whether going public reduces information asymmetries. For these tests, we create a proxy for the degree of asymmetric information using within-firm dispersion in banks' PD assessments. Intuitively, if there is less asymmetric information, banks' beliefs should more closely coincide with each other. This approach is in line with the literature that uses split bond ratings (e.g., Morgan (2002), Iannotta (2006) and Livingston and Zhou (2010)) and analyst dispersion (e.g., Flannery and Kwan (2004)) as proxies for asymmetric information.[52] Our measure has the advantage of incorporating

[50] A potential concern with analyzing banks' risk assessments is that banks may misrepresent them (e.g., Plosser and Santos (2018) and Behn, Haselmann, and Vig (2022)). However, the inclusion of bank by time fixed effects absorbs any effects of banks' incentives to misreport at the aggregate level. Moreover, risk-weighted capital requirements have been far from binding in the US during our sample period (Greenwood et al. (2017), Walz (2024) and Dubois and Rintamäki (2025)), reducing banks' incentives to manipulate their risk assessments.

[51] See also Bird, Karolyi, and Ruchti (2019), who show that information sharing reduces interest rates on bank debt. Going public can reduce the cost of equity for under-diversified insiders (e.g., Longstaff (1995), Heaton and Lucas (2004), Hall and Woodward (2010), Bernstein (2022) and Ewens and Farre-Mensa (2022)). However, this channel should not apply to loan rates.

[52] Using these other proxies is not possible given that private firms rarely have credit ratings or analyst coverage prior to going public.

the private information of multiple sophisticated financial institutions that have direct financial incentives to accurately assess borrower risk.[53]

Our measure of dispersion is the cross-sectional standard deviation of PD estimates across banks within each firm-quarter. To ensure that our results are not driven by changes in the composition of lending banks after the IPO, we calculate PD dispersion only for banks present prior to the IPO.[54] Moreover, for this analysis, we employ a slightly different matching approach than in our previous tests. Because the level of PD and the number of banks are likely correlated with the cross-sectional standard deviation of PD estimates, we match using the Mahalanobis distance, treating PD and the number of banks as non-exact matching variables, while, as before, requiring exact matching based on their two-digit NAICS industry and VC backing. This approach allows us to create a well-matched control group specifically for analyzing the differences in PD dispersion between IPO and non-IPO firms.

Figure 5 shows that, compared to matched private firms, the cross-sectional standard deviation in banks' PD estimates decreases significantly after firms go public. This decline begins immediately after the IPO and persists through the four-year post-IPO period we analyze. By year four, the dispersion in PD estimates for IPO firms is just over 1.5 percentage points lower than for matched control firms that remain private, representing roughly half of one standard deviation (3 percentage points).[55]

These results, which indicate that information asymmetry declines after firms go public, provide a potential mechanism for why newly public firms can borrow at better terms. Finally, although we observe only dispersion in bank investors' beliefs, the post-IPO convergence in banks' risk assessments likely reflects improvements in the broader information environment that enhance the firm's ability to raise capital from all types of investors.

While firms become more transparent after going public, their business models may also undergo fundamental changes. For example, firms may become more standardized as they transition from innovation to commercialization (e.g., Rajan (2012), Bernstein (2015), Larrain et al. (2025) and Bernstein (2022)). This could lead to a reduction in

[53]For example, the fact that credit and equity research analysts are not paid directly for the accuracy of their ratings, but rather reputational concerns, can lead to dishonest reporting (e.g., Ottaviani and Sørensen (2006)).

[54]While banks present prior to the IPO are likely privy to more information than public markets, they can still learn substantially from the firm going public. First, public equity prices aggregate diverse information from a large number of market participants, providing a valuable signal to lenders about firm quality. Second, equity analyst coverage generates independent research and forecasts that supplement banks' proprietary assessments. Third, the mandatory disclosure requirements imposed on public firms are more standardized and comprehensive than the information banks typically obtain through private lending relationships.

[55]It is possible that the dispersion in banks' PDs reflects differences of opinion, i.e., disagreement, rather than differences in information. However, in theory, lower disagreement leads to lower prices (e.g., Miller (1977)), whereas in contrast, we observe higher prices, i.e., improved terms on bank debt, after a reduction in PD dispersion.

dispersion in risk assessments, not because new information from the IPO is revealed, but because the firm's business model is more easily evaluated. However, under this alternative channel, we should observe a slow decrease in PD dispersion beginning before the IPO, rather than a sharp decrease following the IPO. Indeed, Bias et al. (2025) document that organizational changes associated with going public—such as increased formalization, standardization of processes, and professionalization of management—begin well before the actual IPO event. Hence, while firm fundamentals may be changing gradually around the IPO date, the sharp post-IPO drop in dispersion in risk assessments is most likely attributable to a sudden increase in transparency.

Finally, going public clearly expands the amount of publicly available, verifiable information. In practice, much of this information is produced and disseminated during the IPO process itself: prior to listing, the firm files an S-1 and undergoes underwriter due diligence[56], and it conducts roadshows with prospective investors and analysts that help market participants evaluate the firm.[57] After the IPO, the firm enters the regular reporting cycle (e.g., 10-Ks/10-Qs, earnings releases and calls), further expanding standardized, verifiable information.

However, more public information does not necessarily imply a reduction in asymmetric information or the cost of capital. For example, increased information can actually increase adverse selection if more sophisticated investors are better able to interpret new information (Pagano and Volpin (2012)) or if transparency induces socially inefficient information production (Dang, Gorton, and Holmstrom (2009) and Dang et al. (2017)).[58] Public information can also crowd out valuable private information production (Tang (2014), Goldstein and Yang (2017) and Goldstein and Yang (2019)) or inhibit risk-sharing (Hirshleifer (1971)).[59] For these reasons, whether the increased transparency reduces asymmetric information and the cost of capital is an empirical question. Our empirical innovation on this issue is to measure asymmetric information directly using lenders' internal risk assessments, rather than inferring it indirectly.

[56]Investment banks play a key role in certifying the information released by the firm by staking their reputational capital (Booth and Smith II (1986)).

[57]For example, Bill Gurley, a prominent venture capitalist, stated: "IPOs are remarkably intense, and represent the most thorough inspection that a company will endure in its lifetime. This is why companies and their board of directors agonize over whether or not they are "ready" to go public. Auditors, bankers, three different sets of lawyers, and let us not forget the S.E.C., spend months and months making sure that every single number is correct, important risks are identified, the accounting is all buttoned up, and the proper controls are in place. Conversely, these late stage private rounds have no such pageantry or process. There is typically just a single PowerPoint deck presentation" Gurley (2015).

[58]Firms may also have the benefit of selectively disclosing information to certain investors (Farre-Mensa (2017)).

[59]In Diamond and Verrecchia (1991), the effect of disclosure on a firm's cost of capital is non-monotonic.

3.5 Going Public and Firms' Debt Composition

In Section 3.4, we show that after firms go public, the dispersion in banks' private risk assessments drops, which we attribute to a reduction in asymmetric information. Reduced information asymmetries not only can affect the terms of firms' debt, but also the types of debt firms issue. In this section, we explore how firms' debt composition changes after they go public.

First, reduced information asymmetries can enable firms to borrow from a broader pool of banks as less-informed banks face a smaller adverse selection problem when competing to lend to the firm. To test this prediction, we use the same matched time-series regressions as in Section 3.2 and plot the estimated coefficients using the number of banks the firm borrows from as the dependent variable. As shown in Figure 6, four years after going public, IPO firms borrow from just under one more bank relative to control firms, starting from a baseline average of 2.3 banks. In the Appendix, we also estimate the regression using a fixed-effect Poisson model (e.g., Cohn, Liu, and Wardlaw (2022)) and find very similar results.

Reduced information asymmetries may also facilitate the use of market-based debt financing, such as public bonds and syndicated loans. For example, Dunn (2025) states:[60]

> "In addition to the capital raised in an IPO, going public provides the company with access to the public capital markets for future financings, including for debt and hybrid securities."

Similarly, Dennis and Mullineaux (2000) argue that firms are more likely to use syndicated loans when information about the borrower is more transparent.[61] Consistent with this idea, firms often receive new syndicated credit facilities from banks after going public.[62] Based on this motivation, we test whether firms increase their usage of syndicated debt and public bonds after going public.

Figure 7 analyzes the change in the ratio of syndicated debt to total debt, i.e., Syndicated Debt/Debt.[63] Before the IPO, there is no evident pre-trend in the use of syndicated

[60] Moreover, Florou and Kosi (2015) find that after an increase in the transparency of financial statements, firms are more likely to issue public bonds than borrow privately from banks, and Kovner and Wei (2014) finds that public bond spreads are higher when they are issued by private firms.

[61] As discussed in Dennis and Mullineaux (2000) and Gadanecz (2004), syndicated loans involve elements of both traditional, private relationship bank lending and public bond offerings, given that the loans are often widely held by dispersed investors. In recent years, syndicated loans are more often securitized and sold to CLOs and hedge funds (Bhardwaj and Mukherjee (2022)).

[62] See US companies going public could lift related bank lending.

[63] To calculate the total amount of syndicated loans on borrower firms' balance sheets, we divide the loan size of each syndicated loan by the lender's share of the loan, which is recorded in Y-14. We then identify loans across different banks in the same syndicate if they are classified as syndicated, share the same origination date, maturity date, and loan type. We then calculate the median adjusted size across loan observations within the same syndicate. We then sum up the total amount of syndicated debt across all syndicated loans. The benefit of this approach is that it accounts for syndicated debt not held by Y-14 banks, provided that at least one Y-14 bank holds it.

loans; however, after going public, the proportion of IPO firms' debt increases by about 12 percentage points relative to peers that remain private. This represents a 143% increase relative to the baseline syndicated debt to total debt ratio of 8.4% among IPO firms. These results may lead one to wonder whether our results regarding the drop in interest rates are entirely due to the increase in loan syndication (e.g., Table 7). However, in Appendix Table C18, we reestimate the regressions, but control for whether the loan is syndicated and find almost identical results. Similarly, Appendix Figure C2 shows that our results on PD dispersion are similar, albeit with less power, when we only include non-syndicated loans in the measure of PD dispersion.

We next examine changes in the use of public bonds after the IPO by creating a variable, Bonds/Debt, defined as the ratio of total bonds outstanding (from FISD) to total debt. Before going public, IPO firms' bonds constitute 2.5% of their total debt. Figure 8 shows that after going public, IPO firms experience a large increase in the proportion of bonds in their debt, with an almost 6 percentage points increase by year four. Moreover, this increase occurs only after the IPO, not before. Taken together, these results suggest that firms' debt mix becomes more concentrated in market-based debt after going public, which we argue is facilitated by the increased transparency and resulting reduction in asymmetric information following the IPO.[64]

3.6 Treatment Versus Selection Effects

The analysis in this paper explores 1) the relationship between ex-ante characteristics and the IPO decision, and 2) changes in firm outcomes following their IPOs. While the first tests explicitly examine selection effects (i.e., which firms choose to go public), the second set of tests captures both treatment (i.e., the causal impact of the IPO on firm outcomes) and selection effects. For example, the observed increase in investment after the IPO is almost certainly attributable to both treatment and selection effects. If the IPO reduces firms' cost of external capital, as we find evidence, firms should invest more after going public. However, firms that anticipate investing more in the future should also find it more advantageous to go public, which we argue is a critical reason why firms go public.[65]

As noted in the introduction, there is a growing body of empirical work that isolates the treatment effect of IPOs on firm outcomes. Specifically, these papers consider sam-

[64]One may wonder whether improved bond market access simply reflects that bond offerings require similar disclosure to IPOs. However, private firms can already issue bonds through Rule 144A private placements, which have no specific SEC disclosure requirements. Indeed, the majority of private firms that issue bonds do so under Rule 144A (Choi, Qin, and Zhu, 2025), and even among public firms, private placements dominate the high-yield market (Carr, 2020). Hence, our results on improved bond access are unlikely to be purely about meeting disclosure thresholds; rather, they reflect reduced asymmetric information.

[65]For example, in Pástor and Veronesi (2005), firms go public when their growth options become more attractive.

ples of firms that announce IPOs, some of which are completed and others withdrawn. Because the decision to complete an IPO is endogenous, these papers instrument for IPO completion using plausibly exogenous market-wide stock returns (Bernstein (2015)) after the IPO filing date. Unfortunately, this instrument has limited power in our sample, which precludes its use in our time-series analysis for three reasons. First, our sample begins in 2012, resulting in a relatively short period. Second, the 2012 JOBS Act allowed firms to file and withdraw their IPOs confidentially, potentially reducing the number of withdrawn IPOs observable to researchers (Dambra, Field, and Gustafson (2015), Boeh and Dunbar (2021), and Bias (2021)). Third, as mentioned above, we only have a subsample of completed (or withdrawn) IPOs over this period.

