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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 going public.[1] Intuitively, IPOs increase firms' transparency, thereby reducing information asymmetries, which allows firms to raise capital more easily and at a lower cost. However, empirical support for this rationale is mixed,[2] and even if access to capital was an important motive for going public in the past, the rapid growth of private capital markets in recent years raises the question of whether this presumed advantage of public markets is still relevant.[3]

This paper provides 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—by far the largest IPO market in the world—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 how both firms' cost of capital and the degree of asymmetric information change after the IPO.

Our main hypothesis is based on the idea that public firms are more transparent and hence less subject to informational asymmetries than private firms and, consequently, face fewer adverse selection and hold-up problems when they raise capital. The increased transparency is both due to public firms being subject to stringent disclosure rules and because information is revealed during the security trading process.[4] Motivated by these ideas, 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

[1]One of the express goals of the 2012 JOBS Act was to spur IPO activity to improve access to capital markets (see The JOBS Act: A Landmark Reform to U.S. Securities Laws).

[2]See Lowry et al. (2017) and Bernstein (2022) for excellent discussions of this issue.

[3]See Ewens and Farre-Mensa (2020), who show that the deregulation of securities laws has led to an increase in the supply of private capital to late-stage private startups.

[4]There is a large theoretical literature providing reasons why reducing information asymmetries can improve a firm's access to capital. These include reductions in adverse selection costs (e.g., Stiglitz and Weiss (1981) and Myers and Majluf (1984)) and hold-up problems (e.g., Sharpe (1990) and Rajan (1992)). In addition, the information reflected in the stock prices of public firms can improve their investment decisions (e.g., Subrahmanyam and Titman (1999)). Other papers that analyze how differences in the information environment of public and private firms influence the IPO choice include Holmström and Tirole (1993), Chemmanur (1993), Pagano and Röell (1998), and Chemmanur and Fulghieri (1999).

future. Specifically, we find that a one standard deviation increase in a firm's financing deficit increases its likelihood of going public by 73%. 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.[5]

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 to matched control firms, IPO firms' capex and total assets increase by over 40% four years following the IPO, with growth observed in both tangible and intangible assets. 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. 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.[6] We find that after controlling for these risk assessments, firms' borrowing costs drop by 38bps after going public, suggesting that the drop in interest rates at least partially reflects an improvement in borrowing 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.[7] Given that firms often borrow from multiple banks at the 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.[8]

[5]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).

[6]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.

[7]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.

[8]Differences of opinion, such as in bond ratings and analyst forecasts, is 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.

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 that IPO firms borrow from after going public. Second, we find that IPO firms increase their use of syndicated loans and bonds dramatically after going public.[9] These results suggest that going public not only provides firms with additional equity but also facilitates access to syndicated loan and public bond markets, the former of which is consistent with anecdotal evidence that IPO activity is an important determinant of aggregate bank lending.[10]

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) and Maksimovic, Phillips, and Yang (2020)).[11] 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.[12]

Our contribution to this literature is as follows: First, our analysis uses the most detailed data on US private firms in the literature.[13] In comparison, many papers use the Census Longitudinal Business Database (LBD), which contains incomplete income

[9]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)).

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

[11]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)).

[12]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.

[13]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.

statement and balance sheet information, and no information on firms' borrowing terms.[14] Second, we provide evidence from many different angles that ex-ante investment needs predict IPOs 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 risk of the borrower* and this coincides with a decrease in the dispersion in 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)).[15] Finally, our paper is the first to show that, due to large increases in debt, firms' leverage levels revert to their pre-IPO levels within four years of the IPO and that firms increase their use of market-based debt financing after going public.[16]

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 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

[14]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.

[15]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.

[16]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.

approach.[17] 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 prior to 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.[18]

Finally, there are other studies that find evidence of public firms obtaining 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[19] 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.[20]

2 Data

In this section, we describe our source of data on private firms, IPOs, and the construction of our firm-level and loan-level samples.

[17]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)).

[18]We also find that firms increase their use of market-based debt financing after the IPO, but not before.

[19]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.

[20]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.

2.1 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 that are consistent with other papers that use 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 92), and public administration and government entities (NAICS code 53).[21] 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 to those that remain private, we remove all public firms that are never private in 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.

Many firms in the Y-14 data borrow from multiple banks in a given quarter, and potentially have multiple loans from those banks. Hence, we take the median financial record across each loan within each firm-quarter.[22] After we aggregate the loan-level data to the firm-level, we have a quarterly panel with over one million firm/quarter observations with over just over 100,000 unique private firms.

2.2 IPO Firms

We obtain US IPO data from SDC Platinum from LSEG Data and Analytics. 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

[21]See Appendix A for additional details. We also make several minor adjustments to the firm's financial data, which we describe in Appendix A.1.

[22]Firm financials often differ across banks, given that there are no standard reporting requirements for private firms.

receipts (ADRs), limited partnerships, 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 423 unique IPOs (a 30% match rate) in the Y-14 data within a three-year window prior to the IPO.[23]

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.[24] Although our match rate is less than half on an absolute basis, we match the majority of larger IPOs. Specifically, Appendix Table C1, shows that the matched IPOs account for 61% of the aggregate IPO proceeds, suggesting that our sample of IPOs tends to be larger private firms.[25] Appendix Table C2 compares IPO firm-quarters for IPOs in our sample to those outside our sample, using pre-IPO financial data from Compustat. IPOs in our sample are indeed much larger in terms of both 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 over 500 pharma and biotech IPOs over this period and only 37 in our sample. However, this industry effect appears to be entirely explained by firm size. Appendix Table C3 includes regressions where the dependent variable is a dummy that equals one 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) as a control variable, pharma and biotech 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 larger private firms that borrow from large banks suggests that these firms already have relatively good access to capital and, thus, lower needs for going public. In this respect, this sample selection likely works against the access to capital mechanism we explore in our analysis.

[23]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.

[24]Many of these firms enter our dataset *after* they go public. Indeed, we show below that firms expand the number of lenders they borrow from after going public, increasing the likelihood that firms 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.

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

2.3 Firm-Level Panel

We use the Y-14 data to construct a quarterly panel of private firms from 2012 to 2023, which we supplement with data on VC financing from the Preqin VC funding database.[26] We merge the Preqin data with the Y-14 data using industry, location, and firm name via the FedMatch text string matching algorithm (Cohen et al. (2021)).[27] We use similar matching methods to identify private firms that are acquired based on the SDC Platinum mergers and acquisitions dataset and to identify the amount of bonds outstanding each firm has using the Mergent FISD dataset.[28]

Appendix Tables C4 and C5 display the industry and location composition of IPO firms in our sample, and Appendix Tables C6 and C7 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 a variety of cities, they are clustered in technology-related industries, and a large number are located in the San Francisco-Oakland-Hayward and Palo Alto-San Jose core-based statistical areas (CBSAs), which includes Silicon Valley. By contrast, the top industries for the broader 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.

We define a firm's IPO quarter as the latest quarter in which we observe Y-14 data within the one-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).[29] 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 includes summary statistics that compare financial information for IPO firm-quarters to non-IPO firm-quarters. Unsurprisingly, IPO firms are larger in terms of 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). 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. This variable is standard in the literature (e.g., Frank and Goyal (2003)); however, we exclude some smaller components which are not available or as well populated in the Y-14 data, such as changes in net working capital.

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

[27] 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 in Preqin, the investment firm must take a minority stake in the target firm. We refer to all of these deals as VC investments.

[28] We describe the details of the Preqin, SDC, and FISD merges in Appendix A.3.

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

On average, IPO firms have a financing deficit close to zero, while the average financing deficit of non-IPO firms is significantly negative (-0.12), i.e., 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 science industries (23% versus 6%).[30]

2.4 Loan-Level Sample

We also construct a loan-level sample for our tests that examine changes in bank lending terms. To do this, we merge the firm-level balance sheet, income statement, cash flow, location, public status, IPO status, and private financing characteristics from our panel of private firms with the respective firm's specific loan-level records from the Y-14 data, which contain the terms of each loan at origination.

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 borrower's probability of default (PD) and the loan's expected loss given default (LGD). 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).*"[31] 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.*" Recent work has also shown that these risk assessments strongly predict future realized default (Beyhaghi, Fracassi, and Weitzner (2025) and Weitzner and Howes (2025)) and public equity and bond returns (Beyhaghi, Howes, and Weitzner (2022)).

Following Beyhaghi, Fracassi, and Weitzner (2025), we apply several additional filters to the loan-level data. Specifically, we exclude observations where the interest rate is zero or negative. We also drop observations in which the PD or LGD is missing, zero, or greater than one. Loan records can appear in the data for multiple quarters so long as the loan remains on the lending bank's balance sheet, but because we are interested in the terms at origination, we only keep newly originated loans. Table 2 contains summary statistics for the loan-level sample.

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

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

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 how firms' borrowing costs drop after the IPO. In Section 3.4, we analyze how asymmetric information changes after the IPO. In Section 3.5, we explore how the composition of firms' debt changes 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 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:

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

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 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 (e.g., 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.[32]

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

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

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 (0.42) is associated with a just over 100% increase in the likelihood of a firm going 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, this effect is a bit smaller on a relative basis: a one standard deviation increase in leverage (0.26) is associated with a 10% increase in IPO likelihood, and the coefficient is only statistically significant in the 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 73% increase in likelihood of a firm going 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.[33]

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 private Italian firms,[34] 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.[35] 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 has a positive relationship 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.[36] Across these alternative specifications with more restrictive fixed effects, the coefficients remain fairly similar except for the coefficient of leverage,

[33]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.

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

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

[36]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.

which becomes more than three times as large and statistically significant once we control for industry effects.[37] 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

One might expect that this isn't important for tech and biotech firms. First, a large portion of our IPOs are these types of firms. Second our effects are larger. Third, these firms actually engage in Capex.

