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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. Firms with higher external capital needs are more likely to go public. Following the IPO, firms increase investment and debt issuance, leaving their leverage ratios un-changed from pre-IPO levels. Finally, newly public firms borrow from an expanded pool of lenders on improved terms, and the within-firm dispersion in banks' private risk assessments declines. Our analysis suggests that firms go public to improve their access to capital, which is facilitated by reduced asymmetric information, and that the benefit extends beyond the IPO itself to new sources of debt.

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1 Introduction

A central function of financial markets is to allocate capital to firms with valuable investment opportunities. Going public is one of the most consequential changes a firm can make in how it accesses capital markets. By changing the firm's information environment, an initial public offering (IPO) can reshape its financing opportunities and, in turn, its ability to undertake valuable investments. Understanding why firms go public is therefore a fundamental question in corporate finance.

Despite the importance of this question and the vast literature on IPOs, we still have a limited understanding of why private firms go public. Two questions are central to understanding the IPO decision. First, which types of private firms choose to go public? Second, what happens to these firms after they go public? Answering these questions requires detailed data on firms that ultimately go public as well as comparable firms that remain private, observed both before and after the IPO. Such data are difficult to obtain, particularly in the US, the world's largest IPO market. Existing studies have consequently examined disparate aspects of the IPO decision using different datasets from different countries; however, basic questions about firms' IPO decisions remain unanswered. For example, how do firms' capital structures and funding sources change after going public? These changes are central to understanding how the IPO affects firms' access to capital. However, the most commonly used private-firm datasets in the US have little, if any, information on firms' financing decisions. More generally, no prior study has followed a panel of US private firms with detailed financial statements and financing information and jointly analyzed which firms go public and how their investment and financing decisions subsequently change.

In this paper, we conduct such an analysis using Federal Reserve Y-14Q data. The data include detailed quarterly financial information for a broad set of US private firms, including balance sheet and income statement information, along with granular information on bank borrowing and banks' private risk assessments. Our analysis produces a consistent picture of the IPO decision based on the idea that improved access to capital, driven by reductions in asymmetric information, is a key motive for firms going public. The financing benefit, however, extends beyond a one-time infusion of equity capital. Going public expands firms' broader financing capacity, including access to syndicated loans and public bonds.[1] This improved access is also associated with better terms: firms receive lower interest rates on their bank borrowing conditional on lenders' own assessments of credit risk. At the same time, consistent with reduced asymmetric infor-

[1]Consistent with this mechanism, shortly after its IPO, SpaceX issued its first bond, of $25bn, which was rated investment grade. Bankers advising OpenAI and Anthropic have likewise sought investment-grade credit ratings for the firms ahead of their planned IPOs, to help facilitate access to bond financing. See Musk's SpaceX Adds Billions In Debt While Cutting Interest Costs and Anthropic and OpenAI bankers push for top-tier credit ratings post-IPO.

mation, the dispersion in those assessments falls immediately after the IPO. Together, our findings suggest a broader, more dynamic view of the IPO. Going public changes the firm's information environment, and it is this change, rather than the offering itself, that expands the firm's access to capital across debt as well as equity markets.

We begin our analysis by examining which types of private firms are more likely to go public using predictive regressions similar to Pagano, Panetta, and Zingales (1998). We find that firms more reliant on external capital, as proxied by their financing deficit, (Capex − EBITDA)/Assets, are more likely to go public in the future. Specifically, we find that a one-standard-deviation increase in a firm's financing deficit is associated with a 45% higher likelihood of going public. In addition, when we separately analyze the two components of the financing deficit, we find that ex-ante investment, i.e., Capex/Assets, positively predicts future IPOs, while profitability, i.e., EBITDA/Assets, negatively predicts future IPOs. Moreover, the relationship between ex-ante investment and going public is stronger for less profitable firms.[2]

We next analyze firms' investment and financing choices before and after they go public by matching IPO firms with comparable firms that remain private. Compared with matched control firms, IPO firms' capex and total assets increase by 55% and 40%, respectively, three years after their IPOs. This post-IPO asset growth is not financed solely by the influx of equity capital from the IPO; it 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 from those of control firms three 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, this drop in rates may instead be driven purely by reductions in risk.[3] To distinguish between these explanations, 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.[4] We find that after controlling for these risk assessments, firms' borrowing costs drop by 45 bps after going public. These results suggest that the lower interest rates firms receive on their loans after going public are not solely due to reduced risk, but also reflect more favorable terms.

Our explanation for the improvement in bank loan terms is that the reduction in

[2]The link between capital needs and going public was articulated by John Collison, Stripe's 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).

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

[4]Beyhaghi, Fracassi, and Weitzner (2026) show that 1) these risk assessments strongly predict future loan performance and 2) interest rates no longer predict firm performance after controlling for them.

information asymmetries following the IPO reduces the information rents that informed financiers can extract from the firm. Because firms often borrow from multiple banks at the same time, we can proxy for the degree of asymmetric information using the within-firm dispersion in banks' PD assessments. Consistent with a reduction in asymmetric information, we find that PD dispersion drops after the IPO.

If going public reduces asymmetric information, firms should be able to expand their borrowing beyond their existing lenders. Accordingly, our final tests examine how the composition of firms' debt changes after the IPO. We first document a significant increase in the number of banks IPO firms borrow from after going public. We then show that firms substantially increase their use of syndicated loans and public bonds following the IPO. These findings suggest that, beyond providing equity capital, going public expands firms' access to debt financing beyond their pre-IPO lending relationships, facilitating access to both syndicated loan and public bond markets.[5]

Our post-IPO estimates capture both treatment and selection effects. As we discuss in more detail below, we cannot use the standard Bernstein (2015) instrument during our sample period to separate the two.[6] While isolating the treatment effects of IPOs is clearly important, selection effects, i.e., which types of firms *choose* to go public, are also important. For example, if an IPO lowers firms' cost of external capital, as our analysis suggests, firms will invest more after going public; at the same time, firms that anticipate greater future investment will be more likely to go public in the first place. Several of our findings regarding the access-to-capital channel, however, are difficult to reconcile with selection alone. If the convergence in bank risk assessments induced firms to go public, we would expect it to occur before the IPO; instead, it occurs only after.[7] Similarly, we find that firms receive improved terms on their bank debt after going public, whereas selection would predict that firms are less likely to go public if they anticipate an improvement in terms regardless of their listing status.

As discussed above, the literature on why firms go public is vast. Because of data limitations, much of this work analyzes individual aspects of the IPO decision in isolation. However, establishing that access-to-capital is a primary motive for going public requires jointly showing that (i) firms with greater external financing needs are more likely to go public, (ii) firms raise additional capital and increase investment after going public, (iii)

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

[6]This instrument uses data on firms that file to go public but may ultimately withdraw, instrumenting for the completion decision with market-wide returns. See also Babina, Ouimet, and Zarutskie (2020), Borisov, Ellul, and Sevilir (2021), Cornaggia et al. (2021), Cornaggia et al. (2022) and Larrain et al. (2025).

[7]As we discuss below, the sudden drop in PD dispersion right after the IPO is also inconsistent with our results being driven by changes in the firm's business model, which begin well before the IPO (Bias et al., 2025).

the cost of external finance falls, and (iv) to the extent the lower cost of external finance reflects reduced asymmetric information, asymmetric information falls after the IPO. We document all four within a single sample of US firms. We also provide new results on how firms' information environment changes after going public. Finally, we offer a broader perspective on the mechanism, showing how the financing benefits extend beyond the equity raised in the IPO to firms' subsequent access to debt capital. Below, we discuss how our findings relate to, contrast with, and extend the literature examining individual pieces of this mechanism.

We first contribute to the literature examining which private firms *choose* to go public (e.g., Pagano, Panetta, and Zingales, 1998; Chemmanur, He, and Nandy, 2010; Aslan and Kumar, 2011; Gopalan and Gormley, 2013; Maksimovic, Phillips, and Yang, 2023). The seminal study by Pagano, Panetta, and Zingales (1998), which examines private firms in Italy, finds a negative relationship between ex-ante investment and going public, whereas more recent studies by Chemmanur, He, and Nandy (2010) and Aslan and Kumar (2011) find a positive relationship in samples of US manufacturing firms and UK firms, respectively. Inconsistent with the access-to-capital channel, studies using European data also find that more profitable firms are more likely to go public (e.g., Pagano, Panetta, and Zingales, 1998; Aslan and Kumar, 2011). In contrast with the existing literature on European firms, we find that profitability negatively predicts IPOs, and the relationship between investment and going public is stronger for less profitable firms. Together, these results point specifically to the need for external capital as a driver of firms' IPO decisions.

A second part of the literature examines firms' financing and investment decisions *after* they go public. Pagano, Panetta, and Zingales (1998) find that investment declines after the IPO, while more recent studies document increased investment or specifically analyze the use of IPO proceeds to fund investment (e.g., Jain and Kini, 1994; Mikkelson, Partch, and Shah, 1997; Kim and Weisbach, 2008; Aslan and Kumar, 2011). Larrain et al. (2025) use the instrument in Bernstein (2015) to estimate the effect of IPO completion among European firms that have filed to go public, finding increases in sales and profitability.

An increase in investment after the IPO does not, by itself, establish that improved access to capital drives expansion, or that this is why firms go public in the first place. First, improved access to capital may be a consequence of the IPO, not the reason firms go public. Our ex-ante results, however, show that firms with higher external capital needs *choose* to go public. Second, going public may raise demand for firms' products, whether through greater visibility or because a market price certifies firm quality to customers and suppliers, encouraging expansion even without improved financing opportunities (Stoughton, Wong, and Zechner, 2001; Maksimovic and Pichler, 2001; Demers and Lewellen, 2003). Moreover, firms may simply fund the new investment with equity raised in the offering rather than through subsequent capital raises. Distinguishing these explanations requires examining how firms' financing changes alongside their investment.

Importantly, our data also let us examine how firms finance their post-IPO investment and how their capital structures and sources of funds evolve relative to comparable firms that remain private.[8] Whereas Pagano, Panetta, and Zingales (1998) find a decline in leverage following IPOs, we find that firms rebalance by increasing their debt issuance after the IPO. We also document that firms borrow from more banks and increase their use of syndicated loans and public bonds after the IPO.[9] These results suggest that going public expands subsequent financing capacity beyond the equity raised in the offering.

We also show that this increase in debt financing corresponds to IPO firms receiving better debt terms after the IPO. While a few studies find that public firms borrow at lower interest rates than private firms or that borrowing costs decline around IPOs (e.g., Pagano, Panetta, and Zingales, 1998; Schenone, 2010; Saunders and Steffen, 2011; Lin and Zhang, 2025),[10] these comparisons do not necessarily imply more favorable financing terms. Firms' operations and capital structures change substantially around the IPO, so lower borrowing costs may reflect improvements in credit risk rather than changes in financing terms. We find that bank borrowing costs decline following the IPO relative to those of comparable firms that remain private, even after conditioning on banks' internal risk assessments. Thus, our evidence links the expansion in debt financing to improved borrowing terms not explained by risk.

Finally, the convergence in lenders' private assessments provides new evidence consistent with a reduction in asymmetric information after the IPO and a potential explanation for the improvement in borrowing terms. Theories of disclosure and informed finance show how reduced asymmetric information can lower adverse-selection costs and the information rents earned by informed financiers (e.g., Diamond, 1985; Sharpe, 1990; Diamond and Verrecchia, 1991; Rajan, 1992; Chemmanur and Fulghieri, 1999; Easley and O'Hara, 2004). Moreover, the convergence persists in subsequent years, suggesting that the information benefit is relevant to capital providers well after the IPO itself.

Taken together, across both ex-ante and ex-post dimensions, we find evidence consistent with access to capital being a central motive for going public. Firms with greater external capital needs not only choose to go public, but going public also appears to create a persistently different information environment that expands firms' financing capacity across bank loans, syndicated loans, bonds, and equity, thereby supporting subsequent investment. In this sense, the IPO is not simply a single equity financing event, but a

[8]Commonly used US Census datasets provide broad coverage of private firms or detailed information on production and investment, but lack the financing information needed to examine these outcomes jointly. Alti (2006) analyzes leverage ratios after the IPO; however, he compares different types of IPO firms, not IPO firms to those that remain private.

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

[10]Schenone (2010) and Lin and Zhang (2025) study changes in borrowing costs among US IPO firms without a private control group, while Saunders and Steffen (2011) compare public and private firms in the UK.

transition to a different information and financing environment.

2 Data

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

2.1 Sample of Private Firms

Our main data source 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 for all corporate loans exceeding $1 million. 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 an FR Y-9C report (Bidder, Krainer, and Shapiro, 2020). Our sample of private firms starts in 2012, when borrower financial data became fully populated.

We apply several filters consistent with other papers using the Y-14 data (e.g., Gustafson, Ivanov, and Meisenzahl, 2020; Beyhaghi, Fracassi, and Weitzner, 2026). 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), and public administration and government entities (NAICS code 92).[11] We also drop firms with less than $10mm in assets because these firms are unlikely to go public. Additionally, because we compare private firms that go public with those that remain private, we exclude public firms that never appear as private during our sample period. We identify public firms, as well as their subsidiaries, in the Y-14 data using a multi-step process similar to that of Beyhaghi et al. (2024), which we discuss in detail in Appendix A.2.