We do, however, believe that several of our findings regarding changes in access to capital and asymmetric information that we document are difficult to explain by selection alone. For example, it is not obvious why a firm would go public in anticipation of a convergence in bank risk assessments, and if it did, we would expect this convergence to occur before the IPO; however, we observe no such convergence prior to the IPO. For the same reason, this makes it unlikely that firms are going public in response to becoming more transparent.[66] Similarly, if firms anticipate an improvement in terms of their bank debt in the future, we would expect these firms to be *less likely to IPO*. In contrast, we find that these firms are *more likely to IPO*. Hence, we argue it is difficult to explain the improvement in bank debt terms purely through selection alone.

4 Conclusion

An often-cited reason firms go public is to improve their access to capital. However, in recent years, private capital markets have expanded substantially, potentially reducing this presumed benefit of public markets. In this paper, we provide evidence that, despite this trend, improved access to capital is an important motive for why firms go public. Our evidence also suggests that at least part of this improvement in access to capital is due to the reduction in asymmetric information that arises from the increased transparency following IPOs.

We show that private firms with higher financing deficits (i.e., lower profitability coupled with elevated investment needs) are more likely to go public. After going public, these firms increase their investments relative to a matched sample of firms that remain private. In addition to the equity raised in the IPO, newly public firms expand their use of debt, resulting in leverage ratios that are similar to those of control firms that remain private four years after the IPO. Consistent with a reduction in adverse selection, we show that firms' borrowing costs, conditional on their risk, decline after the IPO. We also

[66] This also makes it hard to argue that firms are using more market-based debt financing for reasons other than being public, given that we only observe this behavior after the IPO.

find evidence of reduced information asymmetries, i.e., the dispersion in banks' private risk assessments drops after going public. Finally, we find evidence that going public facilitates access to syndicated loan and public bond markets.

While our analysis focuses on the cross-section of firms' IPO decisions, our results may also provide insights into aggregate IPO activity. In particular, the access to capital channel we study may also help explain the well-documented decline in both the number of IPOs and public firms in the US over the past 25 years.[67] While there have been several explanations for this phenomenon,[68] our results suggest that when external capital needs decrease, fewer firms will go public. Indeed, Covarrubias, Gutiérrez, and Philippon (2020) show that over this period, investment decreased and profitability increased, implying a decrease in external capital needs, which may have contributed to the decline in IPOs.

Our focus on the access to capital motive complements other well-documented motives for going public. For example, IPOs provide liquidity and diversification for founders, early investors, and employees (e.g., Bodnaruk et al. (2008) and Pástor, Taylor, and Veronesi (2009)), and allow firms to use their publicly traded stock as acquisition currency (e.g., Brau and Fawcett (2006) and Celikyurt, Sevilir, and Shivdasani (2010)). While these motives differ from ours in their specific objectives, they are also driven by the increased transparency and liquidity of firms' equity following the IPO. Hence, while the benefits of going public may differ across these alternative channels, reductions in asymmetric information play an important role in all of them. Nonetheless, our paper provides strong evidence that firms use this improved access to capital to make new investments and that this is a key motive for going public.

Finally, while we focus on IPO decisions, the richness of the Y-14 data that we use allows for many potentially interesting analyses related to private firms' financing decisions. For example, future work could analyze in more detail the types of private firms that are acquired. This issue is closely related to the analysis in this paper, given that being acquired is an alternate way in which firms gain access to public capital markets.

[67] E.g., Gao, Ritter, and Zhu (2013), Doidge, Karolyi, and Stulz (2013), Doidge, Karolyi, and Stulz (2017), Ewens and Farre-Mensa (2022), Chemmanur et al. (2022), and Doidge et al. (2025).

[68] These include 1) increased regulatory and compliance burdens on public firms (e.g., Weild and Kim (2010) and Ewens, Xiao, and Xu (2024)), 2) M&A activity (Eckbo and Lithell (2025)), 3) increases in economies of scope (e.g., Gao, Ritter, and Zhu (2013)), and 4) the deregulation of private capital markets (e.g., Ewens and Farre-Mensa (2020)).

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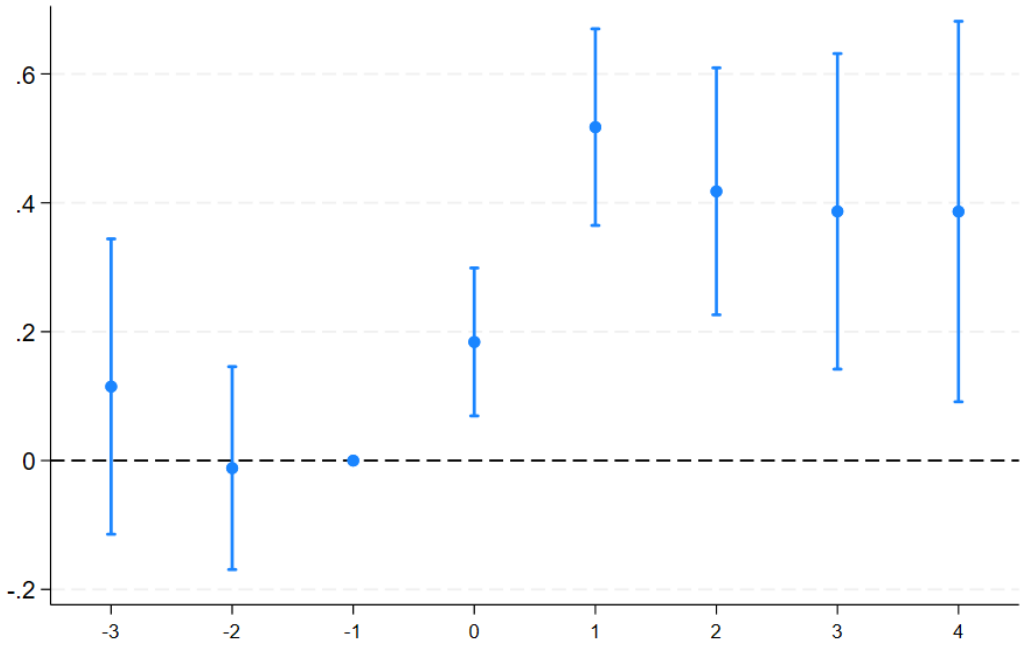
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Figure 1: Investment Dynamics

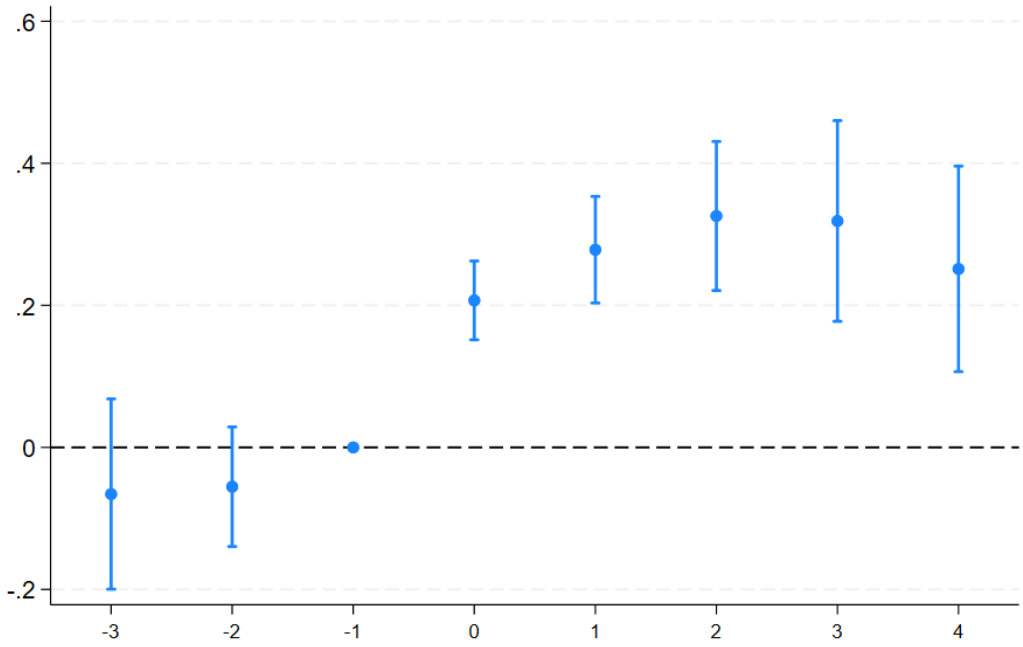


Note: In this figure, we analyze the dynamics of firm investment, i.e., log(1+Capex), before and after the IPO using a matched sample. We form a matched sample by estimating propensity scores using the ex-ante regression (1) with date by industry by CBSA fixed effects, in which, for each IPO firm, we classify its last quarter before the IPO as "treated" and all other observations as "controls". The matched sample includes the three closest firms by propensity score in the same quarter, with exact matching on their two-digit NAICS industry and VC-backing status. The dots are point estimates of the interaction coefficients between treated (IPO firms) and year dummies, and the bars are the 90% confidence intervals from the following regression:

$$Log(1+Capex)_{i,c,t} = \sum_{k=-3}^{4} \beta_k (d_{i,c} \times \lambda_{k,c}) + \alpha_{i,c} + \delta_{t,c} + u_{i,c,t},$$

where i, c, and t index firm, cohort (matched group), and time, respectively, $d_{i,c}$ is a dummy that equals one if the firm is treated (i.e., is an IPO firm), $\lambda_{k,c}$ is a dummy for event-year k, where $k = 0$ is the year of the IPO, $\alpha_{i,c}$ are firm/cohort fixed effects and $\delta_{t,c}$ are time/cohort fixed effects. Standard errors are clustered by firm.

Figure 2: Asset Dynamics

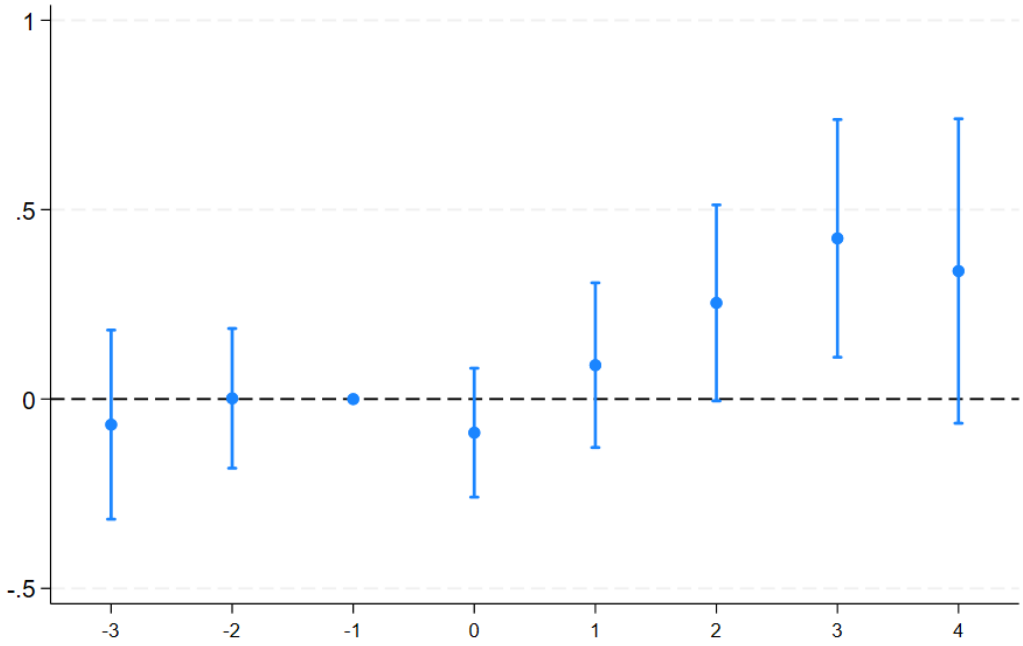


Note: In this figure, we analyze the dynamics of firm assets, i.e., log(assets), before and after the IPO using a matched sample. We form a matched sample by estimating propensity scores using the ex-ante regression (1) with date by industry by CBSA fixed effects, in which, for each IPO firm, we classify its last quarter before the IPO as "treated" and all other observations as "controls". The matched sample includes the three closest firms by propensity score in the same quarter, with exact matching on their two-digit NAICS industry and VC-backing status. The dots are point estimates of the interaction coefficients between treated (IPO firms) and year dummies, and the bars are the 90% confidence intervals from the following regression:

$$Log(Assets)_{i,c,t} = \sum_{k=-3}^{4} \beta_k (d_{i,c} \times \lambda_{k,c}) + \alpha_{i,c} + \delta_{t,c} + u_{i,c,t},$$

where i, c, and t index firm, cohort (matched group), and time, respectively, $d_{i,c}$ is a dummy that equals one if the firm is treated (i.e., is an IPO firm), $\lambda_{k,c}$ is a dummy for event-year k, where $k = 0$ is the year of the IPO, $\alpha_{i,c}$ are firm/cohort fixed effects and $\delta_{t,c}$ are time/cohort fixed effects. Standard errors are clustered by firm.

