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

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March 2025

Abstract

We analyze firms' IPO decisions using detailed supervisory data on a large sample of US private firms. We find that less profitable firms with higher investment needs are more likely to go public. Newly public firms increase their investment expenditures relative to their counterparts that remain private. These firms tend to finance the new investment with bank debt, maintaining leverage ratios close to their pre-IPO levels. After going public, firms borrow from an expanded pool of lenders at more attractive rates. Finally, we find that the within-firm dispersion in banks' private risk assessments drops after the IPO. Overall, our evidence is consistent with firms going public to reduce information asymmetries, thereby improving their access to capital.

*We thank Jason Abrevaya, Adolfo De Motta, Paolo Fulghieri, Charlie Hadlock, Steve Kaplan, Borja Larrain, Michelle Lowry, Aaron Pancost and conference and seminar participants at the Fed Board, FRA, McGill, Private Equity Research Symposium, PUC Chile and Virtual Corporate Finance Friday for the helpful comments and discussions. We thank Linda Du and Siddhartha Lewis-Hayre for excellent research assistance. The views expressed in this paper are solely those of the authors. They do not necessarily reflect the views of the Federal Reserve Board or the Federal Reserve System.

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1 Introduction

Improved access to capital is often cited as a primary motive for firms going public.[1] Intuitively, going public reduces information asymmetries through increased transparency, allowing firms to raise capital more easily and at a lower cost. However, empirical support for this rationale is mixed.[2] Moreover, even if access to capital was an important motive for going public in the past, the rapid growth of private capital markets in recent years raises the question of whether this presumed advantage of public markets is still relevant.[3]

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

Our main hypothesis is based on the idea that public firms are more transparent and less subject to informational asymmetries than private firms and, consequently, face fewer adverse selection and hold-up problems when they raise capital. The increased transparency is both due to public firms being subject to stringent disclosure rules and

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

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

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

because information is revealed during the security trading process.[4] Motivated by these ideas, we investigate three related issues: i) Are private firms with greater needs for external capital more likely to go public?, ii) do firms gain improved access to capital and increase their investment after going public?, and if so iii) is the improved access to capital after the IPO due to a reduction in information asymmetries?

We first show that firms that are more reliant on external capital, as proxied by ex-ante investment, i.e, CapEx/Assets, and less profitable firms as measured by EBITDA/Assets, are more likely to go public in the future. Specifically, we find that a one standard deviation increase in ex-ante investment increases the likelihood of a firm going public by 40% and that this relationship is stronger for firms with lower profitability.[5]

We next compare the investment choices of firms before and after they go public. To do so, we match IPO firms to comparable private firms and analyze their differences along various dimensions over a window of 3 years prior to their IPO to 4 years after. We find that compared to matched control firms, IPO firms substantially increase their investment: CapEx and total assets increase by 50% and 40%, respectively, reflecting growth in both tangible and intangible assets.

In addition to the influx of equity capital from the IPO, we find that post-IPO asset growth is largely funded by bank debt obtained from an expanded pool of lenders. Moreover, although the leverage ratios of newly public firms initially drop after going public, their leverage ratios are not significantly different than those of control firms four years later. These results suggest that going public facilitates the issuance of bank debt as well as equity and are consistent with evidence of IPO activity being an important determinant of aggregate bank lending.[6]

[4]There is a large literature that describes reasons why reducing information asymmetries can improve a firm's access to capital. These include reductions in adverse selection costs (e.g., Stiglitz and Weiss (1981) and Myers and Majluf (1984)) and hold-up problems (e.g., Sharpe (1990) and Rajan (1992)). In addition, the information reflected in the stock prices of public firms can improve their investment decisions (e.g., Subrahmanyam and Titman (1999)).

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

[6]See US companies going public could lift related bank lending. This dynamic 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.

If the increase in the use of bank debt reflects improved access to bank capital, the terms on the bank debt should improve after the IPO. While we do find that interest rates on bank debt drop after the IPO, this could simply reflect firms becoming less risky after going public. To test whether this drop in interest rates reflects an improvement in terms, we take advantage of banks' loan-level risk assessments (i.e., the probability of default and loss given default) reported in the Y-14Q data. This data allows us to examine how interest rates change after controlling for the underlying risk of the borrower, as perceived by banks.[7] Consistent with an improvement in bank loan terms, we find that *conditional on their risk*, firms' borrowing costs decline by 41bps after going public.[8]

Why do firms obtain more favorable terms on their bank debt after the IPO? One possibility is that a reduction in information asymmetries across investors reduces the information rents informed investors can extract.[9] To test this hypothesis, we create a proxy for the degree of asymmetric information based on the within-firm dispersion in banks' probability of default (PD) assessments.[10] Intuitively, if there is less asymmetric information, banks' beliefs should be more closely aligned with each other. We find that the dispersion in PDs drops substantially immediately after the IPO, consistent with a reduction in information asymmetry.