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

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

a quarterly panel with over one million firm-quarter observations and just over 100,000 unique private firms. Firms are in the panel when they obtain at least one loan from at least one qualified bank. Firms exit the panel if they default, their loans end and are not renewed, or the bank sells the firm's loan or loans to another bank or financial firm not in the Y-14 sample.

2.2 IPO Firms

We use SDC Platinum (from LSEG Data and Analytics) to obtain US IPO data. Following Bernstein (2015), we exclude financial firms (SIC codes between 6000 and 6999), unit trusts, closed-end funds, real estate investment trusts (REITs), American depositary receipts (ADRs), limited partnerships, direct listings, "blank check" special purpose acquisition companies (SPACs), and spin-offs. These filters result in 1,364 unique firms in the SDC data that go public between 2013 and 2023. We start the IPO sample in 2013 so that the private firms in our sample have at least one year to go public.

To merge the IPO data into the Y-14 dataset, we use a multi-step matching process, described in more detail in Appendix A.3. Using this process, we identify 433 unique IPOs (a 32% match rate) in the Y-14 data within a three-year window prior to the IPO.[12]

Our data do 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.[13] Although our match rate is less than half on an absolute basis, we match the majority of the larger IPOs. Specifically, Appendix Table C1 shows that the IPOs that we do match account for 62% of the aggregate IPO proceeds, suggesting that our sample of IPOs tends to comprise larger private firms.[14] Appendix Table C2 compares the distribution of total assets prior to the IPO and IPO proceeds for our sample of IPO firms in the Y-14 data with IPO firms in SDC that are not in our sample. Appendix Table C3 compares IPO firm-quarters for IPOs in our sample to those only in SDC, using pre-IPO financial data from Compustat. IPOs in our sample are indeed much larger in terms of sales and assets.

Appendix Table C1 also shows that our IPO sample is not fully representative of all IPOs over this period by industry. For example, there are 520 pharma and biotech IPOs

[12]For comparison, Maksimovic, Phillips, and Yang (2023) identify 48% of the firms from Jay Ritter's IPO data in the US Census data. We choose a three-year window because our ex-ante tests examine which characteristics predict firms going public over this horizon.

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

[14]Our sample includes 65% of IPOs larger than $250mm and 76% of IPOs larger than $500mm in proceeds.

over this period, but only 40 in our sample. However, firm size appears to explain this industry effect entirely. Appendix Table C4 includes regressions in which the dependent variable is a dummy equal to 1 if the IPO firm is in our sample. Column (1) includes dummy variables for the ten largest industries in the overall IPO sample. Consistent with Table C1, the coefficients for pharma and biotech are negative and statistically significant, and the F-statistic suggests that the industry dummies are jointly significant. However, in column (2), when we include Log(1+Sales) to control for firm size, the pharma and biotech coefficients are much smaller in magnitude and no longer statistically significant. Moreover, the F-statistic is barely above one, suggesting that firm size can fully explain the difference in industry composition in our sample.

That our sample consists of relatively large private firms that borrow from large banks suggests that these firms already have relatively good access to capital and thus have less need to go public. In this respect, sample selection likely works against the access-to-capital hypothesis we explore in our analysis. That said, most firms that go public have some debt prior to going public.[15] For example, Barry and Mihov (2015) use pre-IPO financials from Compustat and find that only 11% of firms that go public report zero debt (excluding convertible bonds) prior to the IPO. Similarly, in the sample of IPOs reported in SDC during our sample period, only 13% of firms report zero debt and 19% have less than $1mm of debt prior to the IPO. Moreover, this measure likely overstates the prevalence of debt-free firms, as it excludes debt-like instruments such as convertible preferred and straight preferred stock, which are common financing instruments for VC-backed firms (Metrick and Yasuda, 2021), and firms with undrawn credit lines that appear in our Y-14 sample.

Finally, IPO firms in our sample appear to raise new equity capital rather than merely providing liquidity to pre-IPO shareholders. In our sample, primary shares represent, on average, 95% of the shares sold in the offering, implying that the bulk of IPO proceeds accrues directly to the issuing firms. Kim and Weisbach (2008) document similar patterns in an earlier sample period. In the analysis that follows, we investigate whether capital raising is largely confined to the IPO equity infusion or instead reflects the onset of a broader and more sustained effort to access multiple sources of external capital after going public.

2.3 Firm-Level Panel

We use the Y-14 data to construct a quarterly panel of private firms from 2012 to 2023, supplementing it with VC financing data from the Preqin VC funding database.[16] We merge the Preqin data with the Y-14 data using industry, location, and firm name, as

[15] Bank debt is also common among private firms that do not IPO (e.g., Robb and Robinson, 2014).

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

further detailed in Appendix A.4.[17] We use similar matching methods to identify private firms that are acquired based on the SDC Platinum mergers and acquisitions dataset.[18]

Appendix Tables C5 and C6 display the ten largest industries and locations of the IPO firms in our sample, and Appendix Tables C7 and C8 display the industry and location composition of the other private firms in our sample. While the firms that go public represent a variety of industries and are located in many different cities, they are clustered in technology-related industries, and many are located in the San Francisco Bay Area. By contrast, the top industries for the entire sample of private firms tend to be consumer retail-related, such as auto dealers and restaurants, with locations more aligned with the overall US population distribution.

We define a firm's IPO quarter as the latest quarter in which we observe Y-14 data within the three-year window preceding the IPO. We also create the dummy variable IPO, which equals one if the firm goes public in the next three years. We construct several standard corporate finance variables (e.g., investment and profitability).[19]

Table 1 provides summary statistics comparing financial information for IPO firm-quarters to non-IPO firm-quarters. Unsurprisingly, IPO firms have greater assets and sales than the broader sample of private firms. Moreover, IPO firms invest more (0.08 versus 0.05 Capex/Assets) and are less profitable (0.07 versus 0.16 EBITDA/Assets). As we discuss later, an important variable in our analysis is the financing deficit, defined as (Capex − EBITDA)/Assets, which measures the amount of external financing a firm needs beyond what it generates internally.[20] This variable is standard in the literature (e.g., Shyam-Sunder and Myers, 1999; Frank and Goyal, 2003); however, we exclude some smaller components that are unavailable or poorly populated in the Y-14 data, such as changes in net working capital. On average, IPO firms have a financing deficit close to zero (0.03), whereas the average financing deficit of non-IPO firms is substantially negative (-0.11), implying that the average firm that stays private generates more cash flow internally than it needs to fund its investment. IPO firms are also more likely to be VC-backed than non-IPO firms (32% versus 1%), and are much more likely to be located in Silicon Valley (15% versus 2%) and operate in technology and life sciences industries

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

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

[19]The latest instructions detailing what qualifying banks are required to report can be found here: FR Y-14 Instructions. To minimize the impact of outliers, we winsorize ratio variables at the 1st and 99th percentiles, except for the industry market-to-book ratio, which we winsorize at the 97th percentile due to extreme right-tail skewness. Appendix B contains detailed definitions of the variables used throughout the paper.

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

(32% versus 6%).[21]

2.4 Loan-Level Sample

We also construct a loan-level sample. We form this sample by merging 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 loan-level records from the Y-14 data. The specific set of loan observations we use varies across tests.

In addition to basic information about the loan, such as its size, interest rate, maturity, and syndication status, the data contain each bank's private assessments of the borrower's probability of default (PD) and the loan's expected loss given default (LGD). More specifically, PD is a long-run, borrower-level annual default rate, and LGD is a long-run expected loss per dollar of exposure in default. According to the Basel Committee on Banking Supervision, internal estimates of PD and LGD "*must incorporate all relevant, material and available data, information and methods. A bank may utilize internal data and data from external sources (including pooled data).*"[22] 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.*"

Following Beyhaghi, Fracassi, and Weitzner (2026), we apply a few additional filters to the loan-level data. Specifically, we exclude observations with missing, negative or zero interest rates. We also drop observations in which the PD or LGD is missing, zero, or greater than or equal to one. Table 2 contains summary statistics for newly originated loans in the loan-level sample.

3 Empirical Analysis

Our empirical analysis is divided into six parts. In Section 3.1, we test which characteristics predict the decision to IPO in the cross-section of private firms. In Section 3.2, we examine the dynamics of firm outcomes before and after the IPO based on a matched sample of firms that remain private. In Section 3.3, we examine the change in firms' borrowing costs after the IPO. In Section 3.4, we examine changes in asymmetric information after the IPO. In Section 3.5, we explore changes in the composition of firms' debt

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

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

after they go public. Finally, in Section 3.6, we discuss the extent to which our findings capture both treatment and selection effects.

3.1 Which Firm Characteristics Predict IPOs?

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

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

where i, j, and t index firm, industry, and quarterly date, respectively. The dependent variable $IPO_{i,t+1:t+12}$ is a dummy variable that equals one if the firm goes public within the next twelve quarters, which we multiply by 100, and $X_{i,t}$ is a vector of firm-level predictors. The primary variable of interest is the financing deficit, (Capex − EBITDA)/Assets, which proxies for the firm's expected external financing needs. Under the access-to-capital channel, we expect that firms with higher financing deficits are more likely to go public.

Our other predictors, which closely follow those in Pagano, Panetta, and Zingales (1998), include 1) sales (log(1+Sales)), as there are likely large fixed costs associated with going public, making the IPO more attractive for larger firms (Ritter, 1987); 2) sales growth, because faster-growing firms have higher market valuations; 3) debt/assets, as firms with higher leverage may have less financial flexibility and find it more difficult to raise external capital; and 4) the industry-level market-to-book ratio, which, as Pagano, Panetta, and Zingales (1998) discuss, can proxy for either better investment opportunities or mispricing in the industry. To control for time-specific shocks, we include date fixed effects (δ_t); in other specifications, we instead include date by industry, date by CBSA, or date by industry by CBSA fixed effects. We cluster our standard errors by firm.[23]

Column (1) of Table 3 displays the estimated coefficients of (1) with date fixed effects. First, we find a statistically significant relationship between firms' propensity to IPO and their size. Specifically, a 10% increase in sales is associated with a 6% increase in the likelihood of a firm going public from its base rate of 0.28%. Second, firms with higher trailing one-year sales growth are also more likely to IPO. A one-standard-deviation increase in sales growth (0.43) is associated with about a 54% increase in the likelihood that a firm goes public. These effects are consistent with larger, faster-growing firms being more likely to go public. Third, firms with higher leverage are more likely to go public; however, the coefficient is statistically significant only in specifications with industry by date fixed effects.

Fourth, firms with higher financing deficits are more likely to go public. Specifically,

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

a one-standard-deviation increase in Financing Deficit (0.23) is associated with a 45% increase in the likelihood that a firm goes public. This result suggests that firms with higher external capital needs are more likely to go public. Moreover, after controlling for Financing Deficit, the coefficient on investment (Capex/Assets) is not significant. This implies that in an equivalent regression in which investment and profitability are treated as separate predictors, 1) investment positively predicts IPOs and profitability negatively predicts IPOs, and 2) we cannot reject the null hypothesis that the coefficients on profitability and investment are equal in magnitude.[24]

The fact that profitability negatively predicts firms going public is the opposite of the findings of Pagano, Panetta, and Zingales (1998) and Aslan and Kumar (2011), who estimate similar regressions on samples of private Italian and UK firms, respectively. It is, however, consistent with recent evidence that firms delay going public when their profits increase, allowing them to fund investment with internally generated cash flows. For example, 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.[25] This also mirrors evidence from LBOs, where firms that go private tend to generate higher cash flows internally and have lower investment needs (e.g., Opler and Titman, 1993).

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

In columns (2), (3), and (4) of Table 3, we estimate the same regressions but include industry by date fixed effects, CBSA by date fixed effects, and industry by CBSA by date fixed effects, respectively.[26] Across these alternative specifications with more restrictive fixed effects, the coefficients remain fairly similar except for the coefficient on leverage, which becomes much larger and statistically significant once we control for industry effects.[27] 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 because they lack internal funds to finance investment, we expect this effect to be stronger for firms with greater investment needs. Intuitively, under the access-to-capital motive, internally generated cash flows should matter only to the extent that firms have substantive investment needs to begin with. To test this hypothesis, we re-estimate a regression similar to that in Table 3, but include EBITDA/Assets and Capex/Assets separately, along with their interaction. As shown

[24]Since Financing Deficit equals Capex/Assets − EBITDA/Assets, the coefficient on Capex/Assets tests whether the coefficients on Capex/Assets and EBITDA/Assets differ in magnitude.

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

[26]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.

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

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 less internal cash flow and thus rely more on external capital. Hence, these results provide further evidence that firms are more likely to go public when they have higher external capital needs.