In Appendix Table C8, we reestimate the same regressions, but instead of restricting the sample to VC-backed firms, we limit the sample to technology and life science firms.

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. Moreover, VC-backed firms tend to have proprietary technologies, which can more easily be expropriated when these firms are public.[38] 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 5, 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. These results suggest that even firms with access to private

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

[38]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).

equity capital go public when their external capital needs are high.[39] 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 asymmetric information, and hence, the benefit of being public increases more with their external capital needs.[40]

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 not sufficient to control for the 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 completely comparable, particularly for the high-tech firms, which comprise a high share of the IPO firms in our sample. One concern could be that these "high-tech" firms that IPO tend also to have higher financing deficits. For example, many biotech firms whose drugs have not been 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

[39] The point estimates for Financing Deficit are larger than our baseline results in Table 3, and we find even larger effects in Appendix Table C9, where we restrict the sample to VC-backed technology and life science firms. This latter result suggests that VC-backing is not simply picking up "tech" effects, but rather VC-backing has an independent relationship with external capital needs and the IPO decision.

[40] The main results also hold if we reestimate Table 3, but control for whether the firm is VC-backed (Appendix Table C10). Although our analysis below suggests that the increased transparency benefits firms in terms of their ability to raise capital, we do not claim that the costs of increased transparency are irrelevant. 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 information disclosure affects asymmetric information and expropriation risk similarly. 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, a technology company may not reveal the exact details of its proprietary algorithm 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.

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?

After analyzing which firm characteristics predict firms' decisions to IPO in the future, we now examine how firm outcomes evolve after the IPO. Specifically, we perform an analysis in which we match IPO firms to control firms in the last quarter available in the year prior to the IPO. We form a matched sample by estimating propensity scores based on our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' last quarter in the year prior to the IPO. The matched sample includes the three closest firms in terms of propensity scores while requiring exact matching based 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 using a window of 3 years prior to the IPO 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:

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

where $d_{i,c}$ is a dummy that equals one if the firm is treated (i.e., is an IPO firm), $\lambda_{y,k,c}$ is a dummy equal to one if year y is equal to k and zero otherwise, where $k = 0$ is the year of the IPO. We include firm cohort fixed effects $\alpha_{i,c}$ to compare the change in outcome within the same firm. We 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; however, because the year of the IPO may also contain quarters prior to the IPO, the effect is often smaller in year zero than in years in which all quarters occur after the IPO.

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 jumps after the IPO and increases by a statistically significant 46% 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 40% more than control firms four years after IPO.

While capital expenditures are clearly an important form of investment, certain firms, particularly technology-related ones, also invest in intangible assets such as R&D. Although we do not have data on R&D and intangible investment specifically, we can back out total intangible assets based on the firms' total assets and tangible assets, which are both available in the Y-14 data.[41] In Figure 3 we plot the time series of coefficients for intangible assets (in logs) and find that IPO firms' intangible assets increase 23% more than matched non-IPO firms four years after IPO.

Given that firms dramatically 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 4 shows that IPO firms increase their debt after the IPO, whereby year 4, the amount of debt they have increases by about 65% relative to control firms. Moreover, Figure 5 shows that in the first year, there is a statistically significant drop in leverage of about 4 percentage points. However, after year one, leverage reverts back such that in years 2, 3 and 4, there is no statistically significant difference between IPO firms and their matched counterparts, with the coefficient even positive by year 4. This result differs from Pagano, Panetta, and Zingales (1998) and Aslan and Kumar (2011), who find permanent reductions in leverage after IPOs in Italy and the UK, respectively.

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 finance their asset growth and investments with debt, such that their leverage is unchanged four years after the IPO. In this section, we analyze how the terms of the debt that firms issue 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), Kurlat (2016), 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, firms business models may fundamentally change around IPOs as they move from the innovation to exploitation stage. This could result in banks being less risky.

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

[41] Tangible assets in the Y-14 data encompass any assets that have a physical existence, including cash.

earlier, these risk assessments strongly predict future realized default and public equity and bond returns.[42] 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:

$$\begin{aligned} IR_j = \beta_0 \left(IPO_i \times Post_t\right) + \Gamma_0 X_{i,t} + \Gamma_1 Z_j + \beta_1 PD_j + \beta_2 LGD_j \\ +\beta_3 \left(PD_j \times LGD_j\right) + \alpha_{i,b} + \delta_{,t} + u_j, \end{aligned}$$

where IR_j is the interest rate on a new loan j from bank b to firm i in quarter t. 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_j), which include log(maturity), log(amount) and facility type fixed effects,[43] 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 $IPO_i \times Post_t$, which represents the change in firm i's borrowing cost after going public, controlling for bank b's change in the perceived risk of the firm. We also include bank by firm fixed effects $\alpha_{i,b}$ to control for any time-invariant relationship-specific effect on borrowing costs.

The results are displayed in Table 6. In column (1), we estimate the regression without loan-level controls, bank risk assessments, or bank by year-quarter fixed effects. The estimated coefficient -0.511, is statistically significant, showing that credit spreads decrease by 51bps after firms go public. We find lower magnitudes when we include loan-level controls in column (2) and add bank by date 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 (-0.384). This 38bp drop in borrowing costs compares to an all-in average interest rate of around 401bps and a credit spread of 183bps (compared to the average 10-year treasury rate) for IPO firms prior to going public. Hence, credit spreads drop by 21%, even after *controlling for the underlying risk* of the firm, as perceived by

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

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

the bank.[44]

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 and at a lower cost, as banks can extract fewer information rents from public firms.[45] In the next section, we provide direct evidence for a reduction in asymmetric information after the IPO.

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 based on the 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.[46] Our measure has the advantage of incorporating the private information of multiple sophisticated financial institutions that have direct financial incentives to accurately assess borrower risk.[47]

Our measure of dispersion is the cross-sectional standard deviation of PD estimates across banks within each firm-quarter. For this analysis, we employ a 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 based on the Mahalanobis distance measure using 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 6 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 6 percentage points

[44] 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.

[45] See also Bird, Karolyi, and Ruchti (2019), who show that information sharing reduces interest rates on bank debt.

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

[47] 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)).

lower than for matched control firms that remain private, which represents close to one standard deviation (6.4 percentage points).

To ensure that our results are not driven by changes in the composition of lending banks after the IPO, we conduct the same analysis while fixing the set of banks for each firm throughout the sample period (Appendix Figure C1). This modified test shows a similar decrease in PD dispersion after the IPO.[48] 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, while we only observe the dispersion in bank investors' beliefs, the post-IPO convergence in banks' risk assessments likely reflects improvements in the broader information environment that benefit the firm's ability to raise capital from all types of investors.

A relevant concern is that firms' business models may fundamentally change when they go public. For example, firms may be at the stage of commercialization rather than innovation (e.g., Rajan (2012), Bernstein (2015), Larrain et al. (2025), Bernstein (2022)). This could lead to a reduction in dispersion in risk assessments, not because of new information being revealed from the IPO, but rather because the fundamentals are more easily assessed. However, if this were the case, we would not expect it to happen immediately after the IPO. To the extent the business is changing, we should observe a slower movement in PD dispersion beginning prior to the IPO.[49]

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 the adverse selection problem is lessened. To test this hypothesis, 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 7, 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.

[48] 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.

[49] If this process occurs after the IPO, then we would expect to see a slow drop in dispersion after the IPO, not the large drop we see right away.

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:[50]

> "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.[51] Consistent with this idea, firms often receive new syndicated credit facilities from banks after going public.[52] Based on this motivation, we test whether firms increase their usage of syndicated debt and public bonds after going public.

Figure 8 analyzes the change in the ratio of syndicated debt to total debt, i.e, Syndicated Debt/Debt.[53] Prior to the IPO, there is no evident pre-trend in the use of syndicated loans; however, after going public, the proportion of IPO firms' debt increases by about 15 percentage points relative to peers that remain private. This represents a 167% increase relative to the baseline ratio of syndicated debt to total debt of 9% among IPO firms.[54]

We next examine changes in the use of public bonds after the IPO by creating a variable, Bonds/Debt, which is the ratio of total bonds outstanding, obtained from FISD, over total debt. Prior to going public, IPO firms' bonds make up 3% of their total debt. Figure 9 shows that after going public, IPO firms experience a large increase in the proportion of bonds in their debt, with an almost 8 percentage points increase by year four. Moreover, this increase only occurs after the IPO and not before. Taken together, these results suggest that firms' mix of debt becomes more concentrated in market-based

[50]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.

[51]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)).

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

[53]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 the loans are classified as syndicated, have the same origination date, the same maturity date, and the same loan type. We then calculate the median of the adjusted size across the loan observations identified as being 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, as long as at least one Y-14 bank holds it.

[54]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 6). 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 C3 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.

debt after going public, which we argue is facilitated by the increased transparency and resulting reduction in asymmetric information following the IPO.

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 reason that we observe an increase in investment after the IPO is almost certainly due to both treatment and selection effects. If the IPO leads to a reduction in the cost of external capital for firms, as we find evidence for, 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.

As mentioned in the introduction, there is a growing literature with empirical tests designed to isolate the treatment effect of IPOs on firm outcomes. Specifically, these papers consider samples of firms that announce IPOs, some of which are completed and others of which are 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 us from using it in our time-series analysis for three reasons. First, our sample begins in 2012, giving us a relatively short sample 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 believe, however, that several of our findings regarding the change in access to capital and asymmetric information that we document are difficult to explain through 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.[55] 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

[55] 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.

to explain the improvement in bank debt terms purely through selection alone.

3.7 Alternative Mechanisms

Our paper does not claim other motives are not important. Rather it shows that access to capital is important. Brau and Fawcett (2006) provide several other motives.

Lubos pastor paragraph. Firms file S-1. Stock price trading.