Figure 3: Debt Dynamics

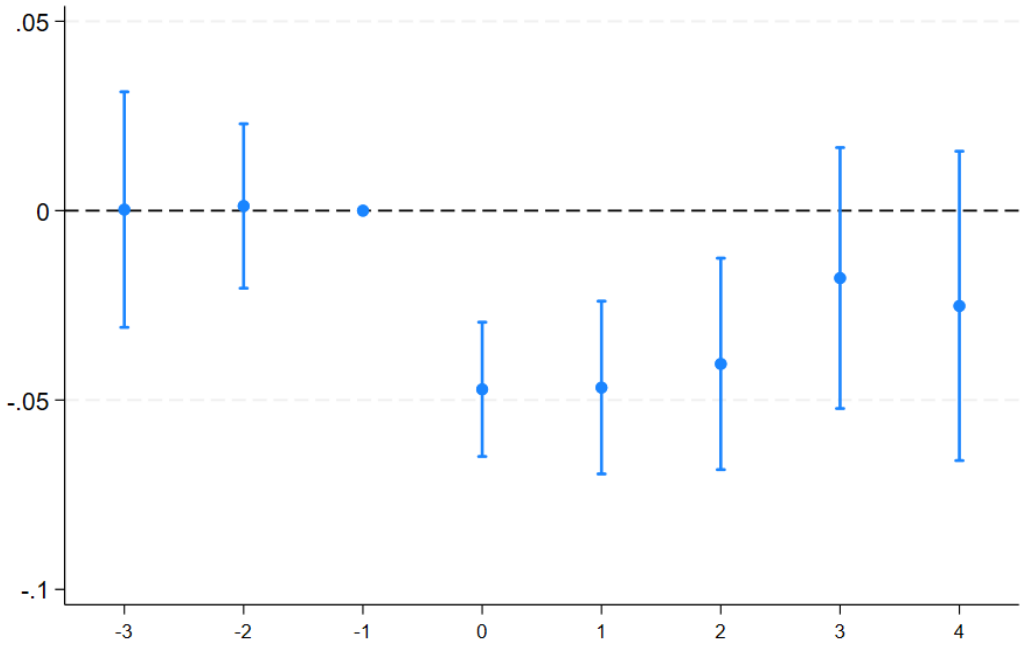


Note: In this figure, we analyze the dynamics of total debt (in logs), before and after the IPO, using a matched sample. We form a matched sample by estimating propensity scores using the ex-ante regression (1) with date by industry by CBSA fixed effects, in which, for each IPO firm, we classify its last quarter before the IPO as "treated" and all other observations as "controls". The matched sample includes the three closest firms by propensity score in the same quarter, with exact matching on their two-digit NAICS industry and VC-backing status. The dots are point estimates of the interaction coefficients between treated (IPO firms) and year dummies, and the bars are the 90% confidence intervals from the following regression:

$$Log(Debt)_{i,c,t} = \sum_{k=-3}^{4} \beta_k (d_{i,c} \times \lambda_{k,c}) + \alpha_{i,c} + \delta_{t,c} + u_{i,c,t},$$

where i, c, and t index firm, cohort (matched group), and time, respectively, $d_{i,c}$ is a dummy that equals one if the firm is treated (i.e., is an IPO firm), $\lambda_{k,c}$ is a dummy for event-year k, where $k = 0$ is the year of the IPO, $\alpha_{i,c}$ are firm/cohort fixed effects and $\delta_{t,c}$ are time/cohort fixed effects. Standard errors are clustered by firm.

Figure 4: Leverage Dynamics

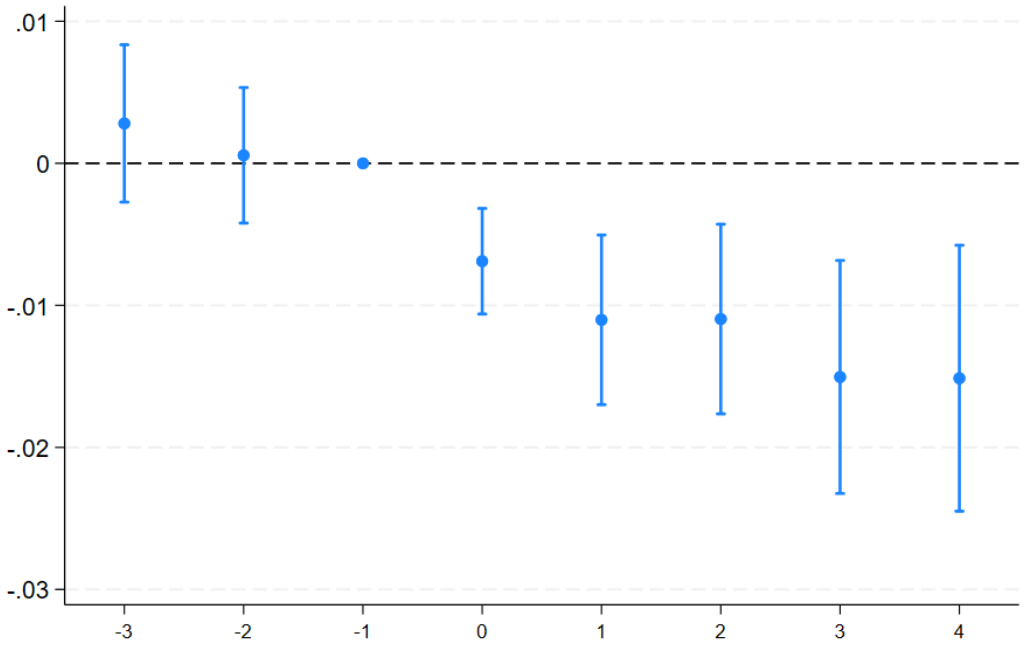


Note: In this figure, we analyze the dynamics of firm leverage, i.e., debt/assets, before and after the IPO using a matched sample. We form a matched sample by estimating propensity scores using the ex-ante regression (1) with date by industry by CBSA fixed effects, in which, for each IPO firm, we classify its last quarter before the IPO as "treated" and all other observations as "controls". The matched sample includes the three closest firms by propensity score in the same quarter, with exact matching on their two-digit NAICS industry and VC-backing status. The dots are point estimates of the interaction coefficients between treated (IPO firms) and year dummies, and the bars are the 90% confidence intervals from the following regression:

$$Debt/Assets_{i,c,t} = \sum_{k=-3}^{4} \beta_k (d_{i,c} \times \lambda_{k,c}) + \alpha_{i,c} + \delta_{t,c} + u_{i,c,t},$$

where i, c, and t index firm, cohort (matched group), and time, respectively, $d_{i,c}$ is a dummy that equals one if the firm is treated (i.e., is an IPO firm), $\lambda_{k,c}$ is a dummy for event-year k, where $k = 0$ is the year of the IPO, $\alpha_{i,c}$ are firm/cohort fixed effects and $\delta_{t,c}$ are time/cohort fixed effects. Standard errors are clustered by firm.

Figure 5: PD Dispersion Dynamics

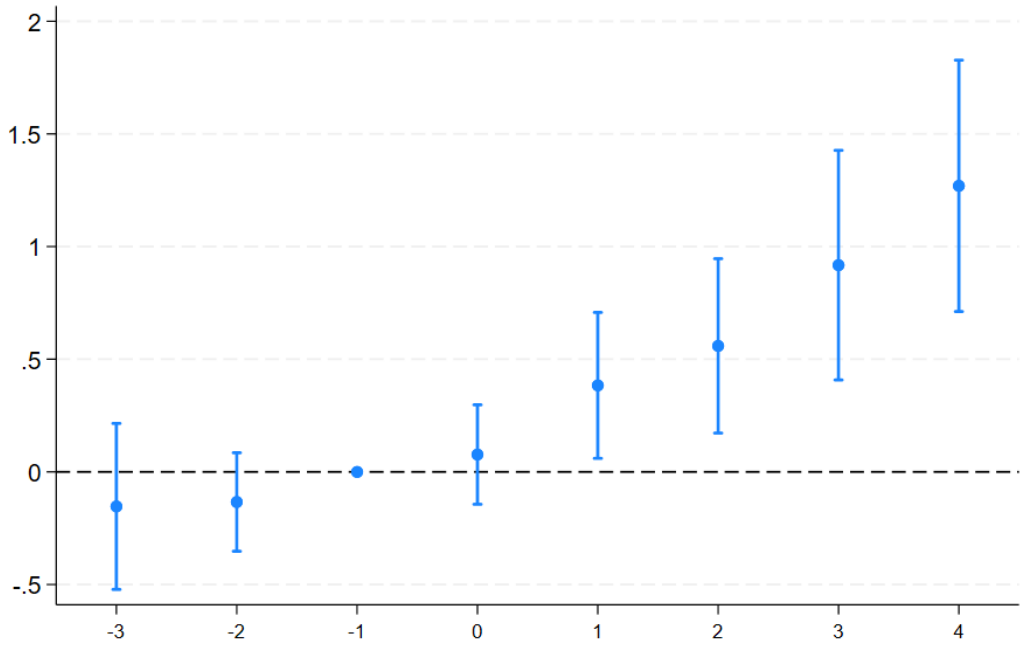


Note: In this figure, we analyze the dynamics of the dispersion in banks' probability of default (PD) estimates, measured as the cross-sectional standard deviation in PD within firm/time among banks present prior to the IPO, using a matched sample. We form a matched sample based on the Mahalanobis distance measure using PD and the number of banks as non-exact matching variables. Each IPO firm is matched with up to three control firms in the same two-digit NAICS industry and with the same VC backing status. The dots are point estimates of the interaction coefficients between treated (IPO firms) and year dummies, and the bars are the 90% confidence intervals from the following regression:

$$SD(PD)_{i,c,t} = \sum_{k=-3}^{4} \beta_k (d_{i,c} \times \lambda_{k,c}) + \alpha_{i,c} + \delta_{t,c} + u_{i,c,t},$$

where i, c, and t index firm, cohort (matched group), and time, respectively, $d_{i,c}$ is a dummy that equals one if the firm is treated (i.e., is an IPO firm), $\lambda_{k,c}$ is a dummy for event-year k, where $k = 0$ is the year of the IPO, $\alpha_{i,c}$ are firm/cohort fixed effects and $\delta_{t,c}$ are time/cohort fixed effects. Standard errors are clustered by firm.