3.1.1 Technology and Life Science Subsample Analysis

We next analyze the subsample of technology and life science firms, which, as mentioned earlier, represent a substantial share of IPO activity.[28] On the one hand, these firms may invest more in intangible assets such as R&D rather than capital expenditures, so our financing deficit measure may not accurately capture their external capital needs. Moreover, technology-related firms tend to have proprietary technologies, which can more easily be expropriated when these firms are public.[29] On the other hand, asymmetric information is likely especially severe for technology and life science firms, suggesting that access to capital may be a particularly important consideration in their decision to go public.

As shown in Appendix Table C9, the technology and life science IPO firms in our sample do engage in meaningful capital expenditures: their Capex/Assets ratio is 0.07 compared to 0.05 for the overall sample of non-IPO firms (Table 1). These technology and life science IPO firms also have a reasonable level of leverage, with a debt-to-assets ratio of 0.22, compared with 0.30 for all non-IPO firms.

In Table 5, we also re-estimate our baseline regressions while restricting the sample to technology and life science firms. The coefficient estimates on Financing Deficit are larger than the baseline in this subsample, suggesting that technology and life science firms' IPO decisions are *more* sensitive to their financing deficits.[30] This result is consistent with technology and life science firms being particularly subject to asymmetric information.[31]

[28]Specifically, these firms represent 48% of the SDC IPOs and 32% of the IPOs in our Y-14 sample.

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

[30]We confirm that the coefficient estimates are statistically different by estimating a single pooled regression in which we interact each of the right-hand-side variables with the technology and life sciences dummy. These results are available upon request.

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

3.1.2 VC-Backed Subsample Analysis

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

In Table 6, we re-estimate the same regressions from Table 3 but include only firms that we identify as VC-backed. Across all specifications, the coefficient estimates for Financing Deficit are larger than our baseline results in Table 3. These results suggest that even firms with access to private equity capital go public when their external capital needs are high. Moreover, the fact that the magnitudes are even larger than in our baseline tests is consistent with VC-backed firms being more subject to asymmetric information; hence, the benefit of being public increases more with their external capital needs. These results also help rule out the concern that our results on the financing deficit are purely picking up whether a firm is VC-backed to begin with.

3.1.3 Robustness Tests

In this subsection, we conduct various robustness tests of our main results in Table 3.

One concern is that some of the smaller 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 C10, we show that our results are robust to excluding firms that exit via acquisition. In addition, in Appendix Table C11, we show that our results are robust to excluding all non-IPO firms that exit the sample for any reason within three years.

Another concern is that linear independent variables and fixed effects are insufficient to control for potentially large differences between IPO and non-IPO firms. In particular, Table 1 shows that IPO firms are, on average, almost seven times as large (in terms of assets) as firms that do not go public. In Appendix Table C12, we estimate the same regressions as in Table 3, but interact the existing fixed effects with asset decile fixed effects to compare firms of similar size, and find qualitatively similar results. In addition, we show that our results are robust to including firms with less than \$10mm in assets (Appendix Table C13) and to excluding all firms with less than \$50mm in assets (Appendix Table C14).

Although we include industry by date fixed effects in our regressions, firms within industries may still not be fully comparable, particularly high-tech firms, which make up a large share of the IPO firms in our sample. One concern is that the high-tech firms that go public also tend to have larger financing deficits. For example, many biotech firms that have not had their drugs approved by the FDA have zero revenue before going public. In Appendix Table C15, we show that the main results in Table 3 are robust to

excluding all technology and life science firms and firms located in Silicon Valley.

3.2 How Do Firm Outcomes Evolve after the IPO?

Having analyzed which firm characteristics predict future IPO decisions, we now examine how firm outcomes evolve after the IPO. For each IPO firm, we take its last quarter of available data in the year before the IPO and match it to peer firms observed in that same quarter. To obtain matched firms, we estimate a propensity score from a variant of regression (1) on the full firm-quarter panel, with date by industry by CBSA fixed effects, where the dependent variable equals one only in each IPO firm's matching quarter. Each IPO firm is matched to up to five firms with the closest propensity scores in the same quarter, with exact matching on two-digit NAICS industry and VC-backing status. We then follow each IPO firm and its matched firms from three years before to three years after the IPO, classifying the IPO firm as treated and its matched firms as controls.

After identifying cohorts of treated and matched control firms, we employ a cohort generalized difference-in-differences strategy with a window of three years before and up to three 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:

$$Y_{i,c,t} = \sum_{k=-3}^{3} \beta_k (d_{i,c} \times \lambda_{k,c}) + \alpha_{i,c} + \delta_{t,c} + u_{i,c,t}, \tag{2}$$

where $d_{i,c}$ is a dummy that equals one if the firm is treated (i.e., is an IPO firm), and $\lambda_{k,c}$ is a dummy for event year k, where $k = 0$ is the year of the IPO.[32] We include firm by cohort fixed effects, $\alpha_{i,c}$, to compare changes in outcomes within the same firm. We also include time by cohort fixed effects, $\delta_{t,c}$, to ensure we compare the IPO firm only with matched control firms at each point in time. We again cluster standard errors by firm.

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

First, we examine the dynamics of firms' capex (in logs) around the IPO. Figure 1 shows that IPO firms' capex increases dramatically after the IPO relative to matched firms that do not go public. Specifically, capex increases by a statistically significant 55% relative to matched non-IPO firms three 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 almost 40% more than control firms three years after the IPO. Moreover, we find an increase in relative investment after the IPO, even when scaling capex by assets (Figure 3), although the statistical significance is weaker.

[32] Specifically, $k = 0$ contains the quarter of the IPO and the first three quarters after the IPO.

Given that firms substantially increase their assets and investment after going public, a natural question is how they finance this investment. Figure 4 shows that profitability declines after the IPO, suggesting that IPO firms are not generating more cash flows internally to finance their increased investment. Consistent with this idea, Figure 5 shows that financing deficits increase after the IPO relative to those of control firms. These results are consistent with IPO firms having higher expected future external capital needs at the time of the IPO.

We next analyze how IPO firms raise external capital to meet these needs. Figure 6 shows that IPO firms increase their debt by more than 50% relative to control firms by year three post-IPO. Moreover, Figure 7 shows that in the first year, there is a statistically significant drop in leverage of about 4 percentage points.[33] However, the point estimate returns to zero by year three.

3.3 Going Public and Bank Borrowing Costs

In Section 3.2, we find that firms do not simply issue equity after they go public. Rather, they also finance their asset growth and investments with debt. In this section, we analyze how the terms of debt issued by firms change after they go public. In particular, going public may allow firms to raise debt capital on more favorable terms. This can occur if the decrease in information asymmetry following the IPO reduces the information rents that informed investors can extract (e.g., Rock, 1986; Sharpe, 1990; Rajan, 1992; Easley and O'Hara, 2004; Beyhaghi, Fracassi, and Weitzner, 2026).

An empirical challenge to testing for such an improvement in borrowing terms is that firms' risk levels also change after the IPO. For example, as we discuss further below, firms' business models may change around IPOs as they move from the innovation to the commercialization stage. Hence, it is not sufficient to simply show that interest rates decline after firms go public. Fortunately, the availability of banks' internal risk assessments (PD and LGD) in the Y-14 data allows us to make this distinction among firms' bank loans. These risk assessments strongly predict future realized default and public equity and bond returns (Howes and Weitzner, 2025; Beyhaghi, Howes, and Weitzner, 2022; Beyhaghi, Fracassi, and Weitzner, 2026). Moreover, Beyhaghi, Fracassi, and Weitzner (2026) 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 borrower's underlying risk. 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

[33] In Appendix Figure C1, we find similar results if we define leverage as book debt over book capital rather than book assets.

matched sample analysis as before; however, as we argue above, the main confounding variable is the credit risk of the borrower, which is typically unobserved but which our data allow us to observe. To test for an improvement in bank loan terms after the IPO, we estimate the following regression:

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

where IR_ℓ is the interest rate on a new loan ℓ from bank b to firm i in quarter t. $IPO\ Firm_i$ is a dummy variable that equals one if the firm IPOs at any point in the sample, and $Post_{i,t}$ is a dummy variable that equals one if the loan is granted after the IPO. As independent variables, we include firm-level controls ($X_{i,t}$), a vector of loan-level controls (Z_ℓ), which include log(maturity), log(amount) and facility type fixed effects,[34] 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 $IPO\ Firm_i \times Post_{i,t}$, which captures the change in firm i's borrowing cost after going public, controlling for bank b's perceived risk of the firm. We also include bank by firm fixed effects ($\alpha_{i,b}$) and bank by year-quarter fixed effects ($\delta_{b,t}$) to control for any time-invariant relationship-specific effects and bank-specific effects on borrowing costs. Finally, to maintain comparability across specifications, we restrict the sample to observations with non-missing values of PD and LGD.

The results are displayed in Table 7. In column (1), we estimate the regression without loan-level controls, bank risk assessments, or bank by year-quarter fixed effects. The estimated coefficient, -0.512, is statistically significant and indicates that interest rates decrease by 51.2 bps after firms go public. We find similar magnitudes when we include loan-level controls in column (2) and add bank by year-quarter fixed effects in column (3). Finally, in column (4), we also include bank risk assessments. Expected loss is positively related to the loan's interest rate; however, the coefficient on $IPO \times Post$ remains negative and large in magnitude (-0.449). This 45 bp drop in borrowing costs compares with an average all-in interest rate of around 411 bps and a credit spread of 215 bps (relative 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 the bank.[35]

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

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

These results suggest that borrowing from banks becomes more attractive after firms go public. The most plausible mechanism is that information asymmetry drops as firms become more transparent after going public.[36] This reduction in asymmetric information allows firms to borrow from more banks at lower costs, as banks can extract smaller information rents from public firms.[37]

3.4 Going Public and Asymmetric Information

Our next set of tests examines whether going public reduces asymmetric information. For these tests, we proxy for the degree of asymmetric information using within-firm dispersion in banks' PD assessments. Intuitively, with less asymmetric information, banks' beliefs should coincide more closely. This approach aligns with the literature that uses split bond ratings (e.g., Morgan, 2002; Iannotta, 2006; Livingston and Zhou, 2010) and analyst dispersion (e.g., Flannery and Kwan, 2004) as proxies for asymmetric information. These other proxies are not feasible because private firms rarely have credit ratings or analyst coverage before going public. Moreover, our measure has the advantage of incorporating the private information of multiple sophisticated financial institutions with direct financial incentives to assess borrower risk accurately. In addition, banks do not observe other banks' PD assessments when generating their own, so cross-bank dispersion is more likely to capture differences in banks' private information. Individual analyst forecasts and credit ratings, by contrast, are observable to other analysts and rating agencies, making it less likely that differences in them reflect private information (e.g., Aumann, 1976). Credit and equity research analysts are also not paid directly for the accuracy of their ratings, and their reputational concerns can lead to dishonest reporting (e.g., Ottaviani and Sørensen, 2006).

We measure dispersion as the cross-sectional standard deviation of PD estimates across banks within each firm-quarter. To ensure that our results are not driven by changes in the composition of lending banks after the IPO, we calculate PD dispersion only for banks present prior to the IPO.[38] Moreover, for this analysis, we employ a

[36] One may argue that lower interest rates reflect increased competition among banks that is not due to asymmetric information. However, it is not obvious why competition should increase without changes in information.

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

[38] While banks present prior to the IPO are likely privy to more information than public markets, they can still learn substantially from the firm going public. First, immediately after the IPO, they observe the market-clearing IPO price, which aggregates diverse information from many market participants and thus provides a valuable signal to lenders about firm quality. Second, equity analyst coverage generates independent information beyond banks' own internal assessments. Third, mandatory disclosure requirements for public firms are more standardized and comprehensive than the information banks typically obtain through private lending relationships.

slightly different matching approach than in our previous tests. Because the level of PD and the number of banks are likely correlated with the cross-sectional standard deviation of PD estimates, we match using the Mahalanobis distance, treating PD and the number of banks as non-exact matching variables, while, as before, requiring exact matches on two-digit NAICS industry and VC-backing status. 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 8 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 three-year post-IPO period we analyze. By year three, the dispersion in PD estimates for IPO firms is just over 1.5 percentage points lower than for matched control firms that remain private, representing more than half a standard deviation (2.9percentage points).

The dispersion in banks' PDs could also reflect 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 we observe higher prices, i.e., improved terms on bank debt, after a reduction in PD dispersion.

These results, which indicate that information asymmetry declines after firms go public, provide a potential mechanism for why newly public firms can borrow on better terms. More broadly, although we observe only the dispersion in banks' beliefs, the post-IPO convergence in banks' risk assessments likely reflects improvements in the broader information environment that enhance the firm's ability to raise capital from all types of investors (i.e., equity and other types of debt investors). Likewise, the improvement in terms that we observe for bank debt likely extends to other securities.