Standardization story does not mean firms don't go public for need of capital

Barry and Mihov (2015) find that 11 percent of IPO firms have no debt. This excludes convertible bonds and preferred stock.

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 increase in 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 in both tangible and intangible assets 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 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.[56] While there have been several

[56]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).

explanations for this phenomenon,[57] 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.

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.

[57]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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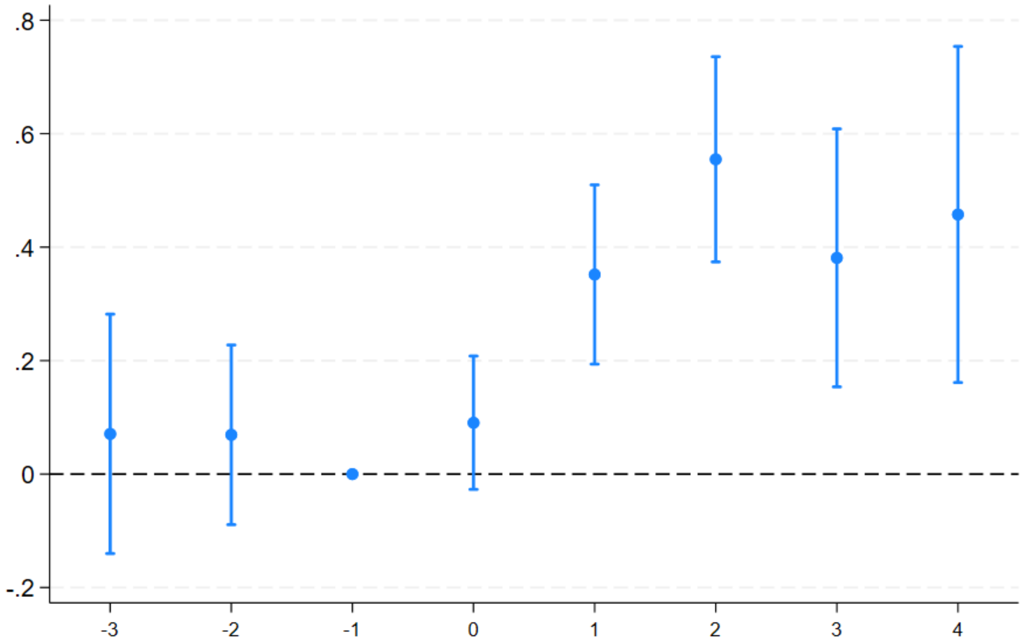
Figure 1: Investment Dynamics

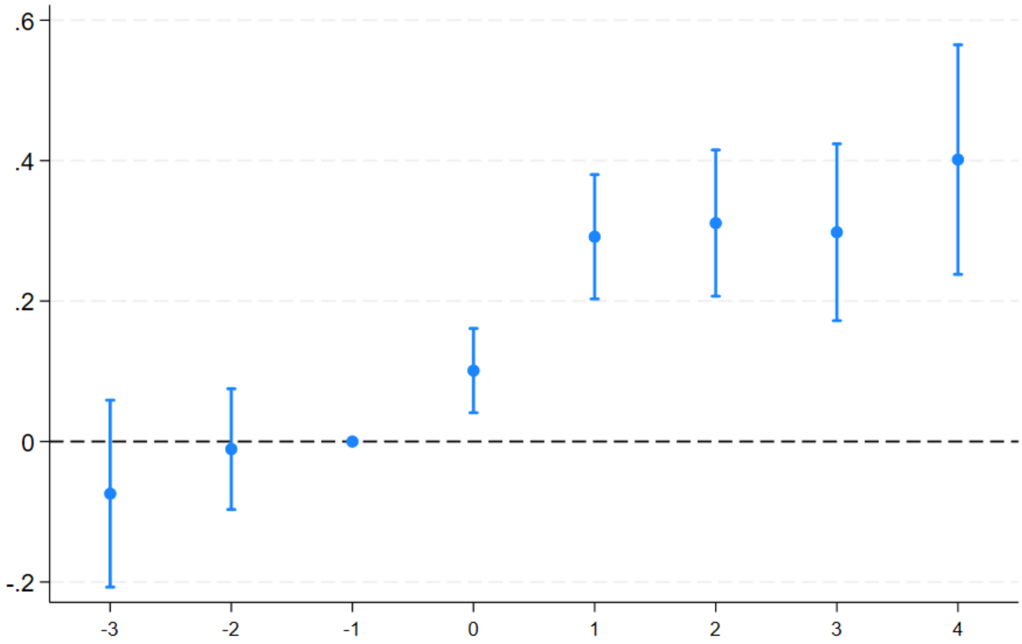


Note: In this figure, we analyze the dynamics of firm investment, i.e., log(1+Capex), before and after the IPO using a matched sample. We form a matched sample by estimating propensity scores based on our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' last quarter in the year prior to the IPO. The matched sample includes the three closest firms in terms of propensity scores that are in the same two-digit NAICS industry and have 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:

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

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). $\lambda_{y,k,c}$ is a dummy equal to one if year y 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 and $\delta_{t,c}$ are time/cohort fixed effects. Year zero contains the quarter in which the firm IPOs. Standard errors are clustered by firm.

Figure 2: Asset Dynamics

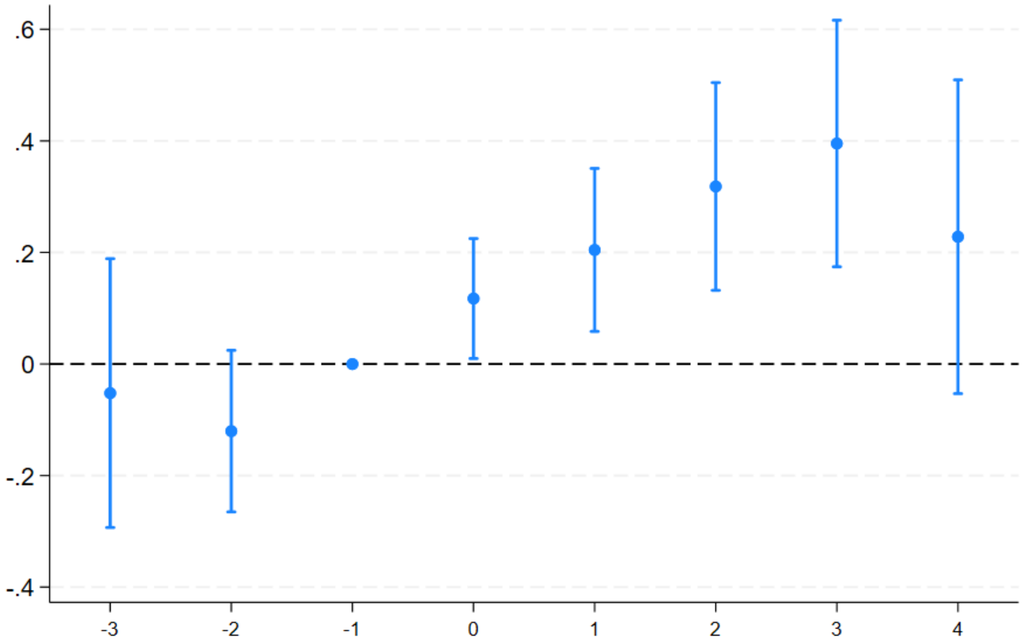


Note: In this figure, we analyze the dynamics of firm assets, i.e., log(assets), before and after the IPO using a matched sample. We form a matched sample by estimating propensity scores based on our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' last quarter in the year prior to the IPO. The matched sample includes the three closest firms in terms of propensity scores that are in the same two-digit NAICS industry and have 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:

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

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). $\lambda_{y,k,c}$ is a dummy equal to one if year y 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 and $\delta_{t,c}$ are time/cohort fixed effects. Year zero contains the quarter in which the firm IPOs. Standard errors are clustered by firm.

Figure 3: Intangible Assets Dynamics

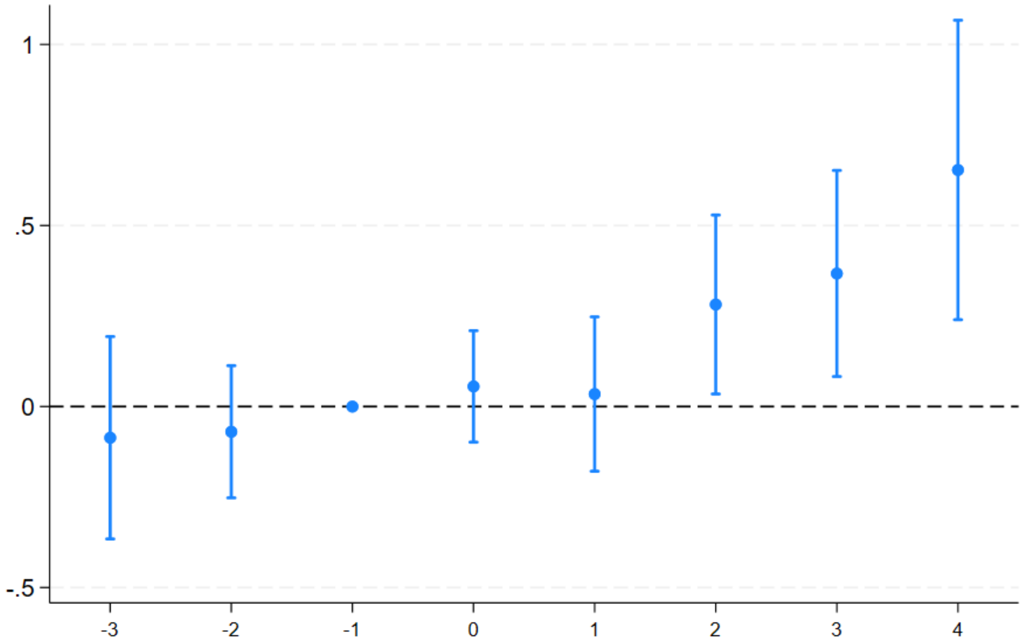


Note: In this figure, we analyze the dynamics of intangible assets, i.e., log(intangible assets), before and after the IPO using a matched sample. We form a matched sample by estimating propensity scores based on our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' last quarter in the year prior to the IPO. The matched sample includes the three closest firms in terms of propensity scores that are in the same two-digit NAICS industry and have 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:

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

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). $\lambda_{y,k,c}$ is a dummy equal to one if year y 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 and $\delta_{t,c}$ are time/cohort fixed effects. Year zero contains the quarter in which the firm IPOs. Standard errors are clustered by firm.