Figure 6: Number of Banks Dynamics

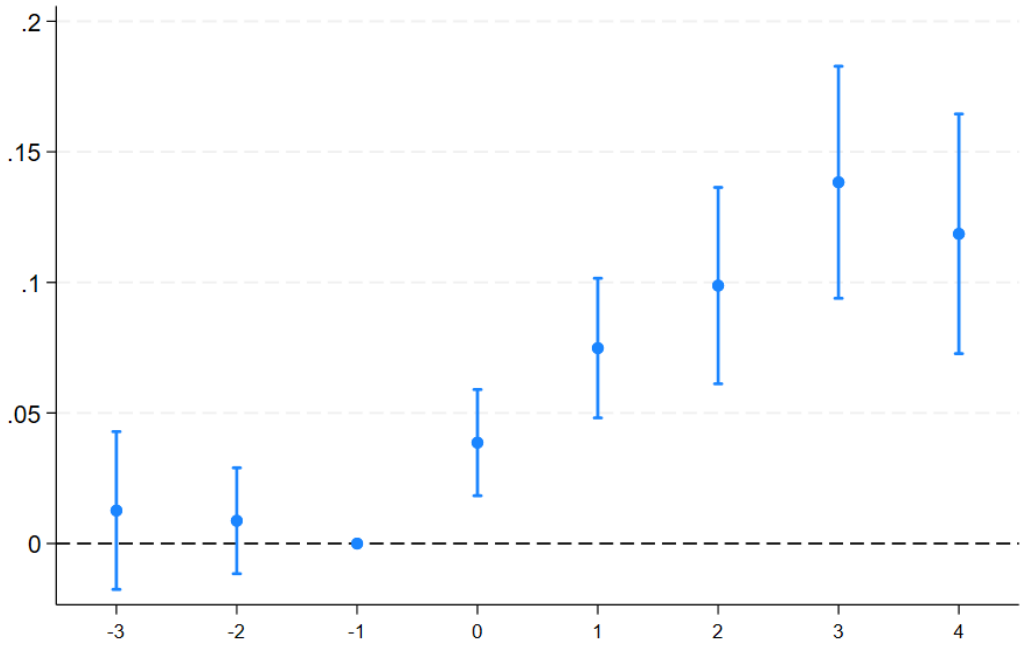


Note: In this figure, we analyze the dynamics of the number of banks the firm borrows from before and after the IPO using a matched sample. We form a matched sample by estimating propensity scores using the ex-ante regression (1) with date by industry by CBSA fixed effects, in which, for each IPO firm, we classify its last quarter before the IPO as "treated" and all other observations as "controls". The matched sample includes the three closest firms by propensity score in the same quarter, with exact matching on their two-digit NAICS industry and VC-backing status. The dots are point estimates of the interaction coefficients between treated (IPO firms) and year dummies, and the bars are the 90% confidence intervals from the following regression:

$$NOB_{i,c,t} = \sum_{k=-3}^{4} \beta_k (d_{i,c} \times \lambda_{k,c}) + \alpha_{i,c} + \delta_{t,c} + u_{i,c,t},$$

where i, c, and t index firm, cohort (matched group), and time, respectively, $d_{i,c}$ is a dummy that equals one if the firm is treated (i.e., is an IPO firm), $\lambda_{k,c}$ is a dummy for event-year k, where $k = 0$ is the year of the IPO, $\alpha_{i,c}$ are firm/cohort fixed effects and $\delta_{t,c}$ are time/cohort fixed effects. Standard errors are clustered by firm.

Figure 7: Syndicated Bank Loan Dynamics

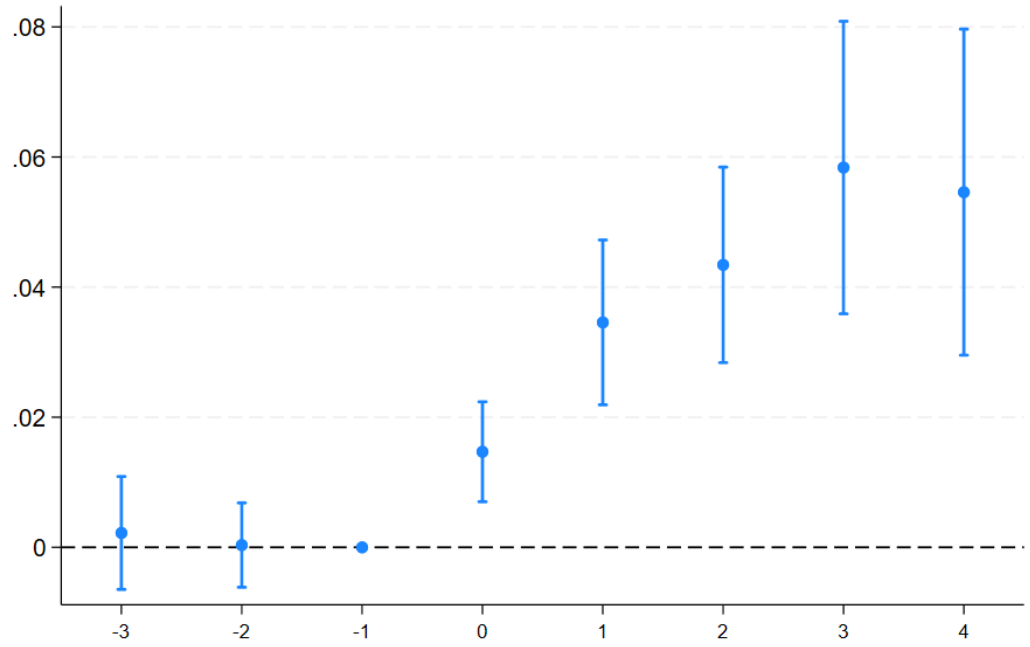


Note: In this figure, we analyze the dynamics of syndicated bank debt usage before and after the IPO using a matched sample. The dependent variable, Syndicated Debt/Debt, equals the ratio of syndicated loans outstanding over total debt. We form a matched sample by estimating propensity scores using the ex-ante regression (1) with date by industry by CBSA fixed effects, in which, for each IPO firm, we classify its last quarter before the IPO as "treated" and all other observations as "controls". The matched sample includes the three closest firms by propensity score in the same quarter, with exact matching on their two-digit NAICS industry and VC-backing status. The dots are point estimates of the interaction coefficients between treated (IPO firms) and year dummies, and the bars are the 90% confidence intervals from the following regression:

$$Syndicated\ Debt/Debt_{i,c,t} = \sum_{k=-3}^{4} \beta_k (d_{i,c} \times \lambda_{k,c}) + \alpha_{i,c} + \delta_{t,c} + u_{i,c,t},$$

where i, c, and t index firm, cohort (matched group), and time, respectively, $d_{i,c}$ is a dummy that equals one if the firm is treated (i.e., is an IPO firm), $\lambda_{k,c}$ is a dummy for event-year k, where $k = 0$ is the year of the IPO, $\alpha_{i,c}$ are firm/cohort fixed effects and $\delta_{t,c}$ are time/cohort fixed effects. Standard errors are clustered by firm.

Figure 8: Bond Dynamics



Note: In this figure, we analyze the dynamics of the bond usage before and after the IPO using a matched sample. The dependent variable, Bonds/Total Debt, equals the ratio of bonds outstanding to total debt. We form a matched sample by estimating propensity scores using the ex-ante regression (1) with date by industry by CBSA fixed effects, in which, for each IPO firm, we classify its last quarter before the IPO as "treated" and all other observations as "controls". The matched sample includes the three closest firms by propensity score in the same quarter, with exact matching on their two-digit NAICS industry and VC-backing status. The dots are point estimates of the interaction coefficients between treated (IPO firms) and year dummies, and the bars are the 90% confidence intervals from the following regression:

$$Bonds/Debt_{i,c,t} = \sum_{k=-3}^{4} \beta_k (d_{i,c} \times \lambda_{k,c}) + \alpha_{i,c} + \delta_{t,c} + u_{i,c,t},$$

where i, c, and t index firm, cohort (matched group), and time, respectively, $d_{i,c}$ is a dummy that equals one if the firm is treated (i.e., is an IPO firm), $\lambda_{k,c}$ is a dummy for event-year k, where $k = 0$ is the year of the IPO, $\alpha_{i,c}$ are firm/cohort fixed effects and $\delta_{t,c}$ are time/cohort fixed effects. Standard errors are clustered by firm.

Table 1: Firm Level Summary Statistics: IPO vs. Non-IPO Firms

This table contains summary statistics comparing IPO firm-quarters to non-IPO firm-quarters. Appendix B contains variable definitions. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on a t-test.

	IPO Firms				Non-IPO Firms				
	N	Mean	Median	SD	N	Mean	Median	SD	Diff w.r.t. IPO firms
Sales ($mm)	2912	1468.60	362.64	6059.89	1447174	416.78	66.22	4592.25	-1051.819***
Assets ($mm)	2912	2032.26	542.44	6391.58	1447174	279.92	31.36	2621.53	-1752.347***
Capex/Assets	2695	0.08	0.03	0.13	1242819	0.05	0.02	0.10	-0.026***
Sales Growth	2701	0.42	0.16	0.72	1376068	0.15	0.07	0.41	-0.271***
EBITDA/Assets	2722	0.08	0.09	0.27	1380622	0.16	0.12	0.22	0.085***
Positive Profits	2722	0.76	1.00	0.42	1380622	0.89	1.00	0.31	0.129***
Financing Deficit	2694	-0.00	-0.05	0.29	1239220	-0.12	-0.09	0.23	-0.120***
Debt/Assets	2912	0.33	0.32	0.26	1447174	0.31	0.26	0.26	-0.020***
Cash/Assets	2909	0.16	0.06	0.22	1443523	0.12	0.07	0.15	-0.041***
VC-Backed	2912	0.29	0.00	0.45	1447174	0.02	0.00	0.12	-0.276***
Silicon Valley	2912	0.14	0.00	0.35	1446280	0.02	0.00	0.15	-0.123***
Tech/Life Science Firm	2912	0.23	0.00	0.42	1447174	0.06	0.00	0.23	-0.169***

Table 2: Summary Statistics: Loan-Level Sample

This table contains summary statistics for the data used in our loan-level analyses. The sample includes new loans. Appendix B contains variable definitions.

	N	Mean	Median	SD	P5	P95
Interest Rate (%)	57847	4.13	3.75	1.99	1.80	7.60
PD (%)	65407	1.58	0.88	2.94	0.14	4.79
LGD (%)	63681	32.93	34.40	14.50	7.13	54.30
PD × LGD (%)	63203	0.50	0.25	1.01	0.03	1.49
Maturity	72208	48.66	57.50	40.55	5.27	109.63
Loan Amount ($mm)	76098	10.42	3.56	29.04	1.00	40.00
Floating Rate	58583	0.67	1.00	0.47	0.00	1.00
Syndicated Loan	76098	0.12	0.00	0.33	0.00	1.00

Table 3: Cross-Sectional Determinants of Firms' IPO Decisions

This table tests which firm characteristics predict whether firms go public within the next three years. The dependent variable IPO is a dummy that equals one if the firm goes public in the next three years, which we multiply by 100. Standard errors are shown below the parameter estimates in parentheses and are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	IPO			
	(1)	(2)	(3)	(4)
Log(1+Sales)	0.240***	0.236***	0.250***	0.253***
	(0.019)	(0.018)	(0.020)	(0.023)
Sales Growth	0.535***	0.334***	0.518***	0.303***
	(0.061)	(0.043)	(0.062)	(0.052)
Debt/Assets	0.079	0.279***	0.121*	0.301***
	(0.061)	(0.063)	(0.064)	(0.084)
Financing Deficit	0.675***	0.640***	0.679***	0.573***
	(0.080)	(0.073)	(0.082)	(0.097)
Capex/Assets	0.144	-0.109	0.167	-0.038
	(0.155)	(0.123)	(0.162)	(0.192)
NAICS4 MTB	0.109***		0.109***	
	(0.014)		(0.014)	
Date FE	Y	N	N	N
Date × NAICS4 FE	N	Y	N	N
Date × CBSA FE	N	N	Y	N
Date × NAICS4 × CBSA FE	N	N	N	Y
N	972946	1233749	966714	926131
R2	0.007	0.031	0.020	0.249

Table 4: Cross-Sectional Determinants of Firms' IPO Decisions: Investment and Profitability

This table tests which firm characteristics predict whether firms go public within the next three years. The dependent variable IPO is a dummy that equals one if the firm goes public within the next three years, which we multiply by 100. Standard errors are shown below the parameter estimates in parentheses and are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	IPO			
	(1)	(2)	(3)	(4)
Capex/Assets × EBITDA/Assets	-1.549***	-0.814***	-1.547***	-1.232***
	(0.378)	(0.283)	(0.395)	(0.410)
Capex/Assets	1.267***	0.769***	1.295***	0.893***
	(0.240)	(0.182)	(0.250)	(0.275)
EBITDA/Assets	-0.553***	-0.567***	-0.559***	-0.470***
	(0.075)	(0.072)	(0.077)	(0.097)
Log(1+Sales)	0.240***	0.236***	0.251***	0.254***
	(0.019)	(0.018)	(0.020)	(0.023)
Sales Growth	0.535***	0.333***	0.518***	0.302***
	(0.061)	(0.043)	(0.062)	(0.052)
Debt/Assets	0.087	0.282***	0.130**	0.306***
	(0.060)	(0.063)	(0.063)	(0.084)
NAICS4 MTB	0.109***		0.109***	
	(0.014)		(0.014)	
Date FE	Y	N	N	N
Date × NAICS4 FE	N	Y	N	N
Date × CBSA FE	N	N	Y	N
Date × NAICS4 × CBSA FE	N	N	N	Y
N	972946	1233749	966714	926131
R2	0.007	0.031	0.020	0.249