While firms become more transparent after going public, their business models may also undergo fundamental changes. For example, firms may become more standardized as they transition from innovation to commercialization (e.g., Rajan, 2012; Bernstein, 2015; Larrain et al., 2025; Bernstein, 2022). This could lead to a reduction in dispersion in risk assessments, not because new information from the IPO is revealed, but because the firm's business model is more easily evaluated. However, under this alternative channel, we should observe a slow decrease in PD dispersion beginning before the IPO, rather than a sharp decrease following the IPO. Indeed, Bias et al. (2025) document that organizational changes associated with going public—such as increased formalization, standardization of processes, and professionalization of management—begin well before the actual IPO event. Hence, while firm fundamentals may be changing gradually around the IPO date, the sharp post-IPO drop in dispersion in risk assessments is most likely attributable to a sudden increase in transparency.

Finally, going public clearly expands the amount of publicly available, verifiable information. In practice, much of this information is produced and disseminated during

the IPO process itself: prior to listing, the firm files an S-1 and undergoes underwriter due diligence, and it conducts roadshows with prospective investors and analysts that help market participants evaluate the firm.[39] After the IPO, the firm enters the regular reporting cycle (e.g., 10-Ks/10-Qs, earnings releases and calls), further expanding standardized, verifiable information.

However, more public information does not necessarily imply a reduction in asymmetric information or the cost of capital. For example, increased information can actually increase adverse selection if more sophisticated investors are better able to interpret new information (Pagano and Volpin, 2012) or if transparency induces socially inefficient information production (Dang, Gorton, and Holmstrom, 2009; Dang et al., 2017).[40] Public information can also crowd out valuable private information production (Tang, 2014; Goldstein and Yang, 2017, 2019) or inhibit risk-sharing (Hirshleifer, 1971). For these reasons, whether the increased transparency reduces asymmetric information and the cost of capital is an empirical question. Our empirical innovation is to measure asymmetric information directly using lenders' internal risk assessments, rather than inferring it indirectly.

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 can affect not only 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 asymmetric information can enable firms to borrow from a broader pool of banks as less-informed banks face a smaller adverse selection problem when competing to lend to the firm. To test this prediction, we use the same matched time-series regressions as in Section 3.2 and plot the estimated coefficients using the number of banks the firm borrows from as the dependent variable.[41] As shown in Figure 9, three years after going public, IPO firms borrow from more than one additional bank relative to control firms, starting from a baseline average of 2.2 banks. In Appendix Figure C2, we also es-

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

[40]Firms may also benefit from selectively disclosing information to certain investors (Farre-Mensa, 2017).

[41]For this analysis, we employ a matching approach similar to the PD dispersion analysis above. We match using the Mahalanobis distance, treating the number of banks as a non-exact matching variable, while, as before, requiring exact matches on two-digit NAICS industry and VC-backing status.

timate the regression using a fixed-effects Poisson model (e.g., Cohn, Liu, and Wardlaw, 2022) and find very similar results.

Reduced asymmetric information may also facilitate market-based debt financing, such as public bonds and syndicated loans. For example, Gibson Dunn (2025) states:[42]

> "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."

Consistent with this idea, SpaceX issued its first bond, at seemingly attractive interest rates, shortly after going public (Seligson and Weinman, 2026).

Similarly, Dennis and Mullineaux (2000) argue that firms are more likely to use syndicated loans when information about the borrower is more transparent.[43] Consistent with this idea, firms often receive new syndicated credit facilities from banks after going public (Reuters, 2019). Motivated by this, we test whether firms increase their use of syndicated debt and public bonds after going public.

Figure 10 analyzes the change in the ratio of syndicated debt to total debt, i.e., Syndicated Debt/Debt.[44] Before the IPO, there is no evident pre-trend in the use of syndicated loans; however, after going public, the syndicated share of IPO firms' debt increases by more than 4 percentage points relative to peers that remain private. This represents a roughly 50% increase relative to the baseline syndicated debt to total debt ratio of 8.4% among IPO firms. These results may lead one to wonder whether our findings on the drop in interest rates are entirely attributable to the increase in loan syndication (Table 7). However, in Appendix Table C16, we re-estimate the regressions while controlling for whether the loan is syndicated and find almost identical results. Similarly, Appendix Figure C3 shows that our results on PD dispersion are similar when we only include non-syndicated loans in the measure of PD dispersion.

We next examine changes in the use of public bonds after the IPO by creating a variable, Bonds/Debt, defined as the ratio of total bonds outstanding (from FISD) to total debt. Before going public, IPO firms' bonds constitute 2.5% of their total debt. Figure 11 shows that after going public, IPO firms experience a large increase in the

[42]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) find that public bond spreads are higher when they are issued by private firms.

[43]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 have increasingly been securitized and sold to CLOs and hedge funds (Bhardwaj and Mukherjee, 2022).

[44]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 classify loans held by different banks as belonging to the same syndicate if they are flagged as syndicated and share the same origination date, maturity date, and loan type. Next, we calculate the median adjusted size across loan observations within the same syndicate. Finally, we sum the adjusted amounts across all of the firm's syndicated loans. The benefit of this approach is that it accounts for syndicated debt not held by Y-14 banks, provided that at least one Y-14 bank holds it.

proportion of bonds in their debt, with an increase of almost 5 percentage points by year three. Moreover, this increase occurs only after the IPO, not before. Taken together, these results suggest that firms' debt mix becomes more concentrated in market-based debt after going public, which we argue is facilitated by the increased transparency and resulting reduction in asymmetric information following the IPO.[45]

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 the IPO. While the first tests explicitly examine selection effects (i.e., which firms choose to go public), the second set of tests captures both treatment (i.e., the causal impact of the IPO on firm outcomes) and selection effects. For example, the observed increase in investment after the IPO is almost certainly attributable to both treatment and selection effects. If the IPO reduces firms' cost of external capital, for which we find evidence, firms should invest more after going public. However, firms that anticipate investing more in the future should also find it more advantageous to go public, which we argue is a critical reason why firms go public.[46]

As noted in the introduction, a growing body of empirical work isolates the treatment effect of IPOs on firm outcomes. Specifically, these papers consider samples of firms that file to go public, some of which complete their IPOs and some of which withdraw. Because the decision to complete an IPO is endogenous, these papers instrument for IPO completion using plausibly exogenous market-wide stock returns following the IPO filing date (Bernstein, 2015). However, the 2012 JOBS Act allowed firms to file and withdraw their IPOs confidentially, substantially reducing the number of withdrawn IPOs observable to researchers (Dambra, Field, and Gustafson, 2015; Boeh and Dunbar, 2021; Bias, 2021). This precludes us from using this instrument in our time-series analysis, given that our sample begins in 2012.

We do, however, believe that several of our findings on changes in access to capital and asymmetric information are difficult to explain by selection alone. For example, it is not obvious why a firm would go public in anticipation of a convergence in bank risk assessments, and if it did, we would expect this convergence to occur before the IPO; however, we observe no such convergence prior to the IPO. For the same reason, it is

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

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

unlikely that firms go public in response to becoming more transparent. Similarly, we find that firms receive improved terms on their bank debt after going public, whereas selection would predict that firms are *less* likely to go public if they anticipate an improvement in terms regardless of their listing status. Hence, we argue it is difficult to explain the improvement in bank debt terms through selection alone.

4 Conclusion

Using the most detailed data on US private firms in the IPO literature to date, we provide evidence that improved access to capital, facilitated by a reduction in asymmetric information, is an important motive for going public. We show that private firms with higher external capital needs are more likely to go public. After going public, these firms increase their investments, which they largely finance with debt, resulting in leverage ratios similar to those of control firms that remain private three years after the IPO. Consistent with reduced adverse selection, we show that firms' borrowing costs, conditional on their risk, decline after the IPO. We also find evidence of reduced asymmetric information: the dispersion in banks' private risk assessments drops after firms go public. Finally, our evidence suggests that going public facilitates access to syndicated loan and public bond markets.

Most of the IPO literature focuses on asymmetric information at the time of the IPO (e.g., Rock, 1986); however, our results suggest that the subsequent reduction in asymmetric information after the IPO also matters. Through reduced asymmetric information, firms can return to the market to raise capital more easily and at a lower cost. Moreover, this increased transparency does not just improve access to equity markets: IPOs appear to lower the cost of debt, which firms exploit by borrowing more after going public. This may be especially important for debt because, unlike equity, it is temporary capital—each refinancing is subject to adverse selection costs that the IPO helps mitigate. This more dynamic view of the IPO can also rationalize why firms often raise relatively small proceeds at the IPO itself.

In this paper, we focus our analysis on the access-to-capital motive. However, this is not to suggest that access to capital is the only channel through which going public benefits firms. For example, IPOs provide liquidity and diversification opportunities for founders, early investors (e.g., VCs), and employees (Pagano, 1993; Bodnaruk et al., 2008; Pástor, Taylor, and Veronesi, 2009) and allow firms to use publicly traded stock as acquisition currency (Brau and Fawcett, 2006; Celikyurt, Sevilir, and Shivdasani, 2010).[47] While these motives differ from ours in their specific objectives, they are also driven by the increased transparency and liquidity of firms' equity following the IPO. Hence, while

[47]IPOs also increase firms' visibility with customers and suppliers (e.g., Demers and Lewellen, 2003).

the benefits of going public may differ across these alternative channels, reductions in asymmetric information play an important role in all of them. To our knowledge, we are the first to provide direct evidence of the reduction in asymmetric information that underlies all of these channels.

Our analysis, which focuses on the cross-section of firms' IPO decisions, also provides 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 publicly listed firms in the United States over the past 25 years.[48] While several explanations for this phenomenon have been proposed,[49] 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 our analysis focuses on IPO decisions, the richness of the Y-14 data also opens the door to many further applications for studying private firms' financing and investment decisions. For example, future work could more closely examine the characteristics of acquired private firms and the role of financing constraints in shaping acquisition outcomes. This line of inquiry is closely related to our analysis, as acquisition is an alternative mechanism through which firms gain access to public capital markets and potentially realize benefits similar to those associated with going public.

[48] 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).

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

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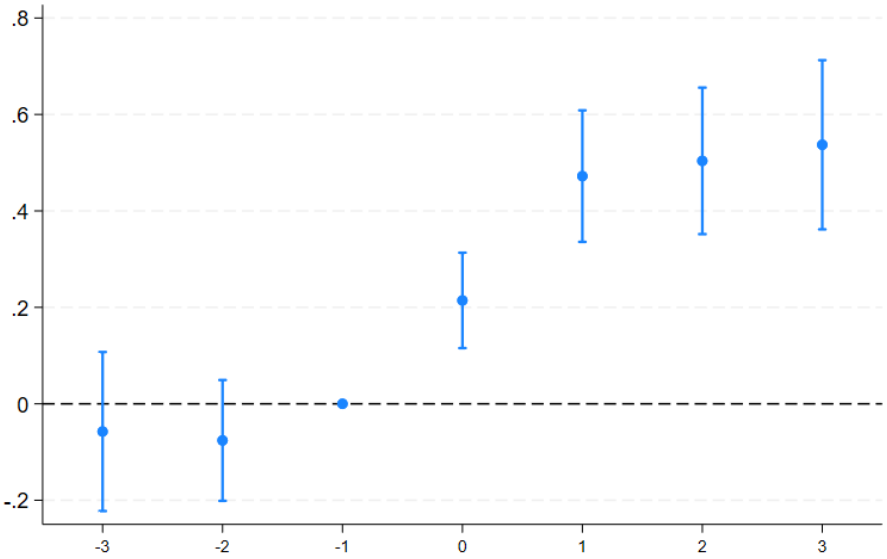
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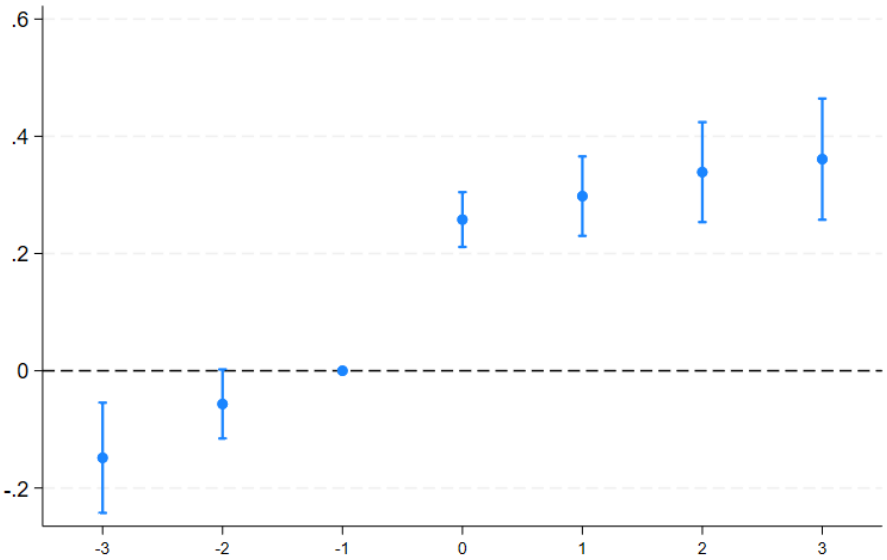
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Figure 1: Investment Dynamics



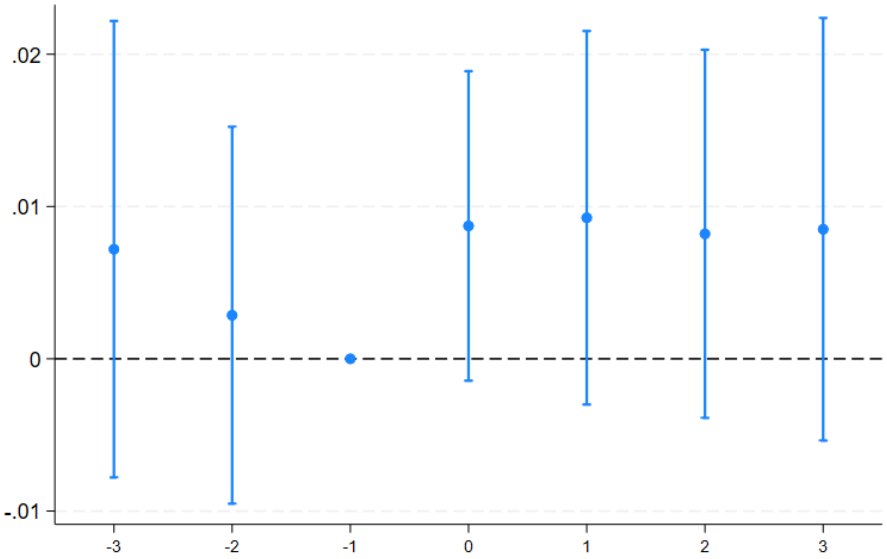
Note: The dependent variable is capital expenditures, $\log(1+Capex)$. Dots are the estimated β_k from equation (2) and bars are 90% confidence intervals, estimated on the matched sample described in Section 3.2. The year before the IPO ($k=-1$) is the omitted reference. Standard errors are clustered by firm.