Figure 4: Debt Dynamics

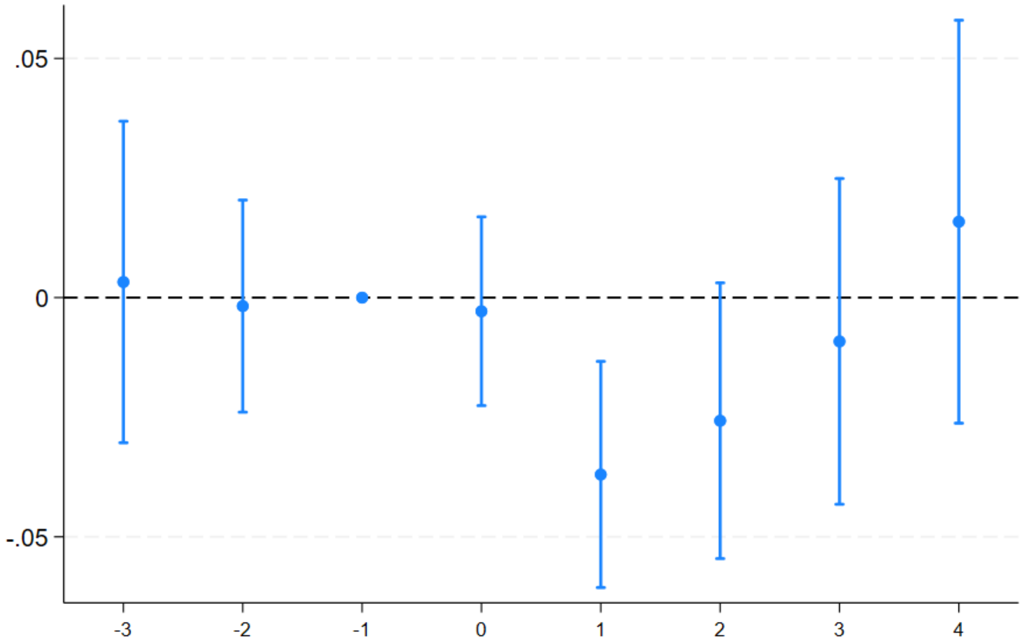


Note: In this figure, we analyze the dynamics of total debt (in logs), before and after the IPO, using a matched sample. We form a matched sample by estimating propensity scores based on our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' last quarter in the year prior to the IPO. The matched sample includes the three closest firms in terms of propensity scores that are in the same two-digit NAICS industry and have 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:

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

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). $\lambda_{y,k,c}$ is a dummy equal to one if year y 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 and $\delta_{t,c}$ are time/cohort fixed effects. Year zero contains the quarter in which the firm IPOs. Standard errors are clustered by firm.

Figure 5: Leverage Dynamics

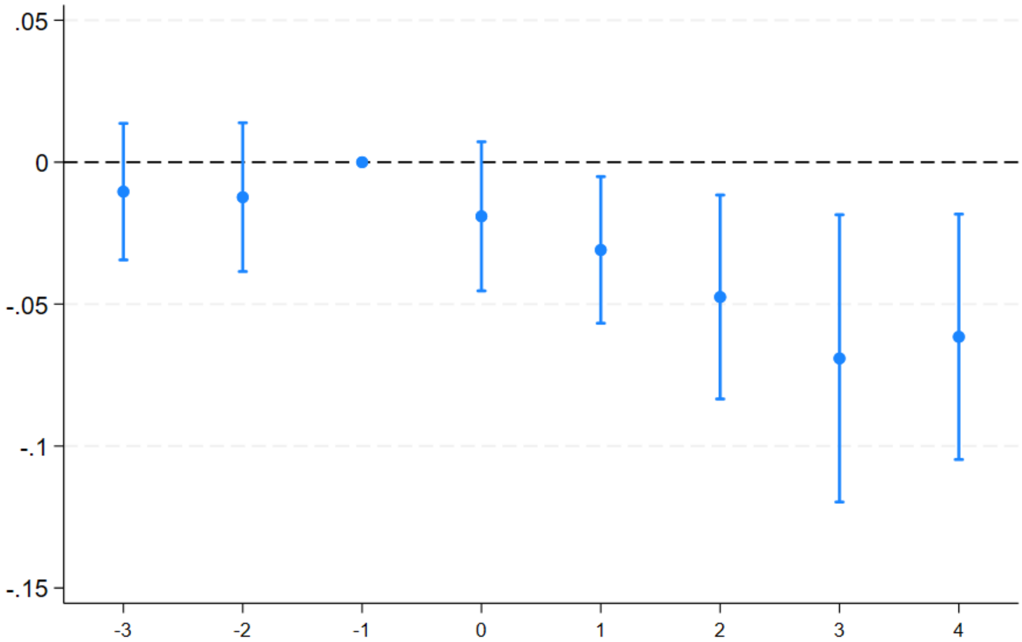


Note: In this figure, we analyze the dynamics of firm leverage, i.e., debt/assets, before and after the IPO using a matched sample. We form a matched sample by estimating propensity scores based on our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' last quarter in the year prior to the IPO. The matched sample includes the three closest firms in terms of propensity scores that are in the same two-digit NAICS industry and have 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:

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

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). $\lambda_{y,k,c}$ is a dummy equal to one if year y 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 and $\delta_{t,c}$ are time/cohort fixed effects. Year zero contains the quarter in which the firm IPOs. Standard errors are clustered by firm.

Figure 6: PD Dispersion Dynamics

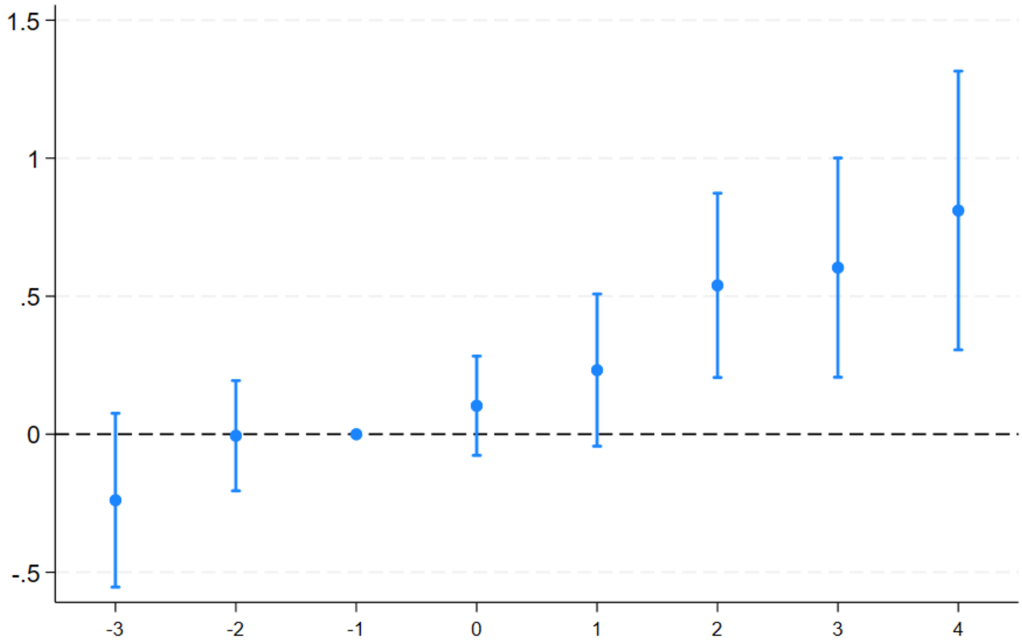


Note: In this figure, we analyze the dynamics of the dispersion in banks' probability of default (PD) estimates, measured as the cross-sectional standard deviation in PD within firm/time, using a matched sample. We form a matched sample based on the Mahalanobis distance measure using PD and the number of banks as non-exact matching variables. Each IPO firm is matched to three control firms that are in the same two-digit NAICS industry and have 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:

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

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). $\lambda_{y,k,c}$ is a dummy equal to one if year y 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 and $\delta_{t,c}$ are time/cohort fixed effects. Year zero contains the quarter in which the firm IPOs. Standard errors are clustered by firm.