Our final set of tests focuses on the subset of private firms with venture capital backing (VC-backed firms), which are particularly interesting for a number of reasons. On the one hand, VC-backed firms' IPO decisions may be less sensitive to the need for external capital because they are likely to have relatively good access to capital as private firms. On the other hand, asymmetric information is likely especially severe for VC-backed firms, suggesting that they may benefit the most from the increased transparency associated with being public. Consistent with the latter channel, we find that for VC-backed firms

[7] Beyhaghi, Fracassi, and Weitzner (2022) show that 1) these risk assessments strongly predict future loan performance and 2) interest rates no longer predict firm performance after controlling for them.

[8] This compares to an average all-in credit spread of 182bps.

[9] E.g., Sharpe (1990) and Rajan (1992).

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

the IPO decision is more sensitive to ex-ante investment and profitability.[11] This result suggests that VC-backed firms particularly benefit from the increased access to capital attained through going public.

The analysis in this paper builds on the literature that uses data on private firms to analyze the ex-ante determinants as well as the ex-post implications of firms' IPO decisions. The seminal paper in this literature is Pagano, Panetta, and Zingales (1998), which studies a sample of private firms in Italy from 1982 to 1992.[12] More recently, several papers (e.g., Babina, Ouimet, and Zarutskie (2020) and Maksimovic, Phillips, and Yang (2020) have used the Census Longitudinal Business Database (LBD) to analyze the going public choice of US private firms.[13] The Census data contains information on total employment, total payroll, firm age, industry but does not have information about the balance sheets or income statements of private firms, nor their borrowing costs, which are central to our analysis on firms' access to capital.[14]

Another related literature compares the behavior and outcomes of public and private firms separately.[15] Saunders and Steffen (2011) show that public firms borrow at lower average interest rates than private firms, which is consistent with our results that firms' borrowing costs drop after the IPO. However, our analysis differs in several key respects. First, our data allows us to track changes in borrowing costs and the amount of borrowing

[11] It should be noted that VC-backed firms concentrate in tech industries, and that tech firms tend to be more subject to asymmetric information. We find that tech firms are more likely to go public, and their IPO decision is affected more by their external capital needs. However, we find even stronger effects among VC-backed tech firms.

[12] Other papers analyzing firms' IPO decisions using data on private firms outside the US include Pagano, Panetta, and Zingales (1996), Pagano, Panetta, and Zingales (1998), Fischer (2000), Aslan and Kumar (2011), Gopalan and Gormley (2013) and Larrain, Sertsios, and Urzúa (2021).

[13] Some papers analyze a small set of private firms in which pre-IPO data is more prevalent (e.g., Lerner (1994), Helwege and Packer (2003), and Aghamolla and Thakor (2022)).

[14] Several papers also analyze private firms' IPO decisions using the Census of Manufacturers and the Annual Survey of Manufacturers data which contains sales and capital expenditures at the plant-level for firms in the manufacturing industry (e.g., Chemmanur, He, and Nandy (2010), Chemmanur and He (2011), Chemmanur et al. (2018) and Chemmanur et al. (2022)). The main drawback of this data is that it excludes all non-manufacturing firms (e.g., high-tech/biotech companies). Additionally, the data contain no information about firms' balance sheets or income statements beyond sales and capital expenditures. Finally, the data is collected for all manufacturing firms every five years while the data is collected annually for plants with more than 250 employees. In contrast, our data contains a quarterly panel of detailed firm financials for an extremely broad set of private firms.

[15] e.g., Brav (2009), Saunders and Steffen (2011), Asker, Farre-Mensa, and Ljungqvist (2015), Gilje and Taillard (2016), Acharya and Xu (2017), Phillips and Sertsios (2017), Maksimovic, Phillips, and Yang (2017), Sheen (2020), Dambra and Gustafson (2021) and Sanati and Spyridopoulos (2023). Bernstein (2022) surveys the literature.

after firms go public. Second, by controlling for firms' underlying risk, as perceived by the bank, we show that this decrease in cost of borrowing is not due to changes in firms' risk.[16] Third, using these private risk assessments, we directly test how asymmetric information changes after the IPO.

The ex-post part of our analysis relates to another literature that focuses on the causal impact of IPOs on ex-post outcomes. This literature, starting with Bernstein (2015), uses data on firms that file to go public but may ultimately withdraw, instrumenting for the completion decision with market-wide returns.[17] As we discuss in more detail below, the Y-14Q data has a relatively short sample and does not include all private firms prior to IPO, limiting the power of this instrument in our sample. However, while we believe it is important to isolate the treatment effects of IPOs, we also believe that selection effects are both interesting and important. For example, if the IPO results in a reduction in the cost of capital, which our data directly allows us to test, firms will invest more because of the IPO but also will be more likely to IPO when they expect to invest more later. Because of this, our results inevitably capture both of these effects. Nonetheless, several of our novel findings regarding the mechanism are difficult to explain through selection alone. For example, if the convergence in bank risk assessments were anticipated, we would expect this convergence to occur before the IPO rather than after. Similarly, that borrowing costs decline after the IPO, even after controlling for banks' internal risk assessments, is difficult to explain purely via selection. Rather, this result suggests that the IPO itself—through increased disclosure and transparency—reduces information asymmetry and improves firms' access to capital.