Figure 2: Asset Dynamics



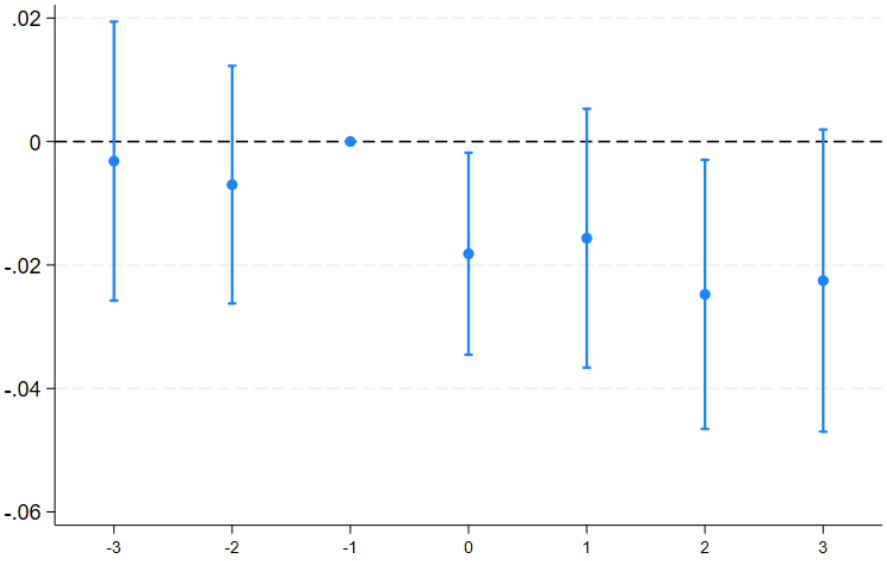
Note: The dependent variable is $\log(Assets)$. Dots are the estimated β_k from equation (2) and bars are 90% confidence intervals, estimated on the matched sample described in Section 3.2. The year before the IPO ($k=-1$) is the omitted reference. Standard errors are clustered by firm.

Figure 3: Investment Dynamics (Scaled by Assets)



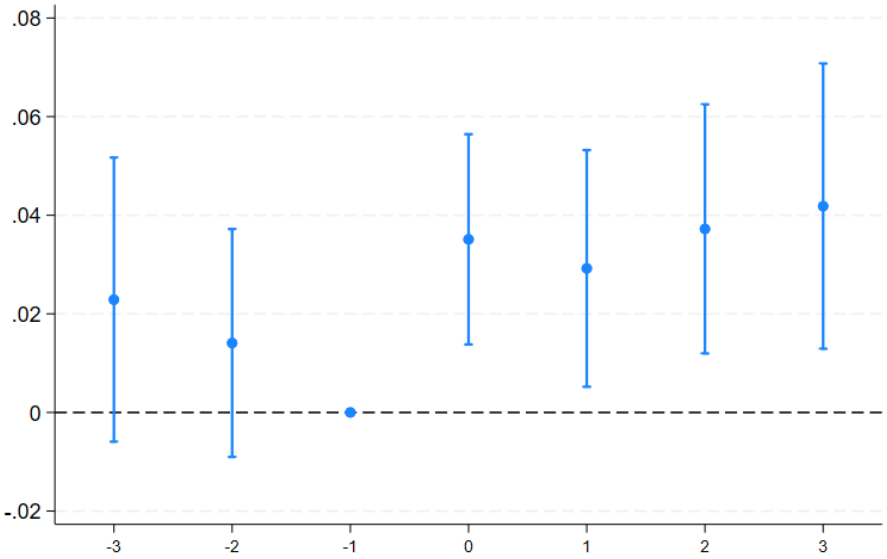
Note: The dependent variable is capital expenditures scaled by assets, $Capex/Assets$. Dots are the estimated β_k from equation (2) and bars are 90% confidence intervals, estimated on the matched sample described in Section 3.2. The year before the IPO ($k = -1$) is the omitted reference. Standard errors are clustered by firm.

Figure 4: Profitability Dynamics



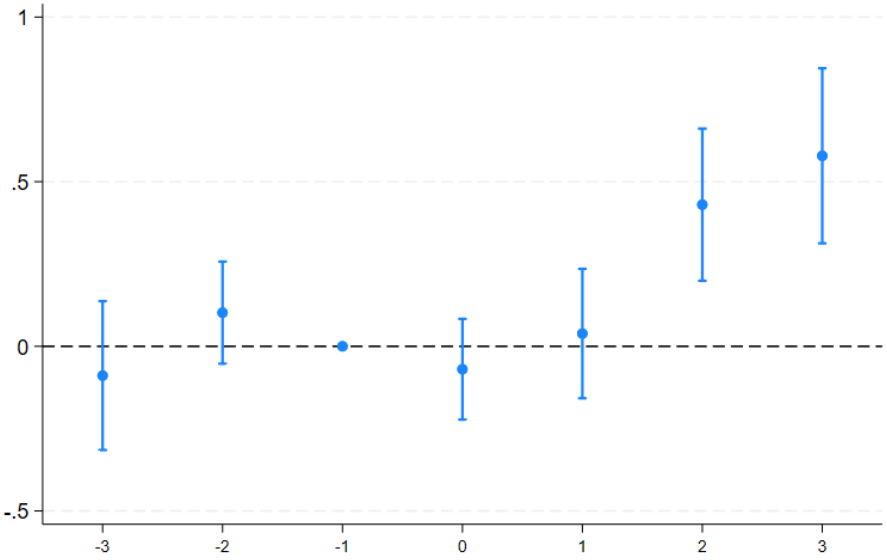
Note: The dependent variable is profitability, EBITDA/Assets. Dots are the estimated β_k from equation (2) and bars are 90% confidence intervals, estimated on the matched sample described in Section 3.2. The year before the IPO ($k = -1$) is the omitted reference. Standard errors are clustered by firm.

Figure 5: Financing Deficit Dynamics



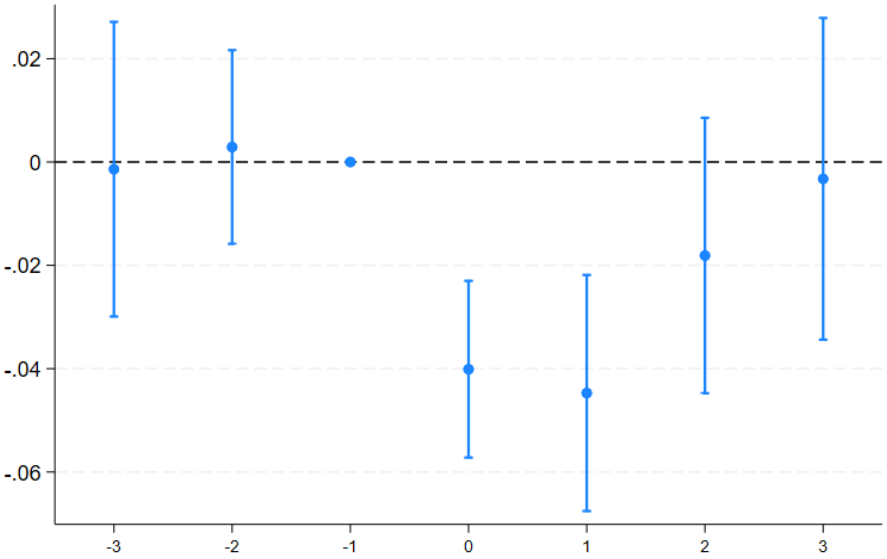
Note: The dependent variable is the firm's financing deficit, defined in Appendix B. Dots are the estimated β_k from equation (2) and bars are 90% confidence intervals, estimated on the matched sample described in Section 3.2. The year before the IPO ($k = -1$) is the omitted reference. Standard errors are clustered by firm.

Figure 6: Debt Dynamics



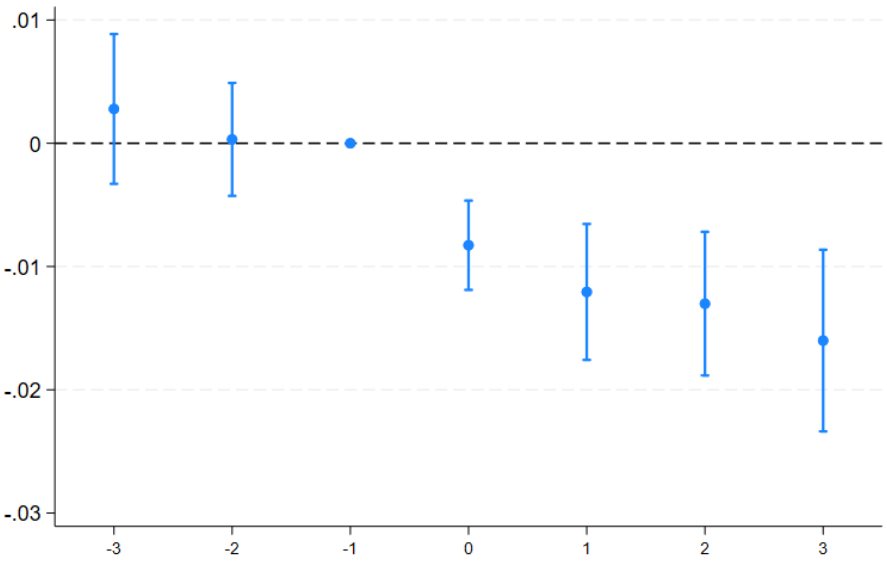
Note: The dependent variable is total debt, $\log(Debt)$. Dots are the estimated β_k from equation (2) and bars are 90% confidence intervals, estimated on the matched sample described in Section 3.2. The year before the IPO ($k = -1$) is the omitted reference. Standard errors are clustered by firm.

Figure 7: Leverage Dynamics



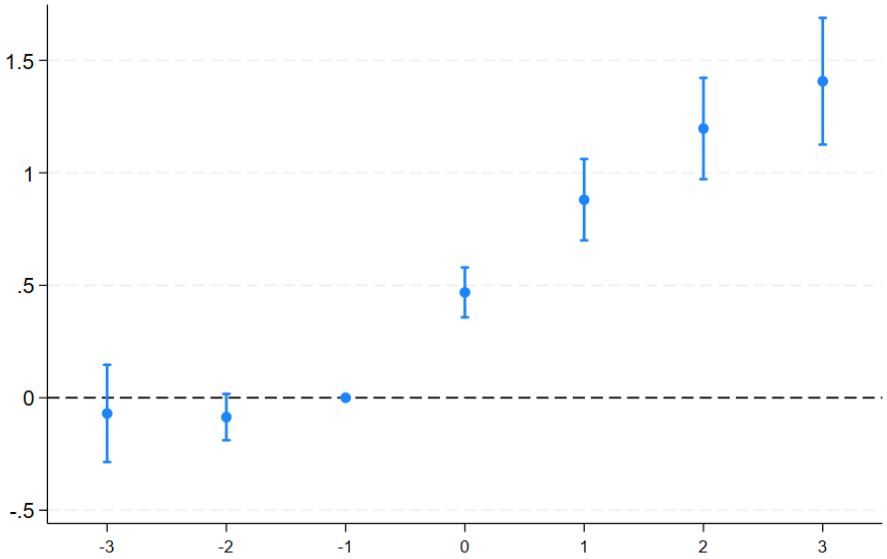
Note: The dependent variable is leverage, *Debt/Assets*. Dots are the estimated β_k from equation (2) and bars are 90% confidence intervals, estimated on the matched sample described in Section 3.2. The year before the IPO ($k = -1$) is the omitted reference. Standard errors are clustered by firm.