Figure 7: Number of Banks Dynamics

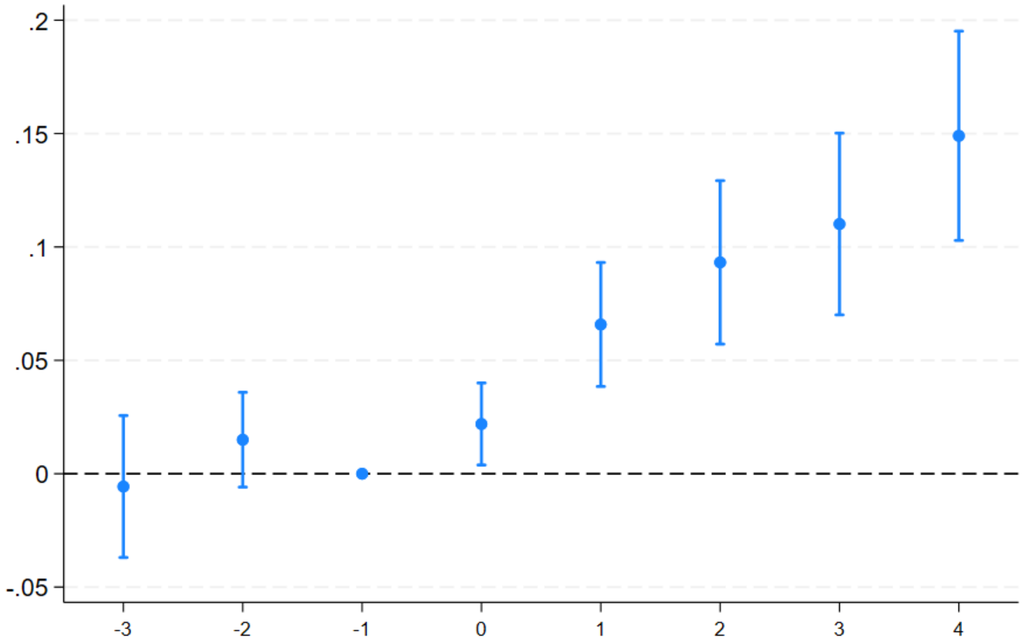


Note: In this figure, we analyze the dynamics of the number of banks the firm borrows from before and after the IPO using a matched sample. We form a matched sample by estimating propensity scores based on our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' last quarter in the year prior to the IPO. The matched sample includes the three closest firms in terms of propensity scores that are in the same two-digit NAICS industry and have 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:

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

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). $\lambda_{y,k,c}$ is a dummy equal to one if year y 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 and $\delta_{t,c}$ are time/cohort fixed effects. Year zero contains the quarter in which the firm IPOs. Standard errors are clustered by firm.

Figure 8: Syndicated Bank Loan Dynamics

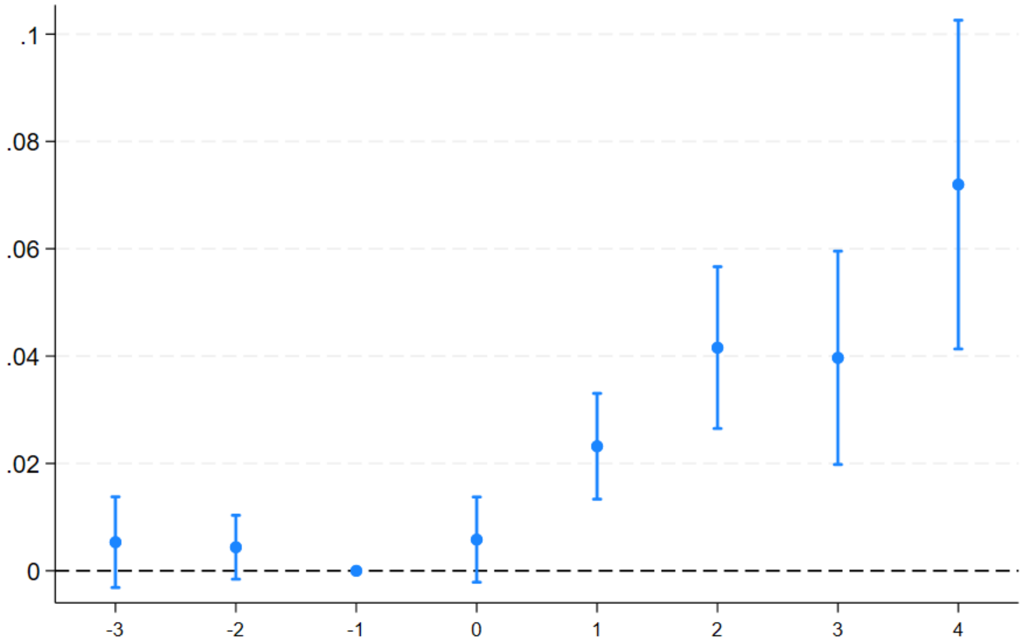


Note: In this figure, we analyze the dynamics of syndicated bank debt usage before and after the IPO using a matched sample. The dependent variable, Syndicated Debt/Debt, equals the ratio of syndicated loans outstanding over total debt. We form a matched sample by estimating propensity scores based on our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' last quarter in the year prior to the IPO. The matched sample includes the three closest firms in terms of propensity scores that are in the same two-digit NAICS industry and have 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:

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

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). $\lambda_{y,k,c}$ is a dummy equal to one if year y 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 and $\delta_{t,c}$ are time/cohort fixed effects. Year zero contains the quarter in which the firm IPOs. Standard errors are clustered by firm.

Figure 9: 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 based on our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' last quarter in the year prior to the IPO. The matched sample includes the three closest firms in terms of propensity scores that are in the same two-digit NAICS industry and have 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:

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

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). $\lambda_{y,k,c}$ is a dummy equal to one if year y 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 and $\delta_{t,c}$ are time/cohort fixed effects. Year zero contains the quarter in which the firm IPOs. 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.

	IPO Firms				Non-IPO Firms				
	N	Mean	Median	SD	N	Mean	Median	SD	Diff w.r.t. IPO firms
Sales ($mm)	2898	1424.45	365.29	5414.61	1439472	414.60	66.37	4530.40	-1009.851***
Assets ($mm)	2898	2019.63	549.01	6301.45	1439472	278.99	31.38	2601.11	-1740.649***
Capex/Assets	2680	0.08	0.03	0.13	1235073	0.05	0.02	0.10	-0.026***
Sales Growth	2684	0.42	0.16	0.73	1367765	0.15	0.07	0.42	-0.271***
EBITDA/Assets	2706	0.08	0.09	0.26	1372216	0.16	0.12	0.22	0.085***
Positive Profits	2706	0.76	1.00	0.43	1372216	0.89	1.00	0.31	0.130***
Financing Deficit	2679	-0.00	-0.05	0.29	1231510	-0.12	-0.09	0.23	-0.120***
Debt/Assets	2898	0.33	0.32	0.26	1439472	0.31	0.26	0.26	-0.021***
Cash/Assets	2895	0.16	0.06	0.22	1435851	0.12	0.07	0.15	-0.039***
VC-Backed	2898	0.29	0.00	0.45	1439472	0.02	0.00	0.12	-0.276***
Silicon Valley	2898	0.14	0.00	0.35	1438585	0.02	0.00	0.15	-0.122***
Tech/Life Science Firm	2898	0.23	0.00	0.42	1439472	0.06	0.00	0.23	-0.170***

Table 2: Summary Statistics: Loan-Level Sample

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

	N	Mean	Median	SD	P5	P95
Interest Rate (%)	58064	4.11	3.75	1.98	1.78	7.60
PD (%)	66620	1.56	0.88	2.89	0.14	4.54
LGD (%)	65034	33.21	34.97	15.00	7.00	54.60
PD $\times$ LGD (%)	64549	0.50	0.25	0.98	0.03	1.49
Maturity	73952	48.47	55.87	40.37	5.73	109.57
Loan Amount ($mm)	77944	10.91	3.80	32.37	1.00	40.00
Floating Rate	58822	0.69	1.00	0.46	0.00	1.00
Syndicated Loan	77944	0.13	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***	0.238***	0.251***	0.253***
	(0.019)	(0.018)	(0.020)	(0.023)
Sales Growth	0.507***	0.313***	0.491***	0.284***
	(0.058)	(0.041)	(0.060)	(0.051)
Debt/Assets	0.081	0.279***	0.123*	0.295***
	(0.061)	(0.063)	(0.064)	(0.084)
Financing Deficit	0.673***	0.637***	0.679***	0.582***
	(0.080)	(0.073)	(0.081)	(0.096)
Capex/Assets	0.154	-0.106	0.183	-0.079
	(0.156)	(0.124)	(0.163)	(0.190)
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	967151	1226028	960914	919120
R2	0.007	0.031	0.020	0.251

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	-1.491***	-0.767***	-1.492***	-1.156***
	(0.368)	(0.276)	(0.385)	(0.397)
Capex/Assets	1.259***	0.755***	1.294***	0.839***
	(0.239)	(0.181)	(0.249)	(0.266)
EBITDA/Assets	-0.556***	-0.568***	-0.563***	-0.486***
	(0.075)	(0.072)	(0.077)	(0.097)
Log(1+Sales)	0.241***	0.238***	0.252***	0.253***
	(0.019)	(0.018)	(0.020)	(0.023)
Sales Growth	0.507***	0.313***	0.492***	0.283***
	(0.059)	(0.041)	(0.060)	(0.051)
Debt/Assets	0.089	0.282***	0.131**	0.299***
	(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	967151	1226028	960914	919120
R2	0.007	0.031	0.020	0.251

Table 5: Cross-Sectional Determinants of Firms' IPO Decisions (VC-Backed Sample)

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)	2.393***	2.809***	2.441***	2.945***
	(0.322)	(0.382)	(0.347)	(0.525)
Sales Growth	1.043***	0.864***	1.009***	0.510*
	(0.328)	(0.307)	(0.337)	(0.288)
Debt/Assets	-3.170**	-2.507*	-2.940*	-2.355
	(1.455)	(1.448)	(1.660)	(2.054)
Financing Deficit	5.061***	6.367***	2.644*	4.143**
	(1.257)	(1.370)	(1.453)	(1.719)
Capex/Assets	3.183	0.787	6.007*	7.039*
	(2.858)	(2.916)	(3.207)	(3.787)
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	20450	18279	18710	11216
R2	0.069	0.224	0.179	0.358

Table 6: Going Public and Firms' Borrowing Costs

This table tests whether firms' borrowing costs drop after the IPO. The sample includes only new loans. 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	-0.511**	-0.435**	-0.427**	-0.384**
	(0.208)	(0.184)	(0.170)	(0.179)
Log(Assets)	-0.075***	-0.061**	-0.048**	-0.056**
	(0.026)	(0.024)	(0.024)	(0.026)
Sales Growth	0.030	0.034	0.047	0.055
	(0.037)	(0.036)	(0.034)	(0.040)
Debt/Assets	0.423***	0.444***	0.414***	0.368***
	(0.092)	(0.082)	(0.081)	(0.093)
EBITDA/Assets	-0.393***	-0.332***	-0.350***	-0.260***
	(0.100)	(0.078)	(0.076)	(0.073)
Capex/Assets	0.208*	0.148	0.154	0.189*
	(0.114)	(0.107)	(0.098)	(0.112)
PD (%)				-0.002
				(0.012)
LGD (%)				0.001
				(0.001)
PD × LGD (%)				0.141***
				(0.036)
Date FE	Y	Y	Y	Y
Bank/Firm FE	Y	Y	Y	Y
Bank/Date FE	N	N	Y	Y
Loan Controls	N	Y	Y	Y
N	37029	35822	35771	29723
R2	0.803	0.866	0.877	0.880

Appendix A. Additional Data Details

In this section, we present additional details primarily relating to our assembly 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, 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 92), and public administration and government entities (NAICS code 53). 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 we 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.