Table 5: Cross-Sectional Determinants of Firms' IPO Decisions (Technology and Life Science Firms Only)

This table tests which firm characteristics predict whether firms go public within the next three years among technology and life sciences firms. The dependent variable IPO is a dummy that equals one if the firm goes public in the next three years, which we multiply by 100. Standard errors are shown below the parameter estimates in parentheses and are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	IPO			
	(1)	(2)	(3)	(4)
Log(1+Sales)	1.081***	0.872***	1.060***	0.879***
	(0.173)	(0.143)	(0.179)	(0.173)
Sales Growth	1.146***	0.738***	1.088***	0.387**
	(0.264)	(0.189)	(0.281)	(0.174)
Debt/Assets	0.966	0.401	0.824	-0.117
	(0.607)	(0.491)	(0.621)	(0.555)
Financing Deficit	2.634***	2.360***	2.310***	1.724***
	(0.423)	(0.350)	(0.429)	(0.359)
Capex/Assets	-0.281	-0.891	-0.417	-0.453
	(1.272)	(1.005)	(1.226)	(1.078)
NAICS4 MTB	0.772***		0.761***	
	(0.210)		(0.240)	
Date FE	Y	N	N	N
Date × NAICS4 FE	N	Y	N	N
Date × CBSA FE	N	N	Y	N
Date × NAICS4 × CBSA FE	N	N	N	Y
N	62841	75825	59529	61462
R2	0.032	0.040	0.119	0.216

Table 6: Cross-Sectional Determinants of Firms' IPO Decisions (VC-Backed Firms Only)

This table tests which firm characteristics predict whether firms go public within the next three years, restricting the sample to VC-backed firms. The dependent variable IPO is a dummy that equals one if the firm goes public in the next three years, which we multiply by 100. Standard errors are shown below the parameter estimates in parentheses and are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	IPO			
	(1)	(2)	(3)	(4)
Log(1+Sales)	2.325***	2.692***	2.354***	2.883***
	(0.326)	(0.384)	(0.350)	(0.528)
Sales Growth	1.169***	0.937***	1.129***	0.559**
	(0.329)	(0.296)	(0.338)	(0.269)
Debt/Assets	-2.565*	-1.858	-2.202	-1.774
	(1.424)	(1.395)	(1.628)	(2.041)
Financing Deficit	3.998***	5.440***	1.438	3.372**
	(1.236)	(1.349)	(1.425)	(1.691)
Capex/Assets	3.889	0.906	6.926**	6.406*
	(2.793)	(2.791)	(3.144)	(3.749)
Date FE	Y	N	N	N
Date × NAICS4 FE	N	Y	N	N
Date × CBSA FE	N	N	Y	N
Date × NAICS4 × CBSA FE	N	N	N	Y
N	20323	18137	18572	11162
R2	0.068	0.225	0.171	0.354

Table 7: Going Public and Firms' Borrowing Costs

This table tests whether firms' borrowing costs drop after the IPO. The sample includes new loans. Loan controls include log(maturity), log(amount) and facility-type fixed effects. Standard errors are shown below the parameter estimates in parentheses and are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Interest Rate (%)			
	(1)	(2)	(3)	(4)
IPO Firm × Post	-0.389*	-0.326*	-0.365**	-0.319**
	(0.206)	(0.183)	(0.152)	(0.162)
Log(Assets)	-0.019	-0.009	-0.045	-0.028
	(0.043)	(0.042)	(0.030)	(0.032)
Sales Growth	-0.010	-0.022	-0.017	-0.030
	(0.022)	(0.020)	(0.019)	(0.020)
Debt/Assets	0.534***	0.464***	0.404***	0.333***
	(0.103)	(0.096)	(0.092)	(0.105)
EBITDA/Assets	-0.258***	-0.247***	-0.267***	-0.141**
	(0.095)	(0.065)	(0.059)	(0.057)
Capex/Assets	0.043	0.081	0.095	0.131*
	(0.094)	(0.080)	(0.079)	(0.078)
PD (%)				0.017
				(0.012)
LGD (%)				0.002**
				(0.001)
PD × LGD (%)				0.094***
				(0.035)
Date FE	Y	Y	N	N
Bank/Firm FE	Y	Y	Y	Y
Bank/Date FE	N	N	Y	Y
Loan Controls	N	Y	Y	Y
N	36827	35774	35729	29845
R2	0.817	0.874	0.885	0.890

Appendix A. Additional Data Details

In this section, we present additional details, primarily on the construction of our sample of private firms from the Y-14 data and our merging processes.

A.1. Filtering the Y-14 raw data: additional details

We apply several filtering measures to the Y-14 raw data. Specifically, we drop firms with missing taxpayer identification numbers (TINs), firms headquartered outside the US, special purpose entities, firms with loans denominated in foreign currencies, borrowers that appear to be high-net-worth individuals (NAICS code 814), financial firms (NAICS code 52), real estate firms (NAICS code 53), religious, grantmaking, civic, professional & similar organizations (NAICS code 813), and public administration and government entities (NAICS code 92).[69] Some financial and non-profit firms have different industry classifications and are not dropped after this first pass, so we also drop any firms that have phrases in the firm names such as: "School of", "CLO", and similar.

We also exclude firms with the following terms in their names: *real estate, subsidiary, properties, investment, newco, credit, family, acquisition, merger, series, holdco, finco, funding, trust, bank, banc mortgage, government, commonwealth, school, university, college, township, financing, finance, lease, leasing, foundation, insurance, retirement, church, temple, jewish, christian, muslim, bible, ymca, yeshiva, methodist, episcopalian, community, jesus, israel, redevelopment, partners, partnership, citigroup, citicorp, jpmorgan, metlife, airport, hathaway, museum, nonprofit, non-profit, public, china, usa, securitization, ubs ag, north america, receivables company, distribution company, client services inc., institutional fund, reit, clo, spv, iii, ii, iv, viii, vii, vi, county of, counties of, city of, town of, state of, board of, district of, borough of, society of, college of, council of, council for, center of, center for, educational estate, national association, non profit, indian tribe, development auth, development and auth, developmentauth, building auth, and housing dev.* We use the name filters in order to exclude records in which industries are incorrectly classified or missing.

We construct a quarterly panel indexed by the period-end date of each borrower's most recent financial statements, as reported by lenders in the Y-14Q filings. To ensure a regular quarterly frequency, we create observations for any intermediate quarters in which a firm is absent from financials panel but appears both before and after. For firms with annual reporting, we carry the most recent annual financials forward for up to three subsequent quarters to populate those quarters that lack updated financial data. Our results are robust to omitting this within-year carry-forward, but including it increases the power of our time-series tests.

[69] We also drop firms that pass these filters, but that have a ticker symbol that includes a number. Our spot checks indicate that these tickers are generally associated with firms traded on non-US exchanges.

For variables constructed from loan-level information, we use the dates associated with the borrower's loan record, rather than the date of the borrower's most recent financials. Because the date fields differ, constructing a panel that includes both the private firm's financial data and its banking characteristics requires creating separate panels using the two date sets and then merging the loans dataset with the firm-level dataset. This process ensures that our panel of borrower financial data and bank debt characteristics are synced correctly.

We make several additional adjustments to clean the data. First, some banks mistakenly record borrowers' capital expenditures as negative. Therefore, we replace all capex records with their absolute values before taking the median across various bank loan records. Prior to aggregating the data to the firm/quarter level, we also drop observations in which assets are less than 50% or greater than 150% of the median value across all loan records for the same firm for the same date, to exclude a small number of records that are reported in different units (i.e., thousands vs. millions). We drop observations in which cash, debt, tangible assets, and depreciation & amortization are greater than assets. We also drop observations with negative debt.[70] Finally, for categorical variables such as NAICS, zip code, borrower firm name, CUSIP, ticker, and year established, we take the mode across loan observations within each firm-quarter.

A.2. Merging the private firms and the IPO firms samples: additional details

We identify public firms and private firms' subsidiaries in the Y-14 data using a merge with Compustat, similar to the process in Beyhaghi et al. (2024). First, we merge the Y-14 panel by TIN and quarter for the borrower, and the borrower's guarantor (if populated), with the panel of firms from Compustat that have non-missing stock prices. We assign all firms in the Y-14 data with TINs that match firms in the Compustat panel in the same quarter, or that have guarantors with TINs associated with public firms.[71] We also assign all firms in the Y-14 data as public if any of the firm's loan records, within the same bank, are associated with a non-missing CUSIP or ticker.

Finally, we exclude the top 1% of firms by assets to avoid misclassifying outliers or large subsidiaries of public firms that were not properly identified.

A.3. Identifying the IPO Firms in Y-14: additional details

Our process for identifying the IPO firms in the Y-14 data involves several steps. First, we merge the IPO firms from the SDC Platinum database with Compustat using CUSIP

[70] We drop roughly 4,100 loan-level observations due to these filters, which represent about 0.1% of the loan-level debt observations.

[71] We designate firms that have public guarantors as public, as these are either subsidiaries of public firms or otherwise linked to a public firm in such a way that the lender likely associates the characteristics of the public guarantor with the otherwise private firm.

identifiers in both databases to obtain TINs for each IPO firm, which are available only in Compustat. We then use TIN identifiers to merge the IPO firms from the SDC Platinum database with the private firms in the Y-14 data.

Some firms in the Y-14 data that change TIN identifiers after going public. Therefore, we also hand-match IPO firms from the SDC Platinum database using each firm's name, location, and industry. For each IPO firm from SDC, we compile all private firms in the Y-14 data with the same state code and two-digit NAICS industry codes. Among these potential matches, we use the FEDMATCH string-matching algorithm to identify the ten closest name matches. We then manually select valid matches, if any, from these options. Through our hand-matching process, we also identify IPO companies' subsidiaries that were missed by our initial filters and exclude them from the sample.

A.4. Identifying firms with VC-backing, merger targets, and bonds in Y-14: additional details

We next explain in more detail our approach to matching the Y-14 with three other datasets: Preqin, the SDC Platinum M&A dataset, and FISD.

Our method for merging the Preqin data involves several steps. First, we select firms from Preqin with deal types related to venture capital financing.[72] For each firm that we identify in Preqin, we assemble all firms in Y-14 with matching state codes and the 2-digit NAICS codes. Secondly, for each Preqin firm's location and industry peers, we employ an embedding string-match method in which we translate each character in each firm's name to a numeric value and retain exact matches. For the remaining non-perfect embedding matches, we select the Y-14 firm with the most similar firm name, ranked by Jaro–Winkler distance, after cleaning the firm names in each database to exclude terms like 'corp' and 'inc' if the best match has a Jaro–Winkler distance below 0.25. Using these methods, we match about 15% of the firms in the Preqin database to our panel of private firms in Y-14, which translates to over 8,000 unique VC-backed private firms.

Our method for identifying private firms that are acquired, based on the SDC Platinum mergers and acquisitions dataset, uses the same string-matching procedure with cleaned firm names, the same requirement that matches share the same location, and 2-digit NAICS industry codes.

Our method for identifying private firms with outstanding bonds using the FISD involves two steps. The FISD data have CUSIP identifiers, which we use as a first-stage merge to Y-14. For firms in FISD that do not merge using CUSIPS, we employ the same matching method described above: we use a string match on cleaned firm names and require that matches share the same location and 2-digit NAICS industry codes.

[72]Specifically, include all firms in Preqin associated with the following deal types: Series A, Series B, Series C, Series D, Series E, Series K, Series H, Series J, Series F, Series G, Series I, Seed, Angel, Pre-IPO, Unspecified Round, Grant, and Growth.

Appendix B. Variable Definitions

Assets: Total assets, from Y-14.

Bonds/Debt: The ratio of total bonds outstanding to total debt, trimmed if > 1, from FISD and Y-14.

Capex: Funds used to acquire a long-term asset resulting in depreciation deductions over the life of the acquired asset, from Y-14.

Capex/Assets: Funds used to acquire a long-term asset resulting in depreciation deductions over the life of the acquired asset, divided by the prior year's total assets, winsorized at [1%, 99%], from Y-14.

Debt: Sum of long-term debt and short-term debt, from Y-14.

EBITDA/Assets: EBITDA/Prior Year Assets, winsorized at [1%, 99%], from Y-14.