Figure 8: PD Dispersion Dynamics



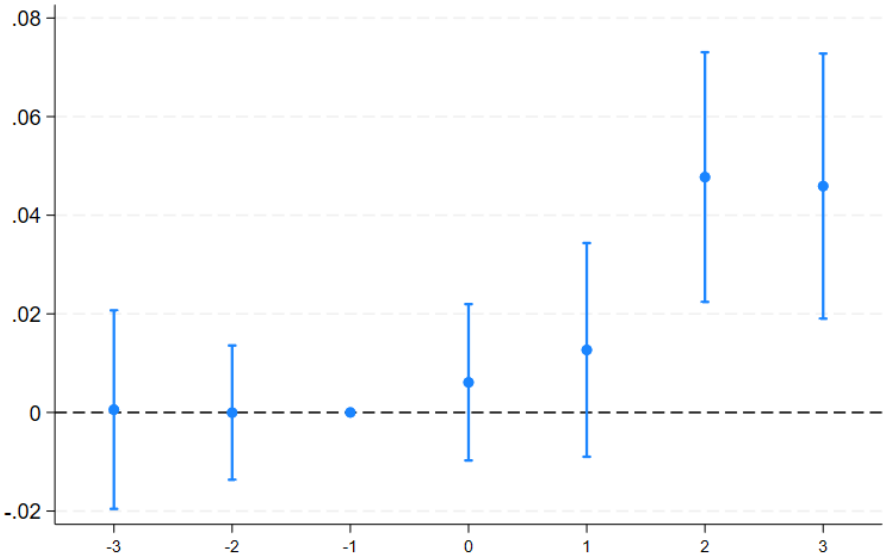
Note: The dependent variable is the cross-sectional standard deviation of banks' probability of default (PD) estimates within each firm-quarter, computed only among banks present prior to the IPO. Dots are the estimated β_k from equation (2) and bars are 90% confidence intervals, estimated on a matched sample formed using the Mahalanobis distance with PD and the number of banks as non-exact matching variables; each IPO firm is matched with up to five control firms in the same two-digit NAICS industry and with the same VC-backing status (Section 3.4). The year before the IPO ($k = -1$) is the omitted reference. Standard errors are clustered by firm.

Figure 9: Number of Banks Dynamics



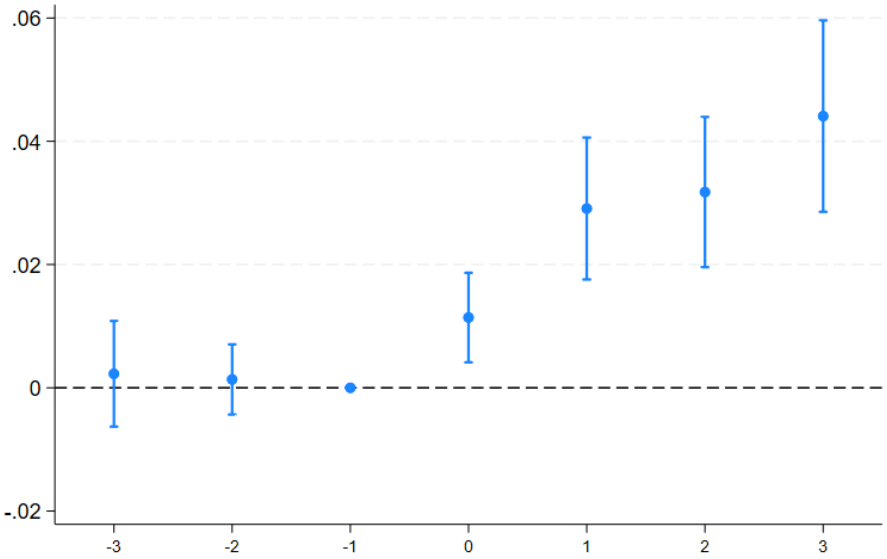
Note: The dependent variable is the number of banks from which the firm borrows. Dots are the estimated β_k from equation (2) and bars are 90% confidence intervals, estimated on a matched sample formed using the Mahalanobis distance with the number of banks as a non-exact matching variable; each IPO firm is matched with up to five control firms in the same two-digit NAICS industry and with the same VC-backing status (Section 3.5). The year before the IPO ($k = -1$) is the omitted reference. Standard errors are clustered by firm.

Figure 10: Syndicated Bank Loan Dynamics



Note: The dependent variable is syndicated bank debt as a share of total debt, *Syndicated Debt/Debt*. Dots are the estimated β_k from equation (2) and bars are 90% confidence intervals, estimated on the matched sample described in Section 3.2. The year before the IPO ($k = -1$) is the omitted reference. Standard errors are clustered by firm.

Figure 11: Bond Dynamics



Note: The dependent variable is the amount of bonds outstanding as a share of total debt, $Bonds/Debt$. Dots are the estimated β_k from equation (2) and bars are 90% confidence intervals, estimated on the matched sample described in Section 3.2. The year before the IPO ($k = -1$) is the omitted reference. Standard errors are clustered by firm.

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

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

	IPO Firms				Non-IPO Firms				
	N	Mean	Median	SD	N	Mean	Median	SD	Diff w.r.t. IPO firms
Sales ($ mm)	2864	725	308	1425	1746551	201	65	682	-524***
Assets ($ mm)	2864	866	439	1053	1746551	127	32	357	-738***
Capex/Assets	2647	0.08	0.03	0.13	1545905	0.05	0.02	0.10	-0.03***
Sales Growth	2650	0.45	0.18	0.75	1665145	0.15	0.07	0.43	-0.30***
EBITDA/Assets	2665	0.07	0.09	0.26	1671553	0.16	0.12	0.21	0.08***
Positive Profits	2665	0.73	1.00	0.44	1671553	0.90	1.00	0.30	0.17***
Financing Deficit	2647	0.03	-0.05	0.32	1541793	-0.11	-0.08	0.23	-0.14***
Debt/Assets	2864	0.31	0.29	0.26	1746551	0.30	0.26	0.25	-0.01**
Cash/Assets	2861	0.18	0.07	0.23	1743286	0.12	0.07	0.15	-0.06***
VC-Backed	2864	0.32	0.00	0.47	1746551	0.01	0.00	0.12	-0.31***
Silicon Valley	2864	0.15	0.00	0.36	1745620	0.02	0.00	0.15	-0.13***
Tech/Life Science Firm	2864	0.32	0.00	0.47	1746551	0.06	0.00	0.24	-0.26***

Table 2: Summary Statistics: Loan-Level Sample

This table contains summary statistics for the loan-level sample used in our analysis of borrowing costs in Section 3.3. The sample includes only newly originated loans. Appendix B contains variable definitions.

	N	Mean	Median	SD	P5	P95
Interest Rate (%)	62593	4.11	3.75	1.96	1.80	7.52
PD (%)	70117	1.54	0.87	2.88	0.14	4.54
LGD (%)	68395	32.95	34.40	14.67	7.50	54.30
PD × LGD (%)	67899	0.49	0.24	0.98	0.03	1.44
Maturity	77702	50.30	57.90	41.64	5.60	119.73
Loan Amount ($mm)	81708	10.21	3.50	28.03	1.00	40.00
Line of Credit	81708	0.43	0.00	0.50	0.00	1.00
Floating Rate	63356	0.67	1.00	0.47	0.00	1.00
Syndicated Loan	81708	0.12	0.00	0.32	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)	0.170***	0.184***	0.177***	0.188***
	(0.014)	(0.014)	(0.015)	(0.017)
Sales Growth	0.348***	0.271***	0.335***	0.245***
	(0.040)	(0.034)	(0.040)	(0.042)
Debt/Assets	0.008	0.183***	0.043	0.212***
	(0.045)	(0.051)	(0.046)	(0.067)
Financing Deficit	0.547***	0.570***	0.539***	0.500***
	(0.066)	(0.070)	(0.066)	(0.086)
Capex/Assets	0.100	-0.135	0.123	-0.049
	(0.118)	(0.107)	(0.122)	(0.150)
NAICS4 MTB	0.034***		0.032***	
	(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	1338383	1532711	1331723	1183993
R2	0.005	0.027	0.014	0.229

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	-1.181***	-0.811***	-1.157***	-1.105***
	(0.286)	(0.254)	(0.295)	(0.345)
Capex/Assets	1.041***	0.738***	1.050***	0.826***
	(0.181)	(0.154)	(0.187)	(0.210)
EBITDA/Assets	-0.445***	-0.506***	-0.446***	-0.427***
	(0.060)	(0.067)	(0.061)	(0.084)
Log(1+Sales)	0.169***	0.183***	0.177***	0.187***
	(0.014)	(0.014)	(0.015)	(0.017)
Sales Growth	0.354***	0.276***	0.340***	0.250***
	(0.040)	(0.035)	(0.040)	(0.042)
Debt/Assets	0.015	0.185***	0.049	0.214***
	(0.045)	(0.050)	(0.046)	(0.067)
NAICS4 MTB	0.035***		0.032***	
	(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	1338383	1532711	1331723	1183993
R2	0.005	0.027	0.014	0.230

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

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

	IPO			
	(1)	(2)	(3)	(4)
Log(1+Sales)	0.946***	0.909***	0.988***	0.997***
	(0.125)	(0.122)	(0.137)	(0.150)
Sales Growth	0.845***	0.844***	0.767***	0.523***
	(0.169)	(0.171)	(0.175)	(0.164)
Debt/Assets	-0.081	-0.350	-0.048	-0.435
	(0.399)	(0.430)	(0.445)	(0.574)
Financing Deficit	2.466***	2.606***	2.186***	1.936***
	(0.353)	(0.377)	(0.361)	(0.400)
Capex/Assets	0.898	0.559	0.934	1.326
	(0.932)	(0.916)	(0.954)	(1.066)
NAICS4 MTB	0.752***		0.737***	
	(0.140)		(0.154)	
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	96147	96147	91971	80023
R2	0.028	0.042	0.084	0.212

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

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

	IPO			
	(1)	(2)	(3)	(4)
Log(1+Sales)	2.393***	2.552***	2.383***	2.643***
	(0.316)	(0.354)	(0.342)	(0.466)
Sales Growth	0.986***	1.025***	0.945***	0.342
	(0.329)	(0.316)	(0.345)	(0.314)
Debt/Assets	-3.715***	-3.033**	-3.632**	-2.486
	(1.406)	(1.518)	(1.653)	(1.960)
Financing Deficit	4.356***	5.173***	2.385**	3.576***
	(1.053)	(1.148)	(1.200)	(1.325)
Capex/Assets	6.530**	3.705	8.643***	7.995**
	(2.622)	(2.573)	(2.955)	(3.248)
NAICS4 MTB	0.573**		0.560*	
	(0.263)		(0.288)	
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	21393	19857	19588	12490
R2	0.066	0.200	0.156	0.335

Table 7: Going Public and Firms' Borrowing Costs

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

	Interest Rate (%)			
	(1)	(2)	(3)	(4)
IPO Firm × Post	-0.512***	-0.518***	-0.500***	-0.449**
	(0.197)	(0.194)	(0.180)	(0.177)
Log(Assets)	0.001	0.005	-0.042	-0.034
	(0.041)	(0.042)	(0.030)	(0.029)
Sales Growth	-0.024	-0.025	-0.021	-0.017
	(0.020)	(0.020)	(0.019)	(0.019)
Debt/Assets	0.439***	0.413***	0.393***	0.331***
	(0.101)	(0.101)	(0.100)	(0.098)
EBITDA/Assets	-0.196***	-0.190***	-0.205***	-0.122**
	(0.064)	(0.063)	(0.055)	(0.055)
Capex/Assets	0.089	0.074	0.107	0.083
	(0.073)	(0.073)	(0.073)	(0.072)
PD (%)				0.016
				(0.011)
LGD (%)				0.002**
				(0.001)
PD × LGD (%)				0.098***
				(0.034)
Date FE	Y	Y	N	N
Bank/Firm FE	Y	Y	Y	Y
Bank/Date FE	N	N	Y	Y
Loan Controls	N	Y	Y	Y
N	32030	32026	31972	31972
R2	0.878	0.880	0.889	0.890

Online Appendix

Appendix A. Additional Data Details

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

A.1. Filtering the Raw Y-14 Data

We apply several filtering measures to the Y-14 raw data. Specifically, we drop firms with missing taxpayer identification numbers (TINs), firms headquartered outside the US, special purpose entities, firms with loans denominated in foreign currencies, borrowers that appear to be high-net-worth individuals (NAICS code 814), financial firms (NAICS code 52), religious, grantmaking, civic, professional & similar organizations (NAICS code 813), and public administration and government entities (NAICS code 92).[50] Some financial and non-profit firms have different industry classifications and are not dropped after this first pass, so we also drop firms whose names contain phrases such as "School of", "CLO", and similar.