The Y-14 data includes the date indicating the period-end for each corresponding borrower firm’s latest financial data, which we use to construct our panel of borrower financial data. For smaller private firms, the financial data are generally updated on an annual basis, while for larger public firms, the financial data are generally updated quarterly. Throughout our analysis, we fill-down intra-year borrower financial data, by at most three quarters, for firms with financial data only reported at annual frequency. Our results are robust to the removal of the within-year fill-down process; however, the fill-down increases the power of our time-series tests.

For variables constructed from loan-level information, we use the dates that correspond to the borrower’s loan record, rather than the date of the borrower’s most recent financials. Because of the different date fields, constructing a panel that contains both the private firm's financial data and its banking characteristics requires constructing separate panels using the two sets of dates 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 a negative number. Therefore, we replace all capex records with their absolute value, prior to 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 also drop observations with negative debt.[58] 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 subsidiaries of private firms, in the Y-14 data using a process involving a merge with Compustat, which is 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.[59] 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 also exclude the top 1% of the largest firms, by assets, to ensure that we exclude miscoded 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 identifiers in both databases, to find TIN identifiers for each IPO firm, which are only included in the Compustat data. We then use TIN identifiers to merge the IPO firms

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

[59] 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.

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 manually select the closest firm, or firms, among these. For instances where we determine that there are no good match candidates, we do not designate a match. Through our hand-matching process, we also identify subsidiaries of IPO companies that were missed by our initial filters and drop 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. For each firm in Preqin, we assemble all firms in Y-14 with matching state codes and the 2-digit NAICS codes. Secondly, among each Preqin firm's location and industry peers, we select the Y-14 firm with the most similar firm name as 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 above 0.85. Using this method, 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 involves the same string-matching procedure using cleaned firm-names, and the same requirement that matches share the same location, and 2-digit NAICS industry codes.

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

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 total assets, winsorized at [1%, 99%], from Y-14.

Debt: Total debt, from Y-14.

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

Financing Deficit: (Capex-EBITDA)/Assets, winsorized at [1%, 99%], from Y-14.

Intangible Assets: Total assets minus tangible assets, from Y-14.

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

IPO: Dummy variable that equals one if the firm goes public within the next three years, multiplied by 100, 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 weight by the committed dollar amount of each loan at the bank/firm/quarter level, from Y-14 trimmed if $LGD = 0$ or $LGD = 1$.

Maturity: Remaining maturity in months weight by the committed dollar amount of each loan at the bank/firm/quarter level, from Y-14.

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

NAICS4 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, from Y-14.

Probability of Default (PD): The bank's expected annual default rate over the life of the loan weighted by the committed dollar amount of each loan at the bank/firm/quarter level, 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.

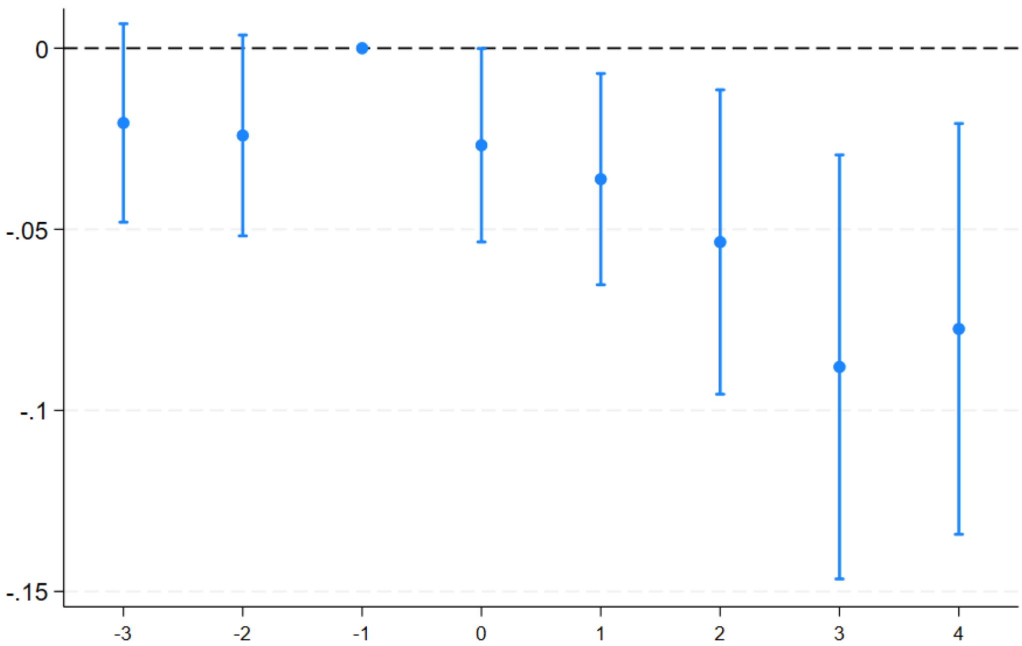
Syndicated Debt/Debt: The ratio of total syndicated bank debt to total debt, trimmed if > 1, from Y-14.

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: PD Dispersion Dynamics (Fixed Set of Banks)

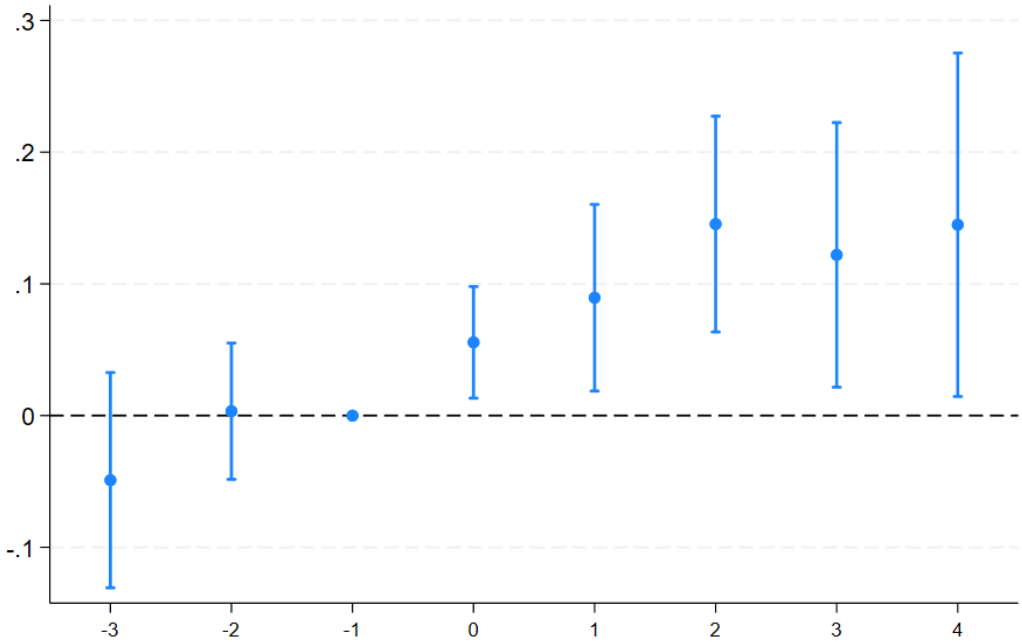


Note: In this figure, we analyze the dynamics of the dispersion in banks' probability of default (PD) estimates, measured as the cross-sectional standard deviation in PD within firm/time, using a matched sample that maintains a fixed set of banks for each firm throughout the analysis period. We form 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 to three control firms that are in the same two-digit NAICS industry and have 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:

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

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). $\lambda_{y,k,c}$ is a dummy equal to one if year y 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 and $\delta_{t,c}$ are time/cohort fixed effects. Year zero contains the quarter in which the firm IPOs. Year zero contains the quarter in which the firm IPOs. Standard errors are clustered by firm.