Financing Deficit: Capex/Prior Year Assets-EBITDA/Prior Year Assets, from Y-14.

Interest Rate: Annual interest rate of the loan, trimmed if negative or zero, in percentages, from Y-14.

IPO: Dummy variable that equals one if the firm goes public within the next three years, from SDC.

IPO Firm: Dummy variable that equals one if the firm goes public at all during the sample period, from SDC.

Leverage: Debt/Assets, winsorized at [1%, 99%], from Y-14.

Loss Given Default (LGD): The bank's estimated loss given default per unit of loan, from Y-14 trimmed if $LGD = 0$ or $LGD = 1$.

Maturity: Remaining maturity in months, from Y-14.

Number of Banks (NOB): The number of banks the firm borrows from as of the current quarter, from Y-14.

NAICS4 Market-to-Book Ratio (MTB): The median market-to-book ratio of publicly

traded companies for a given four-digit NAICS industry within the given quarter, from Compustat.

Positive Profits: Dummy variable that equals one if the firm has a positive EBITDA/Assets, from Y-14.

Post: Dummy variable that equals one if the firm has IPOed as of the current quarter.

Probability of Default (PD): The bank's expected annual, long-run default rate, trimmed if $PD = 0$ or $PD = 1$, from Y-14.

Sales Growth: Annual sales growth, winsorized at [1%, 99%], from Y-14.

Silicon Valley: Dummy variable that equals one if the firm is located in Silicon Valley defined as CBSA San Francisco-Oakland-Hayward (code 41860) or San Jose-Sunnyvale-Santa Clara (code 41940), from Y-14 and HUD.

Standard Deviation of PD: The cross-sectional standard deviation of PD across banks within firm/time, from Y-14.

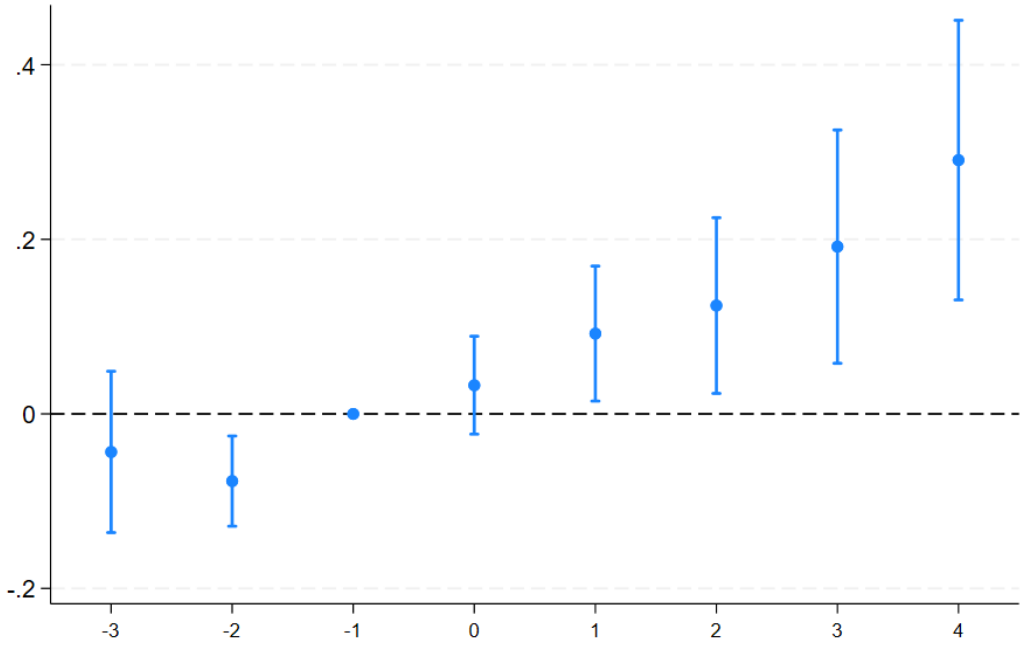
Syndicated Debt/Debt: The ratio of total syndicated bank debt to total debt, trimmed if > 1, from Y-14.

Technology and Life Sciences Firm: Dummy variable that equals one if the firm has one of the following NAICS codes: 3254, 3341, 3342, 3344, 3345, 3364, 5122, 5182, 5191, 5413, 5415, 5417, from Y-14.

VC-Backed: Dummy variable that equals one if the firm has received funding from a private equity fund in the Preqin VC funding dataset, from Preqin.

Appendix C. Additional Tests: For Online Publication

Figure C1: IPO Number of Banks Dynamics (Poisson Regression)

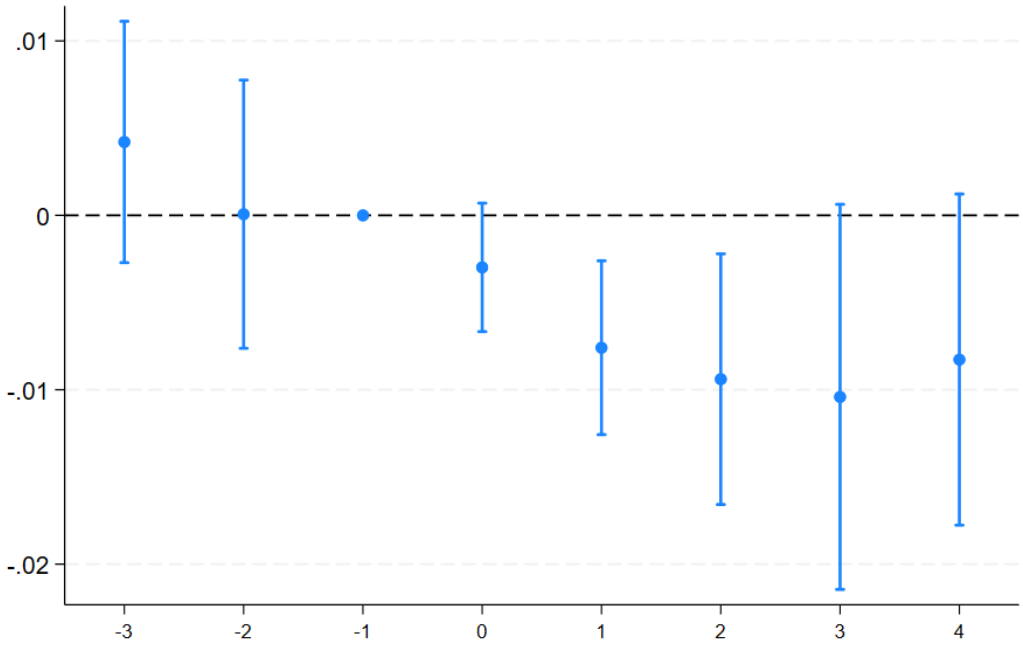


Note: In this figure, we analyze the dynamics of the number of banks firms borrow from before and after the IPO using a matched sample one quarter prior to IPO using a Poisson regression. We form a matched sample by estimating propensity scores using the ex-ante regression (1) with date by industry by CBSA fixed effects, in which, for each IPO firm, we classify its last quarter before the IPO as "treated" and all other observations as "controls". The matched sample includes the three closest firms by propensity score in the same quarter, with exact matching on their two-digit NAICS industry and VC-backing status. The dots are point estimates of the interaction coefficients between treated (IPO firms) and year dummies and the bars are the 90% confidence intervals from the following regression:

$$\log \mathbb{E}[NOB_{i,c,t}|\mathbf{X}_{i,c,t}] = \sum_{k=-3}^{4} \beta_k (d_{i,c} \times \lambda_{k,c}) + \alpha_{i,c} + \delta_{t,c},$$

where i, c and t index firm, cohort (matched group) and time respectively, $\mathbf{X}_{i,c,t}$ is the set of all predictors, $d_{i,c}$ is a dummy that equals one if the firm is treated (i.e., is an IPO firm). $\lambda_{k,c}$ is a dummy equal to one if the year is equal to k and zero otherwise, where $k = 0$ is the year in which the IPO occurs, $\alpha_{i,c}$ are firm/cohort fixed effects and $\delta_{t,c}$ are time/cohort fixed effects. Standard errors are clustered by firm.

Figure C2: PD Dispersion Dynamics (Non-Syndicated Loans)



Note: In this figure, we analyze the dynamics of the dispersion in banks' probability of default (PD) estimates among non-syndicated loans, measured as the cross-sectional standard deviation in PD within firm/time among banks present prior to the IPO, using a matched sample. We form a matched sample based on the Mahalanobis distance measure using PD and the number of banks as non-exact matching variables. Each IPO firm is matched with up to three control firms in the same two-digit NAICS industry and with the same VC backing status. The dots are point estimates of the interaction coefficients between treated (IPO firms) and year dummies and the bars are the 90% confidence intervals from the following regression:

$$SD(PD)_{i,c,t} = \sum_{k=-3}^{4} \beta_k (d_{i,c} \times \lambda_{k,c}) + \alpha_{i,c} + \delta_{t,c} + u_{i,c,t},$$

where i, c, and t index firm, cohort (matched group), and time, respectively, $d_{i,c}$ is a dummy that equals one if the firm is treated (i.e., is an IPO firm), $\lambda_{k,c}$ is a dummy for event-year k, where $k = 0$ is the year of the IPO, $\alpha_{i,c}$ are firm/cohort fixed effects and $\delta_{t,c}$ are time/cohort fixed effects. Standard errors are clustered by firm.

Table C1: IPO Sample Composition

This table shows differences in the composition of our sample of IPO firms in the Y-14 data compared with the full sample of IPOs in SDC. IPO firms are considered in our sample if there is at least one observation within a three-year window prior to the IPO. Book assets are obtained from Compustat using the last available quarter prior to the IPO, when assets are reported. See Section 2.2 for details regarding our matching and filtering processes.

	(1)	(2)	(3)
NAICS 4-Digit Industry:	SDC IPO Sample	Assets Below $10mm	Y14 IPO Sample
Panel A: Number of Unique IPO Firms			
Pharmaceutical and Medicine Manufacturing	284	69	21
Scientific Research and Development Services (Biotech)	234	37	16
Software Publishers	161	34	74
Medical Equipment and Supplies Manufacturing	56	9	12
Computer Systems Design and Related Services	36	4	15
Electronic Instrument Manufacturing	32	8	7
Oil and Gas Extraction	21	0	15
Data Processing, Hosting and Related Services	20	6	10
Full Service Restaurants	18	2	11
Semiconductor and Electronic Component Manufacturing	17	4	6
Other	511	54	238
Total	1,390	227	425
Share of SDC Total		16%	31%
Panel B: Aggregate IPO Proceeds ($bn)			
Total IPO Proceeds	346.2	3.9	212.7
Share of SDC Total		1%	61%

Table C2 IPO Proceeds and Assets: IPO Firms in Y-14 vs. IPO Firms in SDC Only

This table compares total assets prior to the IPO and IPO proceeds for our sample of IPO firms in the Y-14 data with IPO firms in SDC that are not in our sample. Book assets are obtained from Compustat using the last available quarter prior to the IPO. The number of IPOs in the table is lower than the full sample because not all firms report assets in Compustat prior to the IPO.

	N	Mean	SD	p5	p10	p25	Median	p75	p90	p95
Panel A: IPO Proceeds ($mm)										
Y14 Matched	373	364.3	733.2	52.9	79.1	132.3	263.2	475.8	716.8	819.7
Y14 Non-Matched	872	162.9	175.1	8.4	14.4	49.6	105.0	212.9	366.9	579.3
Panel B: Total Assets ($mm)										
Y14 Matched	373	1301.1	3078.9	32.9	61.1	135.2	473.3	1402.0	3200.2	5168.3
Y14 Non-Matched	872	398.5	944.8	1.5	3.8	20.1	72.4	237.8	1157.7	2001.1

Table C3: Summary Statistics (IPO Firms in Y-14 vs. IPO Firms in SDC Only)

This table compares our sample of IPO firms in the Y-14 data with IPO firms in SDC that are not in our sample. We include all firm-quarter observations within three years prior to the IPO. We obtain pre-IPO financial data from Compustat. Appendix B contains variable definitions. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on a t-test.