In contrast to our analysis, which strongly supports the hypothesis that firms go public to improve their access to capital, the existing evidence on the importance of access to capital is mixed. For example, Pagano, Panetta, and Zingales (1998) find that ex-ante investment and profitability negatively (positively) predict IPOs[18] and they find a reduc-

[16] Relatedly, Schenone (2010) shows that borrowing costs go down after the IPO but does not have information on the underlying risk of borrowers nor a set of counterfactual firms that remain private.

[17] e.g., Babina, Ouimet, and Zarutskie (2020), Borisov, Ellul, and Sevilir (2021), Cornaggia et al. (2021), Cornaggia et al. (2022) and Larrain et al. (2022).

[18] Aslan and Kumar (2011) also find that ex-ante profitability positively predicts IPOs among a sample of private firms in the UK.

tion in both investment and leverage after the IPO.[19] Similarly, Asker, Farre-Mensa, and Ljungqvist (2015) find that private firms invest less than public firms; however, their data does not allow them to observe changes in investment following private firms' transition to being public. In contrast, Chemmanur, He, and Nandy (2010) and Aslan and Kumar (2011) find a positive relationship between both ex-ante and ex-post investment among samples of private manufacturing firms and UK firms, respectively.[20] More recently, Larrain et al. (2022) instrument for IPO completion and show that firms in Europe expand their subsidiaries and make acquisitions after IPO, but do not find a statistically significant increase in assets. Our paper is the first to use banks' private risk assessments to provide direct evidence that firms gain improved access to capital, and this improved access is due to reductions in information asymmetry after the IPO.

Finally, while the importance of IPOs in reducing information asymmetries has long been considered important, to our knowledge, this is the first paper providing direct evidence of this. For this reason, our paper contributes to the broader literature on testing information asymmetries in economics and finance.[21] While most studies rely on indirect proxies of asymmetric information, we directly analyze how differences in private information evolve around the IPO, an event where asymmetric information should decrease due to increased transparency and market scrutiny.

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

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

[21]e.g., Chiappori and Salanie (2000), Finkelstein and McGarry (2006), Finkelstein and Poterba (2014), Cohen and Siegelman (2010), Hendren (2013), Finkelstein and Poterba (2014), Beyhaghi, Fracassi, and Weitzner (2022), Weitzner and Howes (2021) and Beyhaghi, Howes, and Weitzner (2022).

2 Data

We use the corporate loans records contained in Schedule H.1 from the Federal Reserve's Y-14Q data to assemble a sample of over 98,000 unique private firms in the US. The Y-14Q loan records contain detailed financial data for borrowing firms as well as detailed loan characteristics.

Within this set of private firms, we identify 391 that go public using data on IPOs from the SDC Platinum database (now owned by Refinitiv). We also draw on several other data sources to identify public companies, companies that have received venture capital financing prior to the IPO, and companies that are acquired, and use these additional data sources to supplement the financial information in Y-14Q. In the following, we outline each of these data sources and describe the filtering and merging methods that we employ to assemble the datasets that we use for our empirical analysis. We describe additional details in Appendix A.

2.1 Sample of Private Firms

The Federal Reserve began collecting the Y-14Q data in 2011 to support Dodd-Frank mandated stress tests and the Comprehensive Capital Analysis and Review (CCAR).Qualified BHCs are required to report detailed quarterly loan-level data on all corporate loans that exceed one million dollars. In 2011, when collection began, 19 BHCs qualified, and as of 2022, 30 BHCs qualify. Schedule H.1 of the Federal Reserve's Y-14Q data includes roughly 15 million records reflecting corporate loans from all bank holding companies (BHCs) with \$50bn or more in total assets, accounting for 70% of all commercial and industrial loan volume from US BHCs (Bidder, Krainer, and Shapiro, 2020) and 85.9% of all assets in the US banking sector (Frame, McLemore, and Mihov, 2020). Our sample of private firms starts in 2012 as the borrower's financial data appear fully populated, starting with the observations in this year.

Consistent with other papers that use Y-14Q data, we apply several filtering measures: we drop firms missing TIN identifiers, firms headquartered outside the US, firms with loans denominated in foreign currencies, borrowers that appear to be high-net-worth individuals, financial firms (NAICS code 52), real estate firms (NAICS code 92), and public administration and government entities (NAICS code 53). Some financial and non-profit firms have different industry classifications and are not dropped after this first pass, so we also drop any firms that have phrases in the firm names such as: "School of", "CLO", and similar.[22] These filters reduce the sample by almost half to roughly 7.3 million loan-level records for loans that appeared on the balance sheets of the various reporting BHCs from 2012-2023.