Figure C2: IPO Number of Banks Dynamics (Poisson Regression)

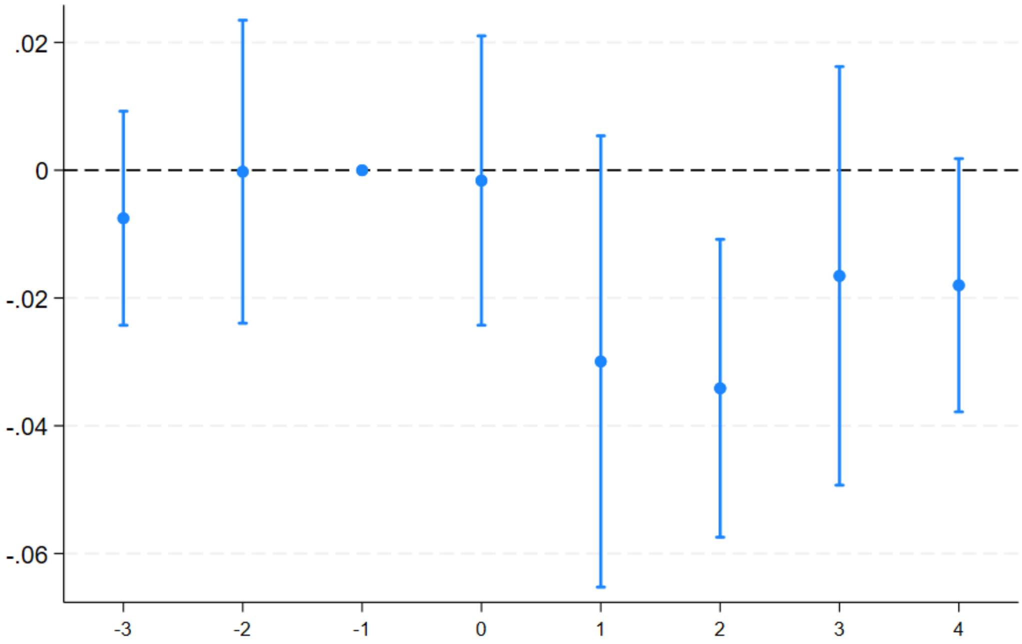


Note: In this figure, we analyze the dynamics of the number of banks firms borrow from before and after the IPO using a matched sample one quarter prior to IPO using a Poisson regression. We form a matched sample by estimating propensity scores based on our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' last quarter in the year prior to the IPO. The matched sample includes the three closest firms in terms of propensity scores that are in the same two-digit NAICS industry and have 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:

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

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). $\lambda_{y,k,c}$ is a dummy equal to one if the year y 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 and $\delta_{t,c}$ are time/cohort fixed effects. Year zero contains the quarter in which the firm IPOs. Standard errors are clustered by firm.

Figure C3: 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, 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 to three control firms that are in the same two-digit NAICS industry and have 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:

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

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). $\lambda_{y,k,c}$ is a dummy equal to one if year y 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 and $\delta_{t,c}$ are time/cohort fixed effects. Year zero contains the quarter in which the firm IPOs. Standard errors are clustered by firm.

Table C1: IPO Sample Composition

This table displays differences in the composition of our sample of IPO firms in the Y-14 data and 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. See Section 2.2 for details regarding our matching and filtering processes.

	(1)	(2)	(3)
NAICS 4-Digit Industry:	SDC IPO Sample	Assets Below $10mm	Y14 IPO Sample
Panel A: Number of Unique IPO Firms			
Pharmaceutical and Medicine Manufacturing	284	69	21
Scientific Research and Development Services (Biotech)	234	37	16
Software Publishers	161	35	72
Medical Equipment and Supplies Manufacturing	56	9	12
Computer Systems Design and Related Services	36	4	15
Electronic Instrument Manufacturing	32	8	7
Oil and Gas Extraction	21	0	15
Data Processing, Hosting and Related Services	20	6	10
Full Service Restaurants	18	2	11
Semiconductor and Electronic Component Manufacturing	17	4	6
Other	511	54	238
Total	1,390	228	423
Share of SDC Total		16%	30%
Panel B: Aggregate IPO Proceeds ($bn)			
Total IPO Proceeds	$346.2	$3.9	$211.8
Share of SDC Total		1%	61%

Table C2: 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, but 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.

	Merged IPO Firms				Unmerged IPO Firms				
	N	Mean	Median	SD	N	Mean	Median	SD	Diff w.r.t. Merged IPO Firms
Sales (*mm*)	2898	1424.45	365.29	5414.61	2932	381.95	0.20	1724.33	-1042.500***
Assets (*mm*)	2898	2019.63	549.01	6301.45	2932	573.42	59.91	1896.86	-1446.216***
Capex/Assets	2680	0.08	0.03	0.13	991	0.07	0.02	0.13	-0.005
Sales Growth	2684	0.42	0.16	0.73	535	0.30	0.21	0.44	-0.124***
EBITDA/Assets	2706	0.08	0.09	0.26	693	-0.19	-0.29	0.32	-0.263***
Positive Profits	2706	0.76	1.00	0.43	693	0.39	0.00	0.49	-0.372***
Debt/Assets	2898	0.33	0.32	0.26	2925	0.34	0.24	0.34	0.011
Cash/Assets	2895	0.16	0.06	0.22	2925	0.43	0.42	0.33	0.265***
VC-Backed	2898	0.29	0.00	0.45	2932	0.19	0.00	0.39	-0.104***
Silicon Valley	2898	0.14	0.00	0.35	2928	0.19	0.00	0.39	0.043***
Tech/Life Science Firm	2898	0.23	0.00	0.42	2932	0.62	1.00	0.48	0.396***

Table C3: Determinants of IPO Firms Being Present in Y-14 Data

This table tests which firm characteristics predict whether IPO firms are in our sample of Y-14 data 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. 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)
Pharma & Medicine Manufacturing	-0.325***	0.037
	(0.040)	(0.049)
Scientific R&D (Biotech)	-0.393***	0.010
	(0.042)	(0.051)
Software Publishers	0.075*	0.093**
	(0.043)	(0.039)
Medical Equipment Manufacturing	-0.210***	-0.030
	(0.080)	(0.072)
Computer Systems Design	0.009	0.048
	(0.098)	(0.093)
Electronic Instrument Manufacturing	-0.134	0.037
	(0.107)	(0.093)
Oil and Gas Extraction	0.073	0.022
	(0.084)	(0.096)
Data Processing & Hosting	-0.015	0.012
	(0.119)	(0.094)
Full-Service Restaurants	0.087	0.079
	(0.101)	(0.079)
Semis & Components Manufacturing	-0.095	0.018
	(0.152)	(0.130)
Log(Sales)		0.091***
		(0.007)
Year FE	Y	Y
N	1036	1036
R2	0.219	0.329
F-statistic (industry dummies)	17.642	0.764
F-test p-value	0.000	0.664

Table C4: 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	41	11.02
Computer Systems Design & Related Services	19	5.11
Data Processing, Hosting, & Related Service	16	4.30
Pharmaceutical & Medicine Manufacturing	15	4.03
Oil and Gas Extraction	13	3.49
Restaurants & Other Eating Places	11	2.96
Electronic Shopping	9	2.42
Support Activities for Mining	8	2.15
Lumber & Other Construction Materials Wholesalers	8	2.15
Other Information Services	7	1.88
Electric Power Gen, Transmission and Distribution	6	1.61
Miscellaneous Durable Goods Manufacturing	6	1.61
Scientific Research & Development Services	6	1.61
Traveler Accommodation	6	1.61
Navigation, Measuring, Electromed, & Control Instruments	5	1.34
Clothing Stores	5	1.34
Architectural, Engineering, & Related	5	1.34
Management, Scientific, & Technical Consulting	5	1.34
Other Amusement & Recreation Industries	5	1.34
Residential Building Construction	4	1.08
Semiconductor & Other Component Manufacturing	4	1.08
Professional & Commercial Equipment & Supplies Wholesalers	4	1.08
Grocery & Related Product Merchant Wholesalers	4	1.08
Advertising Agencies	4	1.08
Business Support Services	4	1.08
Investigation and Security Services	4	1.08
Other Wood Product Manufacturing	3	0.81
Basic Chemical Manufacturing	3	0.81
Soap, Cleaning Comp, and Toilet Prep Manufacturing	3	0.81
Plastics Product Manufacturing	3	0.81

Table C5: Location Composition of IPO Firms

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

Industry	# 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 C6: 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	13,478	13.40
Restaurants & Other Eating Places	2,782	2.77
Wholesale Distribution	2,415	2.40
Computer Systems Design & Related Services	1,939	1.93
Grocery & Related Product Merchant Wholesalers	1,682	1.67
Nonresidential Building Construction	1,574	1.56
Building Equipment Contractors	1,514	1.51
Architectural, Engineering, & Related	1,472	1.46
General Freight Trucking	1,463	1.45
Software Publishers	1,406	1.40
Management, Scientific, & Technical Consulting	1,372	1.36
Other Motor Vehicle Dealers	1,297	1.29
Misc Durable Goods Merchant Wholesalers	1,215	1.21
Plastics Product Manufacturing	1,064	1.06
Offices of Physicians	1,007	1.00
Electric Power Gen, Transmission and Distribution	988	0.98
Apparel & Accessories, Not Elsewhere	926	0.92
Other Amusement & Recreation Industries	919	0.91
Motor Vehicle Parts & Supplies Wholesalers	895	0.89
Professional & Commercial Equipment & Supplies Wholesalers	876	0.87
Household Appliances & Electrical Goods Wholesalers	872	0.87
Lumber & Other Construction Materials Wholesalers	871	0.87
General Medical & Surgical Hospitals	867	0.86
Legal Services	859	0.85
Highway, Street, and Bridge Construction	858	0.85
Management of Companies and Enterprises	852	0.85
Nursing Care Facilities	817	0.81
Support Activities for Mining	774	0.77
Miscellaneous Nondurable Goods Wholesalers	746	0.74
Oil and Gas Extraction	744	0.74