	Merged IPO Firms				Unmerged IPO Firms				
	N	Mean	Median	SD	N	Mean	Median	SD	Diff w.r.t. Merged IPO Firms
Sales ($mm)	2912	1468.60	362.64	6059.89	2926	382.38	0.17	1726.06	-1086.213***
Assets ($mm)	2912	2032.26	542.44	6391.58	2926	573.96	59.75	1898.72	-1458.302***
Capex/Assets	2695	0.08	0.03	0.13	990	0.07	0.02	0.13	-0.005
Sales Growth	2701	0.42	0.16	0.72	533	0.29	0.21	0.44	-0.125***
EBITDA/Assets	2722	0.08	0.09	0.27	692	-0.19	-0.29	0.32	-0.263***
Positive Profits	2722	0.76	1.00	0.42	692	0.39	0.00	0.49	-0.374***
Debt/Assets	2912	0.33	0.32	0.26	2919	0.34	0.24	0.34	0.012
Cash/Assets	2909	0.16	0.06	0.22	2919	0.43	0.42	0.33	0.264***
VC-Backed	2912	0.29	0.00	0.45	2926	0.19	0.00	0.39	-0.105***
Silicon Valley	2912	0.14	0.00	0.35	2922	0.19	0.00	0.39	0.042***
Tech/Life Science Firm	2912	0.23	0.00	0.42	2926	0.62	1.00	0.48	0.398***

Table C4: Determinants of IPO Firms Being Present in Y-14 Data

This table tests which firm characteristics predict whether IPO firms are included in our Y-14 sample or only in SDC. The dependent variable is a dummy that equals one if the firm is in our sample of Y-14 data within a three-year window prior to the IPO. The industry dummies correspond to 4-digit NAICS industry classifications. We obtain pre-IPO financial data from Compustat. Standard errors are shown below the parameter estimates in parentheses and are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	In Y-14 Sample	
	(1)	(2)
Pharmaceutical and Medicine Manufacturing	-0.330***	0.035
	(0.041)	(0.050)
Scientific Research and Development Services (Biotech)	-0.411***	0.003
	(0.043)	(0.054)
Software Publishers	0.077*	0.091**
	(0.044)	(0.039)
Medical Equipment Manufacturing	-0.235***	-0.053
	(0.083)	(0.074)
Computer Systems Design	-0.010	0.042
	(0.097)	(0.094)
Electronic Instrument Manufacturing	-0.127	0.039
	(0.112)	(0.097)
Oil and Gas Extraction	0.128	0.052
	(0.088)	(0.094)
Data Processing & Hosting	0.004	0.042
	(0.122)	(0.098)
Full-Service Restaurants	0.105	0.089
	(0.105)	(0.084)
Semis & Components Manufacturing	-0.085	0.027
	(0.142)	(0.119)
Log(1+Sales)		0.092***
		(0.007)
Date FE	Y	Y
N	1036	1036
R2	0.253	0.360
F-statistic (industry dummies)	18.481***	0.835
F-test p-value	0.000	0.595

Table C5: Industry Composition of IPO Firms

This table displays the distribution of industries, based on four-digit NAICS codes, in our sample of private firms that ultimately go public.

Industry	# of Firms	% of Total
Software Publishers	72	17.02
Pharmaceutical & Medicine Manufacturing	21	4.96
Scientific Research & Development Services (Biotech)	16	3.78
Oil and Gas Extraction	15	3.55
Computer Systems Design & Related Services	15	3.55
Miscellaneous Durable Goods Manufacturing	12	2.84
Full-Service Restaurants	11	2.60
Data Processing, Hosting, & Related Service	10	2.36
Other Information Services	10	2.36
Electric Power Gen, Transmission and Distribution	7	1.65
Navigation, Measuring, Electromed, & Control Instruments	7	1.65
Electronic Shopping	7	1.65
Support Activities for Mining	6	1.42
Residential Building Construction	6	1.42
Semiconductor & Other Component Manufacturing	6	1.42
Manufacturing and Reproducing Magnetic & Optical Media	5	1.18
Management, Scientific, & Technical Consulting	5	1.18
Business Support Services	5	1.18
Apparel & Accessories, Not Elsewhere	4	0.95
Other Food Manufacturing	4	0.95
Plastics Product Manufacturing	4	0.95
Computer & Peripheral Equipment Manufacturing	4	0.95
Clothing Stores	4	0.95
Medical and Diagnostic Laboratories	4	0.95
Other Amusement & Recreation Industries	4	0.95
Traveler Accommodation	4	0.95
Nonmetallic Mineral Mining and Quarrying	3	0.71
Converted Paper Product Manufacturing	3	0.71
Soap, Cleaning Comp, and Toilet Prep Manufacturing	3	0.71
Other General Purpose Machinery Manufacturing	3	0.71

Table C6: Location Composition of IPO Firms

This table displays the distribution of firms' headquarters CBSA in our sample of private firms that ultimately IPO.

Location	# of Firms	% of Total
San Francisco-Oakland-Hayward	43	11.56
New York-Newark-Jersey City	25	6.72
Boston-Cambridge-Newton	23	6.18
Los Angeles-Long Beach-Anaheim	22	5.91
Dallas-Fort Worth-Arlington	17	4.57
San Jose-Sunnyvale-Santa Clara	16	4.30
Chicago-Naperville-Elgin	15	4.03
Washington-Arlington-Alexandria	13	3.49
Philadelphia-Camden-Wilmington	12	3.23
Phoenix-Mesa-Scottsdale	11	2.96
Orlando-Kissimmee-Sanford	10	2.69
Indianapolis-Carmel-Anderson	9	2.42
Austin-Round Rock	8	2.15
Atlanta-Sandy Springs-Roswell	7	1.88
Minneapolis-St. Paul-Bloomington	6	1.61
Raleigh	6	1.61
Cleveland-Elyria	5	1.34
Detroit-Warren-Dearborn	5	1.34
Virginia Beach-Norfolk-Newport News	5	1.34
Bridgeport-Stamford-Norwalk	4	1.08
San Antonio-New Braunfels	4	1.08
Denver-Aurora-Lakewood	4	1.08
Las Vegas-Henderson-Paradise	4	1.08
Miami-Fort Lauderdale-West Palm Beach	4	1.08
Portland-Vancouver-Hillsboro	4	1.08
Salt Lake City	4	1.08
Riverside-San Bernardino-Ontario	4	1.08
Seattle-Tacoma-Bellevue	4	1.08
Cape Coral-Fort Myers	3	0.81
Provo-Orem	3	0.81

Table C7: Industry Composition of Private Firm Sample

This table displays the distribution of industries, based on four-digit NAICS codes, in our sample of private firms.

Industry	# of Firms	% of Total
Automobile Dealers	13,546	13.38
Restaurants & Other Eating Places	2,802	2.77
Wholesale Distribution	2,430	2.40
Computer Systems Design & Related Services	1,940	1.92
Grocery & Related Product Merchant Wholesalers	1,689	1.67
Nonresidential Building Construction	1,578	1.56
Building Equipment Contractors	1,518	1.50
Architectural, Engineering, & Related	1,474	1.46
General Freight Trucking	1,462	1.44
Software Publishers	1,412	1.39
Management, Scientific, & Technical Consulting	1,382	1.37
Other Motor Vehicle Dealers	1,304	1.29
Misc Durable Goods Merchant Wholesalers	1,220	1.21
Plastics Product Manufacturing	1,068	1.06
Offices of Physicians	1,019	1.01
Electric Power Gen, Transmission and Distribution	997	0.98
Apparel & Accessories, Not Elsewhere	931	0.92
Other Amusement & Recreation Industries	927	0.92
Motor Vehicle Parts & Supplies Wholesalers	893	0.88
Professional & Commercial Equipment & Supplies Wholesalers	875	0.86
Household Appliances & Electrical Goods Wholesalers	875	0.86
Lumber & Other Construction Materials Wholesalers	874	0.86
General Medical & Surgical Hospitals	873	0.86
Legal Services	868	0.86
Management of Companies and Enterprises	863	0.85
Highway, Street, and Bridge Construction	858	0.85
Nursing Care Facilities	840	0.83
Support Activities for Mining	774	0.76
Oil and Gas Extraction	761	0.75
Miscellaneous Nondurable Goods Wholesalers	749	0.74

Table C8: Location Composition of Private Firm Sample

This table displays the distribution of firms' headquarters CBSA in our sample of private firms.

Location	# of Firms	% of Total
New York-Newark-Jersey City	9,002	8.93
Los Angeles-Long Beach-Anaheim	4,675	4.64
Chicago-Naperville-Elgin	4,041	4.01
Philadelphia-Camden-Wilmington	2,711	2.69
Indianapolis-Carmel-Anderson	2,620	2.60
Non-Metro Area	2,438	2.42
Dallas-Fort Worth-Arlington	2,312	2.29
Washington-Arlington-Alexandria	2,268	2.25
San Francisco-Oakland-Hayward	2,214	2.20
Miami-Fort Lauderdale-West Palm Beach	2,191	2.17
Boston-Cambridge-Newton	2,179	2.16
Detroit-Warren-Dearborn	2,127	2.11
Atlanta-Sandy Springs-Roswell	1,971	1.95
Seattle-Tacoma-Bellevue	1,449	1.44
Minneapolis-St. Paul-Bloomington	1,351	1.34
Cleveland-Elyria	1,255	1.24
Phoenix-Mesa-Scottsdale	1,200	1.19
Denver-Aurora-Lakewood	1,126	1.12
Charlotte-Concord-Gastonia	1,125	1.12
Orlando-Kissimmee-Sanford	1,041	1.03
Portland-Vancouver-Hillsboro	1,039	1.03
Sacramento-Roseville-Arden-Arcade	971	0.96
San Antonio-New Braunfels	956	0.95
Riverside-San Bernardino-Ontario	931	0.92
Tampa-St. Petersburg-Clearwater	905	0.90
Columbus	899	0.89
Milwaukee-Waukesha-West Allis	837	0.83
Indianapolis-Carmel-Greenwood	824	0.82
San Jose-Sunnyvale-Santa Clara	801	0.79
Grand Rapids-Wyoming	758	0.75

Table C9: Firm Level Summary Statistics: IPO vs. Non-IPO Firms (Technology and Life Science Firms Only)

This table contains summary statistics comparing IPO firm-quarters to non-IPO firm-quarters. Appendix B contains variable definitions. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on a t-test.

	IPO Firms				Non-IPO Firms				
	N	Mean	Median	SD	N	Mean	Median	SD	Diff w.r.t. IPO firms
Sales ($mm)	656	1385.72	320.00	5717.63	81783	323.09	49.62	3059.59	-1062.631***
Assets ($mm)	656	2512.94	831.57	10668.20	81783	371.24	29.04	3699.01	-2141.697***
Capex/Assets	591	0.06	0.02	0.10	76218	0.04	0.01	0.09	-0.011***
Sales Growth	589	0.41	0.18	0.72	77793	0.21	0.09	0.50	-0.195***
EBITDA/Assets	596	0.01	0.08	0.24	78080	0.16	0.13	0.27	0.142***
Positive Profits	596	0.69	1.00	0.46	78080	0.85	1.00	0.35	0.163***
Financing Deficit	591	0.04	-0.05	0.27	75999	-0.11	-0.10	0.28	-0.154***
Debt/Assets	656	0.26	0.22	0.26	81783	0.19	0.13	0.21	-0.074***
Cash/Assets	656	0.26	0.11	0.27	81396	0.18	0.10	0.21	-0.074***
VC-Backed	656	0.42	0.00	0.49	81783	0.10	0.00	0.30	-0.323***
Silicon Valley	656	0.24	0.00	0.43	81754	0.07	0.00	0.26	-0.168***
Tech/Life Science Firm	656	1.00	1.00	0.00	81783	1.00	1.00	0.00	0.000

Table C10: Cross-Sectional Determinants of Firms' IPO Decisions (Controlling for VC Backing)

This table tests which firm characteristics predict whether firms go public within the next three years, controlling for whether the firm is VC-backed. The dependent variable IPO is a dummy that equals one if the firm goes public in the next three years, which we multiply by 100. Standard errors are shown below the parameter estimates in parentheses and are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	IPO			
	(1)	(2)	(3)	(4)
Log(1+Sales)	0.254***	0.245***	0.263***	0.262***
	(0.020)	(0.018)	(0.021)	(0.023)
Sales Growth	0.311***	0.216***	0.314***	0.200***
	(0.054)	(0.040)	(0.056)	(0.049)
Debt/Assets	0.225***	0.355***	0.246***	0.370***
	(0.058)	(0.062)	(0.062)	(0.084)
Financing Deficit	0.215***	0.274***	0.250***	0.231***
	(0.067)	(0.065)	(0.070)	(0.089)
Capex/Assets	0.434***	0.073	0.419***	0.136
	(0.155)	(0.124)	(0.162)	(0.196)
NAICS4 MTB	0.063***		0.065***	
	(0.012)		(0.013)	
VC-Backed	5.190***	3.444***	5.103***	3.294***
	(0.554)	(0.411)	(0.567)	(0.475)
Date FE	Y	N	N	N
Date × NAICS4 FE	N	Y	N	N
Date × CBSA FE	N	N	Y	N
Date × NAICS4 × CBSA FE	N	N	N	Y
N	972946	1233749	966714	926131
R2	0.020	0.037	0.032	0.254