We identify public firms in the Y-14Q data using a multi-step process similar to Beyhaghi et al. (2024). First, we merge the Y-14Q panel by TIN and quarter with the panel of firms from COMPUSTAT that have non-missing stock prices. We assign all firms in the Y-14Q data that match with this COMPUSTAST panel as public. We also assign all firms in the Y-14Q data as public if any of the firm's loan records, within the same bank, are associated with a non-missing CUSIP or ticker. In addition, we also exclude the top 1% of the largest firms (by assets) as a check to ensure that we exclude miscoded outliers large subsidiaries of public firms that we may not have properly identified. We also winsorize variables that are ratios at the 1% and 99% to minimize the impact of outliers. For observations that indicate debt or capital expense are negative, we take the absolute value. Finally, we drop all firms with less than $10 million in assets in order to eliminate the more than a million very small private firms that are unlikely to ever go public.[23]

We supplement the Y-14Q data with additional information on firm location, venture capital financing, and mergers & acquisitions. We merge the zip code fields in the Y-14Q data for firm location using the HUD crosswalk to identify each borrower firm's CBSA. To obtain data on private firm VC funding, we match the borrower firms in the Y-14Q data with the Preqin VC funding database using the FedMatch text string matching

[22]See Appendix A for additional details.
[23]Our qualitative results are not sensitive to these size filters.

algorithm (Cohen et al. (2021)).[24] We are able to match about 15% of the firms in the Preqin database to the panel of private firms in Y-14Q, which translates to more than 5,000 unique private firms that we identify that receive venture-capital financing. We use a similar process using the FEDMATCH string-match engine to merge the SDC Platinum data by firm name, state, and industry to identify which private firms have received venture capital financing and which have been acquired.

2.2 Identifying Private Firms That Execute an IPO

To identify which of the private firms in our sample go public, we assemble an initial set of over 5,500 US-based firms that file for an IPO between 2012-2023 using data from SDC Platinum. Following Bernstein (2015), we apply several filters in order to exclude financial firms (SIC between 6000 and 6999), unit trusts, closed-end funds, REITs, American depositary receipts (ADRs), limited partnerships, special acquisition vehicles, and spin-offs. These filters result in 1,390 unique firms that execute an IPO between 2012 and 2023.

We manually merge the private firms in the Y-14Q data with the sample of 1,390 IPO firms that we outline above, resulting in 532 matches with the private firms in the Y-14 filings data. We describe additional details of our merge process in Appendix A. Our match rate of 38% is slightly lower than similar efforts in the recent related literature such as Maksimovic, Phillips, and Yang (2020) which matches Jay Ritter's IPO data to the US Census data and obtains a 48% match rate. However, our match results are affected by the relative scarcity of biotech, pharmaceutical, and medical equipment firms from the Y-14Q data. These firms use less leverage in general and hence are less likely to be present in the Y-14Q data. Apart from these three industries, our match rate is 61%. As discussed in further detail below, the exclusion of these firms likely weakens our main results.

As a result of dropping all private firms with less than $10 million in assets, we also

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

drop 141 small IPO firms. The result of our filters and merges is a sample of 391 firms that go public for which we have complete data, and have observations in the Y-14Q data that are within three years of the firm's IPO. We remove all observations for other public firms to ensure that our analysis compares private firms that IPO to other private firms that do not IPO.

2.3 Constructing the Firm-level Panel

After merging our sample of IPO firms with our sample of private firms from Y-14Q our main panel of private firm financial data includes over 98,000 unique private firms and 1.3 million firm-quarter observations from 2012 to 2023. Tables 1 and 2 display the industry and location composition of IPO firms in our sample, and Tables 3 and 4 display the industry and location composition of the other private firms in our sample. While we have IPO firms from a wide variety of cities and locations, as expected, they are clustered in technology related industries and in Silicon Valley. By contrast, the top industries for the broader sample of private firms tend to be consumer retail related such as auto dealers and restaurants, with locations more aligned with overall population distribution.

We define an *IPO quarter* as the latest quarter in which we observe Y-14Q data in the one-year window before an IPO. We also create the dummy variable IPO, which equals one if the firm IPOs in the next three years. Table 6 includes summary statistics comparing IPO firm-quarters to non-IPO firm-quarters. IPO firms are larger in terms of assets and sales, relative to the broader sample of private firms. Appendix Table C1 compares IPO firm-quarters that we successfully merged to Y-14Q versus those that we are unable to merge that have pre-IPO financials from Compustat. Appendix B contains detailed definitions of the variables used throughout the paper.

2.4 Constructing the Loan-level Panel

For our tests that examine the specific terms of bank debt financing, we construct a loan-level panel. To do so, we merge the firm-level balance sheet, income statement, cash flow, location, public status, IPO status, and private financing characteristics from our panel of private firms with the respective firm's specific loan-level records from the Y-14 data that contain the terms of each loan at origination. As we show in Table **??**, the Y-14Q data include information pertaining to each loan's size, interest rate, and maturity. In addition, the data contain two credit quality assessments from the lending bank: probability of default (PD) and loss given default (LGD).