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

We construct a quarterly panel indexed by the period-end date of each borrower's most recent financial statements, as reported by lenders in the Y-14Q filings. To ensure a

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

regular quarterly frequency, we create observations for any intermediate quarters in which a firm is absent from the financials panel but appears in both preceding and succeeding quarters. For firms with annual reporting, we carry the most recent annual financials forward for up to three subsequent quarters to populate those quarters that lack updated financial data. Our results are robust to omitting this within-year carry-forward, but including it increases the power of our time-series tests.

For variables constructed from loan-level information, we use the dates associated with the borrower's loan record, rather than the date of the borrower's most recent financials. Because the date fields differ, constructing a panel that includes both the private firm's financial data and its banking characteristics requires creating separate panels using the two datasets 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 is synced correctly.

We make several additional adjustments to clean the data. First, some banks mistakenly record borrowers' capital expenditures as negative. Therefore, we replace all capex records with their absolute values before taking the median across various bank loan records. Prior to aggregating the data to the firm/quarter level, we also drop observations in which assets are less than 50% or greater than 150% of the median value across all loan records for the same firm for the same date, to exclude a small number of records that are reported in different units (e.g., thousands vs. millions). We drop observations in which cash, debt, tangible assets, or depreciation & amortization exceed assets. We also drop observations with negative debt.[51] We remove the largest 1% of private firms to exclude any large subsidiaries that were not removed by the above filters. 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. Identifying Public Firms and Their Subsidiaries in Y-14

We identify public firms and private firms' subsidiaries in the Y-14 data using a merge with Compustat, similar to the process in Beyhaghi et al. (2024). First, we merge the Y-14 panel by TIN and quarter for the borrower, and the borrower's guarantor (if populated), with the panel of firms from Compustat that have non-missing stock prices. We classify as public 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.[52] We also classify a firm as public if any of its loan records, within the same bank, are associated with a non-missing CUSIP or ticker.

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

[52] 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.

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

A.3. Identifying IPO Firms in Y-14

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

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

A.4. Identifying VC-Backed Firms, Merger Targets, and Bonds in Y-14

We next explain in more detail how we match the Y-14 data with three other datasets: Preqin, the SDC Platinum M&A dataset, and FISD.

Our method for merging the Preqin data involves several steps. First, we select firms from Preqin with deal types related to venture capital financing.[53] For each firm that we identify in Preqin, we assemble all firms in Y-14 with matching state codes and two-digit NAICS codes. Second, for each Preqin firm's location and industry peers, we employ an embedding string-match method in which we translate each character in each firm's name to a numeric value and retain exact matches. For firms without an exact match, we first clean the firm names in each database to remove terms such as 'corp' and 'inc', and then select the Y-14 firm with the most similar name, ranked by Jaro–Winkler distance, provided that its Jaro–Winkler distance is below 0.25. Using these methods, we match about 15% of the firms in the Preqin database to our panel of private firms in Y-14, which translates to over 8,000 unique VC-backed private firms.

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

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

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

Appendix B. Variable Definitions

Assets: Total assets, from Y-14.

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

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

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

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

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

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

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

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

IPO Firm: Dummy variable that equals one if the firm goes public at any point 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, trimmed if $LGD = 0$ or $LGD \geq 1$, from Y-14.

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

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

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

traded companies for a given four-digit NAICS industry within the given quarter, winsorized at [1%, 97%], 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 gone public as of the current quarter.

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

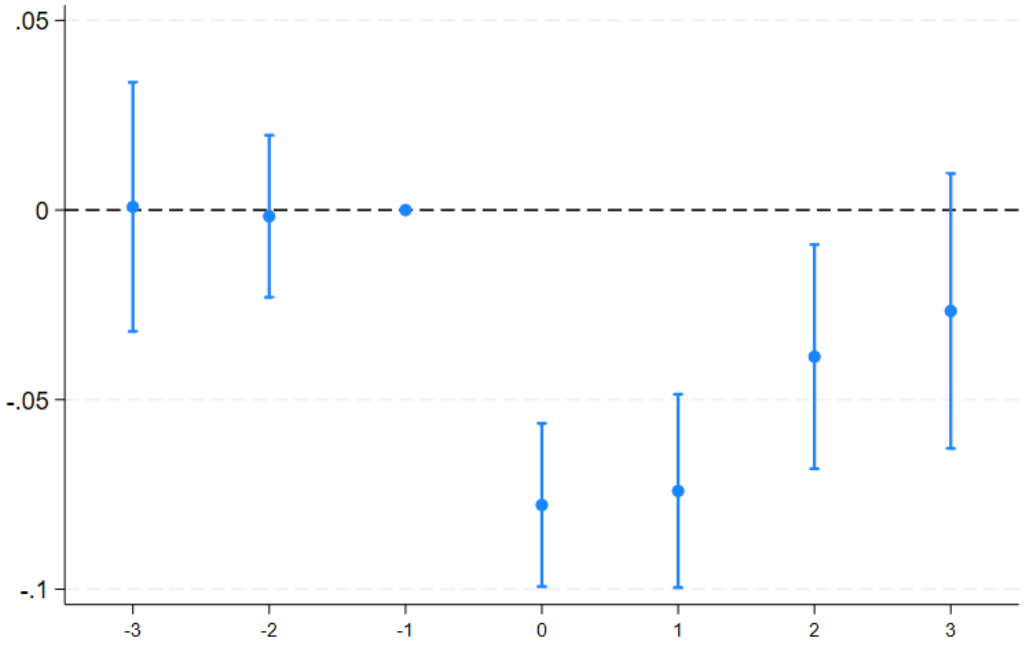
Syndicated Debt/Debt: The ratio of total syndicated bank debt to total debt, trimmed if > 1, from Y-14.

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, 5112, 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

Figure C1: Leverage Dynamics (Debt/Capital)

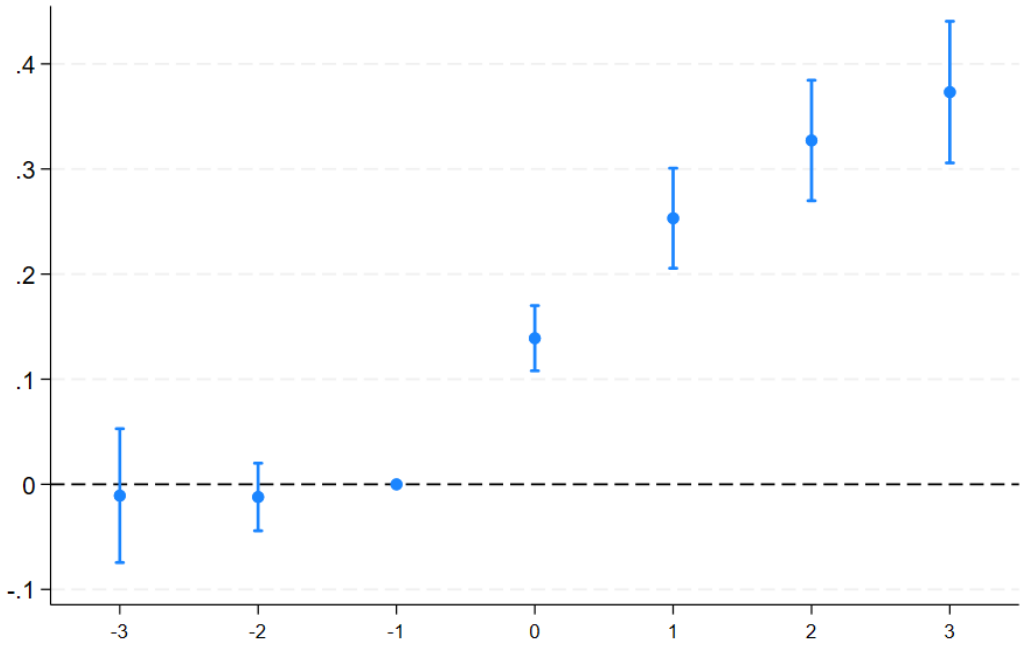


Note: In this figure, we analyze the dynamics of firm leverage, i.e., debt/(book capital), before and after the IPO using a matched sample. We form a matched sample by estimating propensity scores using the ex-ante regression (1) with date by industry by CBSA fixed effects, in which, for each IPO firm,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

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

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

Figure C2: Number of Banks Dynamics (Poisson Regression)

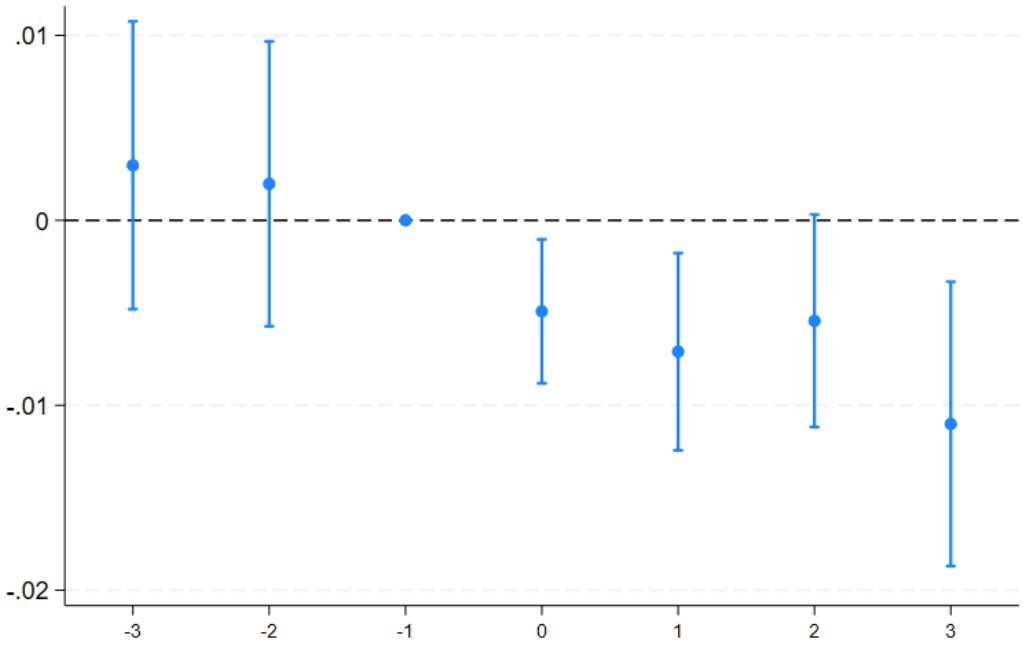


Note: In this figure, we analyze the dynamics of the number of banks from which firms borrow before and after the IPO, using a matched sample and a Poisson regression. We form a matched sample using the Mahalanobis distance, with the number of banks as a non-exact matching variable. Each IPO firm is matched with up to five control firms in the same two-digit NAICS industry and with the same VC-backing status. The dots are point estimates of the interaction coefficients between treated (IPO firms) and year dummies, and the bars are the 90% confidence intervals from the following regression:

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

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

Figure 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 among banks present prior to the IPO, using a matched sample. We form a matched sample based on the Mahalanobis distance measure using PD and the number of banks as non-exact matching variables. Each IPO firm is matched with up to five control firms in the same two-digit NAICS industry and with the same VC-backing status. The dots are point estimates of the interaction coefficients between treated (IPO firms) and year dummies, and the bars are the 90% confidence intervals from the following regression:

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

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

Table C1: IPO Sample Composition

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

	(1)	(2)
NAICS 4-Digit Industry:	SDC IPO Sample	Y14 IPO Sample
Panel A: Number of Unique IPO Firms		
Pharmaceutical and Medicine Manufacturing	283	23
Scientific Research and Development Services (Biotech)	237	17
Software Publishers	159	76
Medical Equipment and Supplies Manufacturing	54	11
Computer Systems Design and Related Services	34	16
Electronic Instrument Manufacturing	33	8
Oil and Gas Extraction	21	16
Data Processing, Hosting and Related Services	19	9
Full Service Restaurants	18	11
Semiconductor and Electronic Component Manufacturing	17	6
Other	489	240
Total	1,364	433
Share of SDC Total		32%
Panel B: Aggregate IPO Proceeds ($bn)		
Total IPO Proceeds	327.3	204.1
Share of SDC Total		62%

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

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

	N	Mean	SD	p10	p25	Median	p75	p90
Panel A: IPO Proceeds ($mm)								
Y-14 Matched	373	365.8	733.7	75.7	132.1	263.9	483.0	721.3
Y-14 Non-Matched	868	162.3	173.8	14.4	49.6	104.9	211.4	366.9
Panel B: Total Assets ($mm)								
Y-14 Matched	373	1454.3	4377.2	61.3	138.4	494.4	1403.9	3200.2
Y-14 Non-Matched	868	398.3	946.5	3.7	19.7	72.2	235.0	1182.4