Table C7: Location Composition of Private Firm Sample

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

Industry	# of Firms	% of Total
New York-Newark-Jersey City	8,948	8.93
Los Angeles-Long Beach-Anaheim	4,644	4.63
Chicago-Naperville-Elgin	4,030	4.02
Philadelphia-Camden-Wilmington	2,692	2.69
Indianapolis-Carmel-Anderson	2,602	2.60
Non-Metro Area	2,417	2.41
Dallas-Fort Worth-Arlington	2,301	2.30
Washington-Arlington-Alexandria	2,248	2.24
San Francisco-Oakland-Hayward	2,209	2.20
Miami-Fort Lauderdale-West Palm Beach	2,177	2.17
Boston-Cambridge-Newton	2,168	2.16
Detroit-Warren-Dearborn	2,120	2.12
Atlanta-Sandy Springs-Roswell	1,960	1.96
Seattle-Tacoma-Bellevue	1,439	1.44
Minneapolis-St. Paul-Bloomington	1,348	1.35
Cleveland-Elyria	1,247	1.24
Phoenix-Mesa-Scottsdale	1,192	1.19
Denver-Aurora-Lakewood	1,122	1.12
Charlotte-Concord-Gastonia	1,117	1.11
Orlando-Kissimmee-Sanford	1,035	1.03
Portland-Vancouver-Hillsboro	1,035	1.03
Sacramento-Roseville-Arden-Arcade	957	0.96
San Antonio-New Braunfels	954	0.95
Riverside-San Bernardino-Ontario	925	0.92
Tampa-St. Petersburg-Clearwater	899	0.90
Columbus, OH	894	0.89
Milwaukee-Waukesha-West Allis	830	0.83
Indianapolis-Carmel-Greenwood	822	0.82
San Jose-Sunnyvale-Santa Clara	800	0.80
Grand Rapids-Wyoming	756	0.75

Table C8: 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)	1.082***	0.861***	1.061***	0.875***
	(0.173)	(0.143)	(0.179)	(0.173)
Sales Growth	1.138***	0.748***	1.085***	0.436**
	(0.263)	(0.189)	(0.279)	(0.178)
Debt/Assets	0.932	0.385	0.785	-0.243
	(0.607)	(0.495)	(0.622)	(0.553)
Financing Deficit	2.672***	2.398***	2.359***	1.839***
	(0.427)	(0.355)	(0.435)	(0.370)
Capex/Assets	0.049	-0.671	-0.053	-0.323
	(1.303)	(1.024)	(1.262)	(1.110)
NAICS4 MTB	0.749***		0.738***	
	(0.210)		(0.239)	
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	62664	75547	59370	61176
R2	0.032	0.041	0.119	0.218

Table C9: Cross-Sectional Determinants of Firms' IPO Decisions (VC-Backed Technology and Life Science Firms Only)

This table tests which firm characteristics predict whether firms go public within the next three years among VC-backed, technology and life science 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)	3.301***	3.532***	3.174***	3.814***
	(0.503)	(0.541)	(0.536)	(0.671)
Sales Growth	1.333***	1.062***	1.183***	0.773**
	(0.360)	(0.328)	(0.347)	(0.344)
Debt/Assets	-4.033**	-4.808***	-4.668**	-3.828
	(1.705)	(1.607)	(1.829)	(2.511)
Financing Deficit	5.230***	6.238***	2.118	5.962***
	(1.779)	(1.717)	(2.100)	(2.063)
Capex/Assets	5.587	1.772	12.563**	5.311
	(4.183)	(3.997)	(5.122)	(4.959)
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	10797	10402	9687	7628
R2	0.097	0.188	0.224	0.329

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)	0.255***	0.247***	0.264***	0.261***
	(0.020)	(0.018)	(0.021)	(0.023)
Sales Growth	0.291***	0.203***	0.295***	0.187***
	(0.052)	(0.038)	(0.054)	(0.048)
Debt/Assets	0.227***	0.355***	0.248***	0.364***
	(0.058)	(0.062)	(0.062)	(0.083)
Financing Deficit	0.214***	0.271***	0.249***	0.240***
	(0.067)	(0.064)	(0.069)	(0.089)
Capex/Assets	0.441***	0.072	0.430***	0.092
	(0.157)	(0.125)	(0.164)	(0.193)
NAICS4 MTB	0.062***		0.065***	
	(0.012)		(0.013)	
VC-Backed	5.174***	3.458***	5.095***	3.317***
	(0.555)	(0.414)	(0.569)	(0.481)
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	967151	1226028	960914	919120
R2	0.020	0.037	0.032	0.256

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 were acquired 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)	0.232***	0.228***	0.242***	0.240***
	(0.019)	(0.018)	(0.020)	(0.022)
Sales Growth	0.510***	0.318***	0.498***	0.299***
	(0.059)	(0.042)	(0.060)	(0.051)
Debt/Assets	0.050	0.241***	0.089	0.253***
	(0.060)	(0.061)	(0.063)	(0.082)
Financing Deficit	0.672***	0.633***	0.682***	0.601***
	(0.081)	(0.074)	(0.082)	(0.097)
Capex/Assets	0.179	-0.079	0.205	-0.085
	(0.157)	(0.124)	(0.164)	(0.189)
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	961535	1219660	955315	913705
R2	0.007	0.030	0.020	0.250

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)	0.443***	0.515***	0.459***	0.454***
	(0.038)	(0.041)	(0.040)	(0.046)
Sales Growth	1.212***	1.039***	1.202***	0.825***
	(0.145)	(0.133)	(0.149)	(0.157)
Debt/Assets	0.187*	0.814***	0.298**	0.829***
	(0.113)	(0.139)	(0.120)	(0.171)
Financing Deficit	1.252***	1.680***	1.300***	1.407***
	(0.159)	(0.194)	(0.163)	(0.251)
Capex/Assets	0.464	-0.622**	0.486	-0.553
	(0.320)	(0.301)	(0.338)	(0.450)
NAICS4 MTB	0.190***		0.200***	
	(0.027)		(0.029)	
Date FE	Y	N	N	N
Date $\times$ NAICS4 FE	N	Y	N	N
Date $\times$ CBSA FE	N	N	Y	N
Date $\times$ NAICS4 $\times$ CBSA FE	N	N	N	Y
N	494040	537783	488297	367318
R2	0.115	0.120	0.109	0.342

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	0.115***	0.015	0.180***
	(0.018)	(0.026)	(0.021)	(0.057)
Sales Growth	0.337***	0.302***	0.348***	0.258***
	(0.041)	(0.040)	(0.045)	(0.063)
Debt/Assets	0.045	0.065	0.089	0.190*
	(0.051)	(0.059)	(0.061)	(0.114)
Financing Deficit	0.376***	0.479***	0.404***	0.576***
	(0.060)	(0.070)	(0.067)	(0.119)
Capex/Assets	0.086	0.099	0.187	0.207
	(0.122)	(0.125)	(0.142)	(0.225)
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	1226248	1210242	1156429	562407
R2	0.012	0.137	0.077	0.410

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)	0.307***	0.379***	0.339***	0.431***
	(0.036)	(0.036)	(0.039)	(0.058)
Sales Growth	0.975***	0.583***	0.943***	0.514***
	(0.119)	(0.084)	(0.122)	(0.115)
Debt/Assets	0.387**	0.543***	0.468***	0.560**
	(0.160)	(0.147)	(0.176)	(0.240)
Financing Deficit	1.325***	1.367***	1.364***	1.463***
	(0.204)	(0.203)	(0.213)	(0.331)
Capex/Assets	0.214	-0.101	0.438	0.086
	(0.407)	(0.317)	(0.442)	(0.496)
NAICS4 MTB	0.234***		0.226***	
	(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	358406	462282	351184	295632
R2	0.007	0.057	0.039	0.313

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)	0.176***	0.178***	0.181***	0.175***
	(0.017)	(0.016)	(0.018)	(0.018)
Sales Growth	0.342***	0.220***	0.349***	0.252***
	(0.053)	(0.038)	(0.055)	(0.050)
Debt/Assets	0.129**	0.266***	0.143**	0.260***
	(0.052)	(0.056)	(0.056)	(0.075)
Financing Deficit	0.387***	0.392***	0.419***	0.451***
	(0.069)	(0.065)	(0.072)	(0.092)
Capex/Assets	0.269*	0.002	0.261*	-0.071
	(0.140)	(0.111)	(0.148)	(0.182)
NAICS4 MTB	0.054***		0.058***	
	(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	887196	1127309	881053	839071
R2	0.005	0.027	0.018	0.258

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***	0.238***	0.251***	0.253***
	(0.019)	(0.018)	(0.020)	(0.023)
Sales Growth	0.507***	0.313***	0.491***	0.284***
	(0.058)	(0.041)	(0.060)	(0.051)
Debt/Assets	0.081	0.279***	0.123*	0.295***
	(0.061)	(0.063)	(0.064)	(0.084)
Financing Deficit	0.673***	0.637***	0.679***	0.582***
	(0.080)	(0.073)	(0.081)	(0.096)
Capex/Assets	0.154	-0.106	0.183	-0.079
	(0.156)	(0.124)	(0.163)	(0.190)
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	967151	1226028	960914	919120
R2	0.007	0.031	0.020	0.251

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 6, but includes an additional control for whether the loan is syndicated. The sample includes only new loans. 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	-0.485**	-0.480**	-0.470***	-0.432**
	(0.203)	(0.190)	(0.178)	(0.186)
Log(Assets)	-0.070***	-0.070***	-0.056**	-0.063**
	(0.027)	(0.025)	(0.024)	(0.026)
Sales Growth	0.028	0.038	0.050	0.058
	(0.037)	(0.036)	(0.034)	(0.040)
Debt/Assets	0.431***	0.431***	0.399***	0.355***
	(0.092)	(0.081)	(0.080)	(0.092)
EBITDA/Assets	-0.394***	-0.329***	-0.348***	-0.260***
	(0.100)	(0.077)	(0.076)	(0.073)
Capex/Assets	0.206*	0.153	0.159	0.189*
	(0.114)	(0.106)	(0.098)	(0.112)
PD (%)				-0.002
				(0.012)
LGD (%)				0.001
				(0.001)
PD × LGD (%)				0.142***
				(0.036)
Date FE	Y	Y	Y	Y
Syndication FE	Y	Y	Y	Y
Bank/Firm FE	Y	Y	Y	Y
Bank/Date FE	N	N	Y	Y
Loan Controls	N	Y	Y	Y
N	37029	35822	35771	29723
R2	0.803	0.866	0.877	0.880