As we construct the loan-level data and variables, we follow several of the filters from Beyhaghi, Fracassi, and Weitzner (2022) which also examines loan-level data. Specifically, we drop observations in which the interest rate is zero or negative. We also drop observations in which the PDs and/or LGD is/are missing, zero, or greater than 1. Loan records can appear in the data for multiple quarters so long as the loan remains on the lending bank's balance sheet, but we only keep observations in which the loan is originated.

3 Empirical Analysis

Our empirical analysis is divided into four parts. In Section 3.1, we analyze the cross-section of private firms to test which characteristics predict firms going public. In Section 3.2, we examine the time-series of firm outcomes before and after the IPO based on a matched sample of firms that remain private. In Section 3.3, we show that firms' borrowing costs drop after the IPO. Finally, in Section 3.4, we provide evidence that asymmetric information drops after the IPO.

3.1 Cross-Sectional Tests

We first examine which ex-ante characteristics predict firms going public. To do so, we estimate the following regression:

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

where i and t index firm and quarterly date, respectively. The dependent variable $IPO_{i,t+1:t+12}$ is a dummy variable that equals one if the firm IPOs within the next twelve quarters, which we multiply by 100.[25] We include a vector of firm characteristics $X_{i,t}$ as well as date fixed effects (δ_t). In some specifications, we also include date by industry, date by CBSA, and date by industry by CBSA fixed effects. We cluster our standard errors by firm.[26]

Column (1) of Table 7 displays the estimated coefficients of (1) with date fixed effects alone. First, we find a statistically significant relationship between firms' propensity to IPO and their size (log(sales)). Specifically, a 10% increase in sales increases the likelihood of a firm going public by 12.5% from its base rate of 0.19%. This result is consistent with high fixed costs of going public (e.g., Ritter (1987)), resulting in larger firms being more likely to go public. Second, firms with higher trailing-one year sales growth are also more likely to IPO. Third, firms' current investment (CapEx/Assets) is positively related to their propensity to IPO. Specifically, a one-standard deviation increase in CapEx/Assets (10%), increases the likelihood of a firm going public by about 41%. This result is consistent with firms that have high investment needs being more likely to go public.

We also find a strong negative relationship between firms' propensity to IPO and profitability (EBITDA/ assets): a one standard deviation decrease in profitability (0.22), increases the likelihood of a firm going public by about 71%. This result is the exact opposite of Pagano, Panetta, and Zingales (1998) who estimate regressions similar to these among a sample of private Italian firms and suggests that less profitable firms, which are less able to generate cash flows internally, are more likely to go public. In combination with our findings that firms with high capital investment intensity are more likely to IPO, our results on firm profitability suggest that firms with acute external financing needs are more likely to IPO.[27]

The negative and significant relationship between profitability and IPO propensity

[25] Our results are very similar if we use a two-year window to define an IPO instead.

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

[27] In the Appendix Table C2 we also obtain similar results if we combine the profitability and investment variables into a funding surplus variable. Specifically, we re-estimate the last column from Table 7, but replace EBITDA/assets and CapEx/assets with Funding Surplus, which is the firm's EBITDA - CapEx divided by Assets. Consistent with our main results, we find a strong negative relationship between the funding surplus and a firm's subsequent likelihood of going public.

is also consistent with anecdotal evidence of firms delaying going public when they can generate cash flows internally. For example, John Collison, the Stripe Co-founder and President, recently stated that more profitable firms do not need to go public because internally generated cash flows can fund their investments.[28]

Finally, we find that a firm's industry-level (we use four-digit NAICS) the median market-to-book ratio (for the publicly traded firms) has a positive relationship with the propensity to go public. As Pagano, Panetta, and Zingales (1998) discuss, this result could be related to investment opportunities or mispricing. The fact that we also find firms with lower ex-ante profitability and higher investment intensity suggests that this result in our setting is more consistent with the former explanation.

In columns (2), (3), and (4), 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.[29] Across these alternative specifications with more restrictive fixed effects, we find that the coefficients remain fairly similar, particularly for the main ones of interest (investment and profitability).

Although we include industry/date fixed effects in our regressions, firms within industries may still not be completely comparable, particularly for high-tech firms. One concern could be that the most "high-tech" firms are the ones that IPO, and these firms tend to be less profitable. For example, many biotech firms have zero revenue before going public. In Table C3, we show that the main results are robust to excluding all tech/biotech firms and firms located in Silicon Valley. Similarly, our results are robust to controlling for firm fixed effects that absorb firm-specific differences not captured by industry (Appendix Table C4).