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

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

	Merged IPO Firms				Unmerged IPO Firms				
	N	Mean	Median	SD	N	Mean	Median	SD	Diff w.r.t. Merged IPO Firms
Sales ($ mm)	2864	725	308	1425	2031	238	5	852	-487***
Assets ($ mm)	2864	866	439	1053	2031	376	81	771	-489***
Capex/Assets	2647	0.08	0.03	0.13	729	0.08	0.03	0.13	-0.00
Sales Growth	2650	0.45	0.18	0.75	429	0.35	0.26	0.51	-0.10***
EBITDA/Assets	2665	0.07	0.09	0.26	507	-0.15	-0.22	0.29	-0.22***
Positive Profits	2665	0.73	1.00	0.44	507	0.39	0.00	0.49	-0.34***
Financing Deficit	2647	0.03	-0.05	0.32	507	0.32	0.35	0.40	0.30***
Debt/Assets	2864	0.31	0.29	0.26	2031	0.27	0.14	0.30	-0.05***
Cash/Assets	2861	0.18	0.07	0.23	2031	0.45	0.54	0.32	0.27***
VC-Backed	2864	0.32	0.00	0.47	2031	0.23	0.00	0.42	-0.09***
Silicon Valley	2864	0.15	0.00	0.36	2014	0.23	0.00	0.42	0.08***
Tech/Life Science Firm	2864	0.32	0.00	0.47	2031	0.67	1.00	0.47	0.35***

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

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

	In Y-14 Sample	
	(1)	(2)
Pharma & Medicine Manufacturing	-0.352***	0.000
	(0.040)	(0.050)
Scientific R&D (Biotech)	-0.411***	-0.028
	(0.042)	(0.052)
Software Publishers	0.064	0.087**
	(0.043)	(0.039)
Medical Equipment Manufacturing	-0.231***	-0.051
	(0.082)	(0.076)
Computer Systems Design	-0.036	0.018
	(0.098)	(0.090)
Electronic Instrument Manufacturing	-0.151	0.011
	(0.108)	(0.094)
Oil and Gas Extraction	0.129**	0.083
	(0.054)	(0.070)
Data Processing & Hosting	-0.037	-0.006
	(0.120)	(0.096)
Full-Service Restaurants	0.133	0.119*
	(0.087)	(0.066)
Semis & Components Manufacturing	-0.093	0.007
	(0.146)	(0.127)
Log(1+Sales)		0.086***
		(0.007)
Year FE	Y	Y
N	1021	1021
R2	0.245	0.343
F-statistic (industry dummies)	21.676	1.115
F-test p-value	0.000	0.348

Table C5: Industry Composition of IPO Firms

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

Industry	# of Firms	% of Total
Software Publishers	76	17.84
Pharmaceutical & Medicine Manufacturing	23	5.40
Scientific Research & Development Services (Biotech)	17	3.99
Oil and Gas Extraction	16	3.76
Computer Systems Design & Related Services	16	3.76
Miscellaneous Durable Goods Manufacturing	11	2.58
Other Information Services	11	2.58
Full-Service Restaurants	11	2.58
Data Processing, Hosting, & Related Service	9	2.11
Navigation, Measuring, Electromed, & Control Instruments	8	1.88

Table C6: Location Composition of IPO Firms

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

Location	# of Firms	% of Total
San Francisco-Oakland-Hayward	45	12.16
Boston-Cambridge-Newton	28	7.57
Los Angeles-Long Beach-Anaheim	28	7.57
New York-Newark-Jersey City	23	6.22
San Jose-Sunnyvale-Santa Clara	18	4.86
Dallas-Fort Worth-Arlington	17	4.59
Chicago-Naperville-Elgin	13	3.51
Indianapolis-Carmel-Anderson	10	2.70
Phoenix-Mesa-Scottsdale	10	2.70
Washington-Arlington-Alexandria	10	2.70

Table C7: Industry Composition of Private Firm Sample

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

Industry	# of Firms	% of Total
Automobile Dealers	13,768	12.61
Lessors of Real Estate	6,375	5.84
Restaurants & Other Eating Places	2,806	2.57
Wholesale Distribution	2,406	2.20
Computer Systems Design & Related Services	1,899	1.74
Grocery & Related Product Merchant Wholesalers	1,688	1.55
Nonresidential Building Construction	1,556	1.42
Building Equipment Contractors	1,516	1.39
Architectural, Engineering, & Related	1,477	1.35
General Freight Trucking	1,459	1.34

Table C8: Location Composition of Private Firm Sample

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

Location	# of Firms	% of Total
New York-Newark-Jersey City	9,485	8.72
Los Angeles-Long Beach-Anaheim	5,302	4.87
Chicago-Naperville-Elgin	4,311	3.96
Philadelphia-Camden-Wilmington	2,892	2.66
Indianapolis-Carmel-Anderson	2,772	2.55
Non-Metro Area	2,514	2.31
Washington-Arlington-Alexandria	2,465	2.26
Dallas-Fort Worth-Arlington	2,455	2.26
Detroit-Warren-Dearborn	2,393	2.20
San Francisco-Oakland-Hayward	2,387	2.19

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

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

	IPO Firms				Non-IPO Firms				
	N	Mean	Median	SD	N	Mean	Median	SD	Diff w.r.t. IPO firms
Sales ($ mm)	917	414.10	204.03	623.56	102781	132.58	48.98	456.17	-281.52***
Assets ($ mm)	917	735.96	337.71	1011.28	102781	140.64	32.03	399.96	-595.33***
Capex/Assets	830	0.07	0.03	0.11	96590	0.04	0.01	0.09	-0.02***
Sales Growth	828	0.58	0.30	0.81	97611	0.25	0.10	0.57	-0.33***
EBITDA/Assets	830	-0.03	0.02	0.26	98021	0.14	0.12	0.27	0.17***
Positive Profits	830	0.54	1.00	0.50	98021	0.81	1.00	0.39	0.27***
Financing Deficit	830	0.13	0.01	0.34	96350	-0.08	-0.09	0.32	-0.21***
Debt/Assets	917	0.22	0.15	0.24	102781	0.19	0.12	0.21	-0.03***
Cash/Assets	917	0.31	0.24	0.27	102420	0.20	0.11	0.22	-0.11***
VC-Backed	917	0.56	1.00	0.50	102781	0.14	0.00	0.34	-0.43***
Silicon Valley	917	0.29	0.00	0.46	102764	0.09	0.00	0.29	-0.20***
Tech/Life Science Firm	917	1.00	1.00	0.00	102781	1.00	1.00	0.00	0.00

Table C10: Cross-Sectional Determinants of Firms' IPO Decisions (Excluding Merger Targets)

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

	IPO			
	(1)	(2)	(3)	(4)
Log(1+Sales)	0.167***	0.177***	0.174***	0.179***
	(0.014)	(0.013)	(0.014)	(0.017)
Sales Growth	0.350***	0.275***	0.338***	0.252***
	(0.040)	(0.035)	(0.040)	(0.042)
Debt/Assets	-0.006	0.157***	0.027	0.184***
	(0.045)	(0.050)	(0.046)	(0.066)
Financing Deficit	0.547***	0.567***	0.541***	0.512***
	(0.066)	(0.071)	(0.067)	(0.086)
Capex/Assets	0.112	-0.119	0.135	-0.060
	(0.118)	(0.107)	(0.122)	(0.150)
NAICS4 MTB	0.034***		0.031***	
	(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	1331622	1525598	1324975	1177949
R2	0.005	0.027	0.014	0.227

Table C11: 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 non-IPO private firms that remain in the Y-14 data for less than three years. To allow for at least three years of data, we end the sample in 2020 in these tests. 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)	0.330***	0.368***	0.345***	0.337***
	(0.028)	(0.029)	(0.030)	(0.034)
Sales Growth	0.947***	0.782***	0.930***	0.624***
	(0.118)	(0.102)	(0.120)	(0.123)
Debt/Assets	0.035	0.463***	0.118	0.513***
	(0.085)	(0.100)	(0.088)	(0.125)
Financing Deficit	0.994***	1.242***	1.018***	1.035***
	(0.149)	(0.168)	(0.151)	(0.210)
Capex/Assets	0.231	-0.532**	0.250	-0.660*
	(0.250)	(0.239)	(0.261)	(0.341)
NAICS4 MTB	0.039***		0.037***	
	(0.013)		(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	619564	693065	614445	493345
R2	0.010	0.052	0.024	0.305

Table C12: 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)	-0.000	0.079***	0.014	0.099***
	(0.015)	(0.016)	(0.019)	(0.030)
Sales Growth	0.329***	0.266***	0.330***	0.216***
	(0.039)	(0.033)	(0.043)	(0.051)
Debt/Assets	-0.009	0.041	0.030	0.163*
	(0.045)	(0.048)	(0.052)	(0.092)
Financing Deficit	0.382***	0.438***	0.398***	0.410***
	(0.064)	(0.067)	(0.069)	(0.100)
Capex/Assets	0.031	0.012	0.115	0.217
	(0.117)	(0.105)	(0.131)	(0.175)
NAICS4 MTB	0.031***		0.032***	
	(0.007)		(0.009)	
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	1338379	1518404	1267243	751996
R2	0.010	0.123	0.069	0.396

Table C13: 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)	0.109***	0.117***	0.115***	0.125***
	(0.008)	(0.008)	(0.009)	(0.010)
Sales Growth	0.191***	0.135***	0.183***	0.126***
	(0.022)	(0.018)	(0.022)	(0.022)
Debt/Assets	0.090***	0.172***	0.111***	0.192***
	(0.026)	(0.028)	(0.027)	(0.034)
Financing Deficit	0.106***	0.096***	0.108***	0.073***
	(0.013)	(0.013)	(0.014)	(0.014)
Capex/Assets	0.155***	0.072**	0.147***	0.074*
	(0.045)	(0.034)	(0.046)	(0.044)
NAICS4 MTB	0.050***		0.047***	
	(0.008)		(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	2279851	2664089	2274542	2197000
R2	0.004	0.018	0.010	0.197

Table C14: 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, including only firms with at least $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)	0.219***	0.311***	0.243***	0.317***
	(0.027)	(0.029)	(0.030)	(0.044)
Sales Growth	0.648***	0.502***	0.617***	0.461***
	(0.077)	(0.067)	(0.079)	(0.094)
Debt/Assets	0.125	0.343***	0.192	0.373*
	(0.114)	(0.120)	(0.123)	(0.194)
Financing Deficit	1.027***	1.191***	1.040***	1.155***
	(0.159)	(0.186)	(0.164)	(0.279)
Capex/Assets	0.222	-0.150	0.353	0.083
	(0.297)	(0.275)	(0.315)	(0.400)
NAICS4 MTB	0.068***		0.055***	
	(0.017)		(0.019)	
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	508866	580076	500653	387345
R2	0.005	0.051	0.030	0.293

Table C15: 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)	0.128***	0.138***	0.132***	0.125***
	(0.013)	(0.013)	(0.013)	(0.014)
Sales Growth	0.177***	0.153***	0.180***	0.181***
	(0.032)	(0.028)	(0.033)	(0.038)
Debt/Assets	0.110***	0.231***	0.119***	0.233***
	(0.038)	(0.044)	(0.040)	(0.057)
Financing Deficit	0.195***	0.268***	0.216***	0.331***
	(0.046)	(0.052)	(0.048)	(0.071)
Capex/Assets	0.258**	-0.002	0.236**	-0.028
	(0.101)	(0.090)	(0.104)	(0.134)
NAICS4 MTB	-0.008**		-0.007*	
	(0.004)		(0.004)	
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	1219734	1409011	1213153	1081031
R2	0.003	0.023	0.013	0.235

Table C16: 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 as in Table 7, with an additional control for whether the loan is syndicated (Syndication FE). The sample includes new loans. Loan controls include log(maturity), log(amount) and facility-type fixed effects. Standard errors are shown below the parameter estimates in parentheses and are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Interest Rate (%)			
	(1)	(2)	(3)	(4)
IPO Firm × Post	-0.539***	-0.555***	-0.528***	-0.477***
	(0.201)	(0.199)	(0.185)	(0.182)
Log(Assets)	-0.006	-0.003	-0.049*	-0.040
	(0.041)	(0.041)	(0.030)	(0.029)
Sales Growth	-0.024	-0.025	-0.021	-0.017
	(0.020)	(0.020)	(0.019)	(0.019)
Debt/Assets	0.436***	0.407***	0.390***	0.328***
	(0.100)	(0.100)	(0.099)	(0.098)
EBITDA/Assets	-0.194***	-0.187***	-0.205***	-0.122**
	(0.064)	(0.063)	(0.055)	(0.055)
Capex/Assets	0.095	0.082	0.114	0.090
	(0.073)	(0.073)	(0.073)	(0.071)
PD (%)				0.016
				(0.011)
LGD (%)				0.002**
				(0.001)
PD × LGD (%)				0.098***
				(0.034)
Syndication FE	Y	Y	Y	Y
Date FE	Y	Y	N	N
Bank/Firm FE	Y	Y	Y	Y
Bank/Date FE	N	N	Y	Y
Loan Controls	N	Y	Y	Y
N	32030	32026	31972	31972
R2	0.878	0.881	0.889	0.890