Table C11: Cross-Sectional Determinants of Firms' IPO Decisions (Excluding Merger Targets)

This table tests which firm characteristics predict whether firms go public within the next three years, excluding firms that are acquired within that period. The dependent variable IPO is a dummy that equals one if the firm goes public in the next three years, which we multiply by 100. Standard errors are shown below the parameter estimates in parentheses and are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	IPO			
	(1)	(2)	(3)	(4)
Log(1+Sales)	0.231***	0.227***	0.242***	0.240***
	(0.019)	(0.017)	(0.020)	(0.022)
Sales Growth	0.539***	0.339***	0.525***	0.319***
	(0.061)	(0.043)	(0.062)	(0.052)
Debt/Assets	0.047	0.240***	0.086	0.258***
	(0.059)	(0.061)	(0.062)	(0.083)
Financing Deficit	0.674***	0.637***	0.683***	0.592***
	(0.081)	(0.074)	(0.083)	(0.097)
Capex/Assets	0.167	-0.084	0.188	-0.045
	(0.155)	(0.124)	(0.162)	(0.191)
NAICS4 MTB	0.109***		0.110***	
	(0.014)		(0.014)	
Date FE	Y	N	N	N
Date × NAICS4 FE	N	Y	N	N
Date × CBSA FE	N	N	Y	N
Date × NAICS4 × CBSA FE	N	N	N	Y
N	967332	1227378	961117	920674
R2	0.007	0.030	0.020	0.248

Table C12: Cross-Sectional Determinants of Firms' IPO Decisions (Excluding Private Firms in the Sample for Less than Three Years)

This table tests which firm characteristics predict whether firms go public within the next three years, excluding private firms that remain in the Y-14 data for less than three years. The dependent variable IPO is a dummy that equals one if the firm goes public in the next three years, which we multiply by 100. Standard errors are shown below the parameter estimates in parentheses and are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	IPO			
	(1)	(2)	(3)	(4)
Log(1+Sales)	0.420***	0.483***	0.438***	0.424***
	(0.037)	(0.039)	(0.039)	(0.045)
Sales Growth	1.101***	0.963***	1.089***	0.758***
	(0.141)	(0.130)	(0.145)	(0.154)
Debt/Assets	0.151	0.701***	0.257**	0.716***
	(0.105)	(0.129)	(0.111)	(0.164)
Financing Deficit	1.035***	1.417***	1.074***	1.189***
	(0.147)	(0.182)	(0.151)	(0.238)
Capex/Assets	0.509*	-0.451	0.542*	-0.389
	(0.296)	(0.287)	(0.311)	(0.436)
NAICS4 MTB	0.169***		0.180***	
	(0.025)		(0.027)	
Date FE	Y	N	N	N
Date × NAICS4 FE	N	Y	N	N
Date × CBSA FE	N	N	Y	N
Date × NAICS4 × CBSA FE	N	N	N	Y
N	496319	540466	490637	369587
R2	0.012	0.059	0.034	0.322

Table C13: Cross-Sectional Determinants of Firms' IPO Decisions (Asset Decile Fixed Effects)

This table tests which firm characteristics predict whether firms go public within the next three years, interacting the main set of fixed effects from Table 3 with asset decile fixed effects. The dependent variable IPO is a dummy that equals one if the firm goes public in the next three years, which we multiply by 100. Standard errors are shown below the parameter estimates in parentheses and are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	IPO			
	(1)	(2)	(3)	(4)
Log(1+Sales)	0.006	0.108***	0.014	0.156***
	(0.018)	(0.026)	(0.021)	(0.057)
Sales Growth	0.357***	0.324***	0.366***	0.263***
	(0.042)	(0.042)	(0.047)	(0.065)
Debt/Assets	0.042	0.056	0.086	0.155
	(0.051)	(0.059)	(0.061)	(0.116)
Financing Deficit	0.376***	0.479***	0.402***	0.533***
	(0.061)	(0.071)	(0.067)	(0.122)
Capex/Assets	0.076	0.094	0.182	0.351
	(0.122)	(0.124)	(0.140)	(0.234)
Date × Assets Decile FE	Y	N	N	N
Date × NAICS4 × Assets Decile FE	N	Y	N	N
Date × CBSA × Assets Decile FE	N	N	Y	N
Date × NAICS4 × CBSA × Assets Decile FE	N	N	N	Y
N	1233969	1218009	1164154	567896
R2	0.012	0.136	0.077	0.406

Table C14: Cross-Sectional Determinants of Firms' IPO Decisions (Including Firms With Less Than $10mm in Assets)

This table tests which firm characteristics predict whether firms go public within the next three years, similar to Table 3 but including firms with less than $10mm in assets. The dependent variable IPO is a dummy that equals one if the firm goes public in the next three years, which we multiply by 100. Standard errors are shown below the parameter estimates in parentheses and are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	IPO			
	(1)	(2)	(3)	(4)
Log(1+Sales)	0.116***	0.116***	0.122***	0.129***
	(0.010)	(0.010)	(0.010)	(0.011)
Sales Growth	0.184***	0.111***	0.177***	0.101***
	(0.023)	(0.017)	(0.023)	(0.021)
Debt/Assets	0.128***	0.196***	0.150***	0.212***
	(0.030)	(0.031)	(0.031)	(0.039)
Financing Deficit	0.050***	0.042***	0.053***	0.040***
	(0.008)	(0.007)	(0.009)	(0.009)
Capex/Assets	0.175***	0.104***	0.170***	0.123**
	(0.046)	(0.035)	(0.048)	(0.051)
NAICS4 MTB	0.053***		0.053***	
	(0.007)		(0.008)	
Date FE	Y	N	N	N
Date × NAICS4 FE	N	Y	N	N
Date × CBSA FE	N	N	Y	N
Date × NAICS4 × CBSA FE	N	N	N	Y
N	1669900	2075598	1664722	1663366
R2	0.004	0.018	0.012	0.210

Table C15: Cross-Sectional Determinants of Firms' IPO Decisions (Excluding Firms with Less than $50mm in Assets)

This table tests which firm characteristics predict whether firms go public within the next three years, but includes only firms with more than $50mm in assets. The dependent variable IPO is a dummy that equals one if the firm goes public in the next three years, which we multiply by 100. Standard errors are shown below the parameter estimates in parentheses and are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	IPO			
	(1)	(2)	(3)	(4)
Log(1+Sales)	0.304***	0.373***	0.337***	0.422***
	(0.036)	(0.036)	(0.039)	(0.057)
Sales Growth	1.043***	0.636***	1.005***	0.567***
	(0.125)	(0.088)	(0.128)	(0.121)
Debt/Assets	0.378**	0.538***	0.457***	0.544**
	(0.160)	(0.147)	(0.176)	(0.240)
Financing Deficit	1.323***	1.377***	1.359***	1.359***
	(0.206)	(0.206)	(0.215)	(0.334)
Capex/Assets	0.179	-0.112	0.398	0.254
	(0.403)	(0.316)	(0.435)	(0.496)
NAICS4 MTB	0.236***		0.227***	
	(0.034)		(0.036)	
Date FE	Y	N	N	N
Date × NAICS4 FE	N	Y	N	N
Date × CBSA FE	N	N	Y	N
Date × NAICS4 × CBSA FE	N	N	N	Y
N	360612	465147	353387	298207
R2	0.008	0.056	0.040	0.310

Table C16: Cross-Sectional Determinants of Firms' IPO Decisions (Excluding Tech/SV)

This table tests which firm characteristics predict whether firms go public within the next three years, excluding technology and life science firms as well as those from Silicon Valley. The dependent variable IPO is a dummy that equals one if the firm goes public in the next three years, which we multiply by 100. Standard errors are shown below the parameter estimates in parentheses and are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	IPO			
	(1)	(2)	(3)	(4)
Log(1+Sales)	0.175***	0.177***	0.180***	0.175***
	(0.017)	(0.016)	(0.018)	(0.018)
Sales Growth	0.365***	0.239***	0.372***	0.278***
	(0.056)	(0.040)	(0.058)	(0.052)
Debt/Assets	0.126**	0.264***	0.140**	0.258***
	(0.052)	(0.056)	(0.056)	(0.076)
Financing Deficit	0.392***	0.400***	0.425***	0.460***
	(0.070)	(0.067)	(0.073)	(0.094)
Capex/Assets	0.290**	0.020	0.280*	-0.012
	(0.140)	(0.111)	(0.148)	(0.186)
NAICS4 MTB	0.053***		0.057***	
	(0.010)		(0.011)	
Date FE	Y	N	N	N
Date × NAICS4 FE	N	Y	N	N
Date × CBSA FE	N	N	Y	N
Date × NAICS4 × CBSA FE	N	N	N	Y
N	892770	1134648	886634	845668
R2	0.005	0.028	0.018	0.256

Table C17: Cross-Sectional Determinants of Firms' IPO Decisions (Firm Fixed Effects)

This table tests which firm characteristics predict whether firms go public within the next three years, controlling for firm fixed effects. The dependent variable IPO is a dummy that equals one if the firm goes public in the next three years, which we multiply by 100. Standard errors are shown below the parameter estimates in parentheses and are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	IPO			
	(1)	(2)	(3)	(4)
Log(1+Sales)	0.240***	0.236***	0.250***	0.253***
	(0.019)	(0.018)	(0.020)	(0.023)
Sales Growth	0.535***	0.334***	0.518***	0.303***
	(0.061)	(0.043)	(0.062)	(0.052)
Debt/Assets	0.079	0.279***	0.121*	0.301***
	(0.061)	(0.063)	(0.064)	(0.084)
Financing Deficit	0.675***	0.640***	0.679***	0.573***
	(0.080)	(0.073)	(0.082)	(0.097)
Capex/Assets	0.144	-0.109	0.167	-0.038
	(0.155)	(0.123)	(0.162)	(0.192)
NAICS4 MTB	0.109***		0.109***	
	(0.014)		(0.014)	
Date FE	Y	N	N	N
Firm FE	Y	Y	Y	Y
Date × NAICS4 FE	N	Y	N	N
Date × CBSA FE	N	N	Y	N
Date × NAICS4 × CBSA FE	N	N	N	Y
N	972946	1233749	966714	926131
R2	0.007	0.031	0.020	0.249

Table C18: Going Public and Firms' Borrowing Costs (Controlling for Syndication)

This table tests whether firms' borrowing costs drop after the IPO by estimating the same regressions in Table 7, but includes an additional control for whether the loan is syndicated (Syndication FE). The sample includes new loans. Loan controls include log(maturity), log(amount) and facility-type fixed effects. Standard errors are shown below the parameter estimates in parentheses and are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Interest Rate (%)			
	(1)	(2)	(3)	(4)
IPO Firm × Post	-0.365*	-0.359*	-0.388**	-0.344**
	(0.202)	(0.186)	(0.156)	(0.165)
Log(Assets)	-0.012	-0.018	-0.052*	-0.035
	(0.044)	(0.042)	(0.030)	(0.032)
Sales Growth	-0.010	-0.023	-0.017	-0.030
	(0.022)	(0.020)	(0.019)	(0.020)
Debt/Assets	0.536***	0.459***	0.401***	0.329***
	(0.104)	(0.095)	(0.091)	(0.105)
EBITDA/Assets	-0.261***	-0.243***	-0.265***	-0.141**
	(0.095)	(0.064)	(0.059)	(0.057)
Capex/Assets	0.036	0.090	0.103	0.138*
	(0.095)	(0.079)	(0.079)	(0.078)
PD (%)				0.017
				(0.012)
LGD (%)				0.002**
				(0.001)
PD × LGD (%)				0.094***
				(0.035)
Syndication FE	Y	Y	Y	Y
Date FE	Y	Y	N	N
Bank/Firm FE	Y	Y	Y	Y
Bank/Date FE	N	N	Y	Y
Loan Controls	N	Y	Y	Y
N	36827	35774	35729	29845
R2	0.817	0.874	0.885	0.890