Another concern could be that the types of firms in the Y-14Q data differ fundamentally from those we are unable to merge. For instance, firms with minimal cash flows may avoid bank debt altogether. However, we would expect access to capital to be even more important for these firms in their decision to IPO. Nonetheless, Compustat also includes

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

[29]Column (2) has slightly 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-14Q data.

two years of pre-IPO financials for firms that ultimately IPO. In Appendix Table C5, we show consistent with this intuition that our results are, if anything, stronger when we include these unmerged firms' pre-IPO data in our sample.[30] Specifically, the point estimates on profitability and investment are larger in magnitude than in Table 7.[31]

If less profitable firms go public due to a lack of internal funds to finance investment, we expect this effect to be stronger for firms with more investment needs. To test this hypothesis, we re-estimate the same regressions from Table 7, but include an additional interaction term between EBITDA/Assets and CapEx/Assets. As shown in Table 8, across all specifications, the interaction coefficient is negative and statistically significant. These results suggest that the relationship between ex-ante investment and going public is even stronger for firms that generate fewer internal cash flows, which 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.

If firms with higher external capital needs are more likely to go public, one might expect that this mechanism would be weaker for 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, they may find public markets particularly attractive. In Table 9, we re-estimate the same regressions from Table 7 but only include firms that we identify as VC-backed.[32] Across all specifications, we find the coefficients are dramatically larger in magnitude for investment and profitability. For example, in column (4) with date by industry by location fixed effects, the investment coefficient is about 20 times as large and the profitability coefficient is about 6 times as large. These results suggest that even firms with access to private equity capital go public when their capital needs are high. Moreover, the fact that the magnitudes are even larger than those in our baseline tests is consistent with firms that have VC-backing being more subject to asymmetric information and hence, the benefit of being public increasing more

[30] In the regressions, we exclude sales growth as an independent variable because it is missing from most of the Compustat observations.

[31] Another concern is that some firms in our sample of firms that remain private are actually acquired. In Appendix Table C6 we show that our results are robust to excluding firms that exit via acquisition.

[32] IPO firms comprise a much larger share of the venture-capital backed sub-sample: 40% of the IPO firms are venture capital backed, but only 1% of the other private firms are venture-capital backed.

with their external capital needs.[33]

In Table 10, we reestimate the same regressions but restrict the sample to firms in technology-related industries. The point estimates for profitability and investment have the same sign and are larger in magnitude than our baseline results in 7, and we find even larger effects in Table 11, where we restrict the sample to VC-backed tech firms. This latter result suggests that VC-backing is not simply picking up "tech" effects and that it has an independent relationship with capital needs and the going public decision.

3.2 Time-Series Tests

After analyzing which firm characteristics predict firms' decisions to IPO in the future, in this section, we examine how firm outcomes evolve after the IPO. To do this, we perform a matched analysis in which we match IPO firms to three control firms in the last quarter available in the year prior to IPO. We form a matched sample by estimating propensity scores based on our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' last quarter in the year prior to the IPO. The matched sample includes the three closest firms in terms of propensity scores while requiring exact matching based on their two-digit NAICS industry and VC-backing.

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

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

where $d_{i,c}$ is a dummy that equals one if the firm is treated (i.e., is an IPO firm), $\lambda_{y,k,c}$ is a dummy equal to one if year y is equal to k and zero otherwise. We include firm

[33]One additional benefit of the Prequin data is that it contains information regarding the year in which each firm was founded, which is not in the Y-14Q data. This allows for us to compare IPO firms with venture capital investments to other venture capital funded private firms that were founded in the same year. In Appendix Table C7, we find similar results when we interact the existing fixed effects with a year-founded fixed effect.

cohort fixed effects $\alpha_{i,c}$ to compare the change in outcome within the same firm. We include time-cohort fixed effect $\delta_{t,c}$ to ensure that the IPO firm is compared only with the matched control firms at each point in time. Standard errors are again clustered by firm.

For each regression, we plot the time-series of coefficients, i.e., β_k, with 90% confidence intervals. We omit the year prior to the IPO, i.e., β_{-1} as the reference point. We estimate annual coefficients rather than quarterly to obtain more precise estimates; however, because the year of the IPO may also contain quarters prior to the IPO, the effect is often smaller in year one than years in which all quarters occur after the IPO.

First, we examine the dynamics of firms' CapEx (in logs) around the IPO. Figure 1 shows that IPO firms' CapEx increases dramatically after the IPO as compared to matched firms that do not go public. CapEx jumps after the IPO and remains a statistically significant 50% larger than matched non-IPO firms four years after the IPO. This increase in investment translates into higher total assets. In Figure 2, we plot total assets (in logs) and find that IPO firms' assets are around 40% larger, four years after IPO.

While capital expenditures are clearly an important form of investment, certain firms, particularly technology related ones, also invest in intangible assets such as R&D. Although, we do not have data on R&D and intangible investment specifically, we can back out total intangible assets based on the firms total assets and tangible assets, which are both available in the Y-14Q data.[34] In Figure 3 we plot the time series of coefficients for intangible assets (in logs) and find that IPO firms' intangible assets are just under 20% higher than matched non-IPO firms four years after IPO.

We have shown that firms dramatically increase their assets and investment after IPO. An obvious question is how firms finance this investment. Is it purely financed through new equity, or do firms use the IPO to facilitate non-equity capital raises? To answer this question, we first analyze how firms' capital structure evolves after the IPO in Figure 4. The figure shows that in year one, there is around a 3pp drop in leverage, which is statistically significant. However, after year one, leverage reverts back such that in

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

years 2 - 4, there is a positive, but not statistically different, difference between matched non-IPO firms. This result goes against Pagano, Panetta, and Zingales (1998), which is the only other paper we are aware of to analyze leverage dynamics, who find a large reduction in leverage after the IPO in Italy.

If firms' leverage is not decreasing after the IPO, given the initial influx of equity, it must be the case that firms are increasing their debt issuance after the IPO. In Figure 5 we plot the coefficients for total bank debt (in logs). By year four, the amount of bank debt IPO firms use increases by almost 30%. Are IPO firms' existing banks simply extending more credit, or are new banks lending to them after they go public? To answer this question, we plot the estimated coefficients for the number of banks as the dependent variable in Figure 6. IPO firms borrow from just over 1 more bank after four years, starting from a baseline average of 3.5 banks. In the Appendix, we also estimate the regression using a fixed-effect Poisson model (e.g., Cohn, Liu, and Wardlaw (2022)) and find very similar results.

We also test whether these effects are still present among VC-backed firms with access to private capital markets. In Appendix C, we find qualitatively similar results among our main time-series tests when we restrict the sample to firms that are VC-backed.

3.3 Going Public and Bank Borrowing Costs

In Section 3.2, we find that firms do not simply issue equity after they go public. Rather, they finance their asset growth and investments with debt from an expanded number of lenders, such that their leverage is unchanged four years after the IPO. Why do firms increase their debt after the IPO? One possibility is that by increasing the number of informed investors, adverse selection costs go down (e.g., Rock (1986)), Sharpe (1990), Rajan (1992), Kurlat (2016) and Beyhaghi, Fracassi, and Weitzner (2022)), resulting in improved borrowing terms as informed investors compete more intensively with each other.

An empirical problem with testing for an improvement in borrowing terms is that the IPO likely causes a reduction in risk. Hence, showing that interest rates go down after the IPO is insufficient to argue that borrower terms improve. Fortunately, the Y-14Q data allows us to make this distinction because it includes banks' internal risk assessments (PD and LGD). Recent work has shown that these risk assessments strongly predict default (Beyhaghi, Fracassi, and Weitzner (2022) and Weitzner and Howes (2021)) and predict public equity and bond returns (Beyhaghi, Howes, and Weitzner (2022)). In fact, Beyhaghi, Fracassi, and Weitzner (2022) show that after controlling for these risk assessments, interest rates no longer predict default at all, suggesting that the risk assessments are sufficient statistics for the underlying risk of the borrower. Hence, we follow the approach of Beyhaghi, Fracassi, and Weitzner (2022) and test how interest rates change *controlling for banks' assessed risk* of the underlying loans.

To examine how the terms of these loans change after the IPO, we use loan-level data and restrict the sample to newly issued loans.[35] We estimate the following regression:

$$IR_{i,t} = \beta_0 \left(IPO_i \times Post_t\right) + \Gamma_0 X_{i,t} + \Gamma_1 Z_{i,t} + \beta_1 PD_{i,t} + \beta_2 LGD_{i,t} + \alpha_{i,b} + \delta_t + u_{i,t},$$

where $IR_{i,t}$ is the interest rate on a new loan to firm i in year/quarter t. As independent variables, we include the same vector of firm-level controls as in Section 3.1 ($X_{i,t}$), a vector of loan-level controls ($Z_{i,t}$), which include log(maturity), log(amount) and facility type fixed effects,[36] as well as banks' internal risk assessments: Probability of Default (PD) and Loss Given Default (LGD). The variable of interest is $IPO_i \times Post_t$, which represents the change in firm i's borrowing cost after going public, controlling for bank b's change in the perceived risk of the firm. We also include bank by firm fixed effects $\alpha_{i,b}$ to control for any time-invariant relationship-specific effect on borrowing costs.

The results are displayed in Table 12. In column (1), we estimate the regression without loan-level controls, bank risk assessments, or bank by year-quarter fixed effects. The estimated coefficient is -0.575 and statistically significant, suggesting that after going public, firms' credit spreads drop by 60bps. We find similar results when we include loan-

[35] Because we are analyzing new loans there are not enough observations to do the same type of matched sample analysis as above; however, our data allows us to observe the banks' perceived risk of the borrower, which arguably makes matching unnecessary.

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

level controls in column (2), and the point estimate marginally decreases in magnitude to -0.553 when we add bank by year by year fixed effects in column (3). Finally, in column (4), we also include bank risk assessments. Consistent with Beyhaghi, Fracassi, and Weitzner (2022), PD and LGD are both positively related to the loan's interest rate. The coefficient for $IPO \times Post$ also remains negative and large in magnitude (-0.436). This 41.3bp drop in borrowing costs compares to an all-in average interest rate of around 400bps and a credit spread of 182bps (compared to the average 10-year treasury rate) for IPO firms prior to going public. Hence, credit spreads drop by almost one quarter, even after *controlling for the underlying risk* of the firm, as perceived by the bank.

These results suggest that borrowing from banks becomes more attractive after firms go public. The most plausible mechanism behind this channel is that increasing their transparency after going public reduces asymmetric information. This allows firms to borrow from more banks and at a lower cost as banks are less able to extract information rents from public firms. In the next section, we directly test for this mechanism, i.e., a reduction in asymmetric information, using banks' private risk assessments.

3.4 Going Public and Asymmetric Information

Our final set of tests examines whether going public reduces information asymmetries. Testing for asymmetric information typically requires access to investors' private information, which is generally unobservable. However, the Y-14Q data is uniquely suited for this purpose as it contains banks' internal risk assessments in the form of probability of default (PD) estimates.

Specifically, we create a proxy for the degree of asymmetric information based on the within-firm dispersion in banks' PD assessments. Intuitively, if there is less asymmetric information, banks' beliefs should more closely coincide with each other. This approach is in line with the literature that uses split bond ratings (e.g., Morgan (2002), Iannotta (2006) and Livingston and Zhou (2010)) and analyst dispersion (e.g., Flannery and Kwan (2004)) as proxies for asymmetric information; however, private firms rarely have credit ratings or analyst coverage prior to going public. Additionally, our measure incorporates the private information of multiple sophisticated financial institutions that have direct financial incentives to accurately assess borrower risk.[37]

Our main measure of dispersion is the cross-sectional standard deviation of PD estimates across banks within each firm-quarter. For this analysis, we employ a slightly different matching approach than in our previous tests. Because the level of PD and the number of banks is likely correlated with the cross-sectional standard deviation of PD estimates, we match based on the Mahalanobis distance measure using PD and the number of banks as non-exact matching variables, while requiring that matches are in the same two-digit NAICS industry and have the same VC-backing as before. 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 7 shows that the cross-sectional standard deviation in banks' PD estimates decreases significantly after firms go public compared to matched private firms. This decline begins immediately after the IPO and persists through the four-year post-IPO period we analyze. By year four, the dispersion in PD estimates for IPO firms is approximately 4pp lower than for matched control firms that remain private, which is just over one half of a standard deviation.

To ensure that our results are not driven by changes in the composition of lending banks after the IPO, we conduct the same analysis while fixing the set of banks for each firm throughout the sample period (Figure C7). In this modified test, we find a similar decrease in PD dispersion after the IPO. We also find a similar decline in PD dispersion after the IPO when we measure PD dispersion using the range between the highest and lowest PD estimates (Figure C8).[38]

These results not only provide direct evidence that information asymmetry declines after firms go public, but this reduction in asymmetric information is consistent with our findings that firms borrow more, from an expanded pool of lenders, and at better terms.

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

[38] Here we also fix the set of banks as the range would likely mechanically increase as the number of banks increases after the IPO.

As discussed earlier, many theories predict that as information asymmetries decrease, the potential for adverse selection and hold-up problems diminishes, allowing firms to access capital from a broader set of lenders at more favorable terms.

It is important to acknowledge that differences in banks' reported PDs could also be driven by disagreement based on common information. However, typically higher disagreement leads to higher prices (e.g., Miller (1977)), while we observe higher prices after a *reduction in belief dispersion*. While it is likely there is some disagreement across banks based on common information, in our view the most plausible explanation for a drop in dispersion is due to decreasing asymmetric information. Moreover, we only need that the drop in dispersion is partially due to a reduction in asymmetric information, rather than entirely driven by reduced disagreement based on common information.

What drives differences in within-firm information across banks? Banks may use different credit assessment models, have different monitoring technologies, relationship histories, or access to private information through their specific interactions with the borrower. Beyhaghi, Howes, and Weitzner (2022) show that credit line drawdowns and different incentives to produce information lead to differences in information across banks within firm/time. These differences in information can be particularly pronounced for private firms that face fewer disclosure requirements and less external scrutiny.

4 Conclusion

One of the most cited reasons for a firm to go public is to improve its access to capital through reduced information asymmetries. However, in recent years, private capital markets have expanded rapidly, casting doubt on this presumed benefit of public markets. In this paper, we provide evidence that despite this trend, improved access to capital is an extremely important motive for firms going public and that this improved access is driven by a reduction in asymmetric information after the IPO.

To summarize, we find that less profitable companies with higher investment needs are more likely to IPO. After going public, these firms increase their investments in both tangible and intangible assets relative to comparable firms that remain private. Firms finance this increased investment not just through equity but also through increases in bank debt from an expanded pool of lenders. We also show that firms' borrowing costs *conditional on their risk* drop after going public. Finally, consistent with a reduction in asymmetric information, we find that the dispersion in banks' private risk assessments drop after the IPO.

Taken together, our results are consistent with going public reducing information asymmetries, thereby reducing firms' cost of capital. Hence, our analysis suggests that recent policies to reduce the regulatory burden of being public, e.g., the 2012 JOBS Act, can help facilitate the flow of capital to NPV positive investments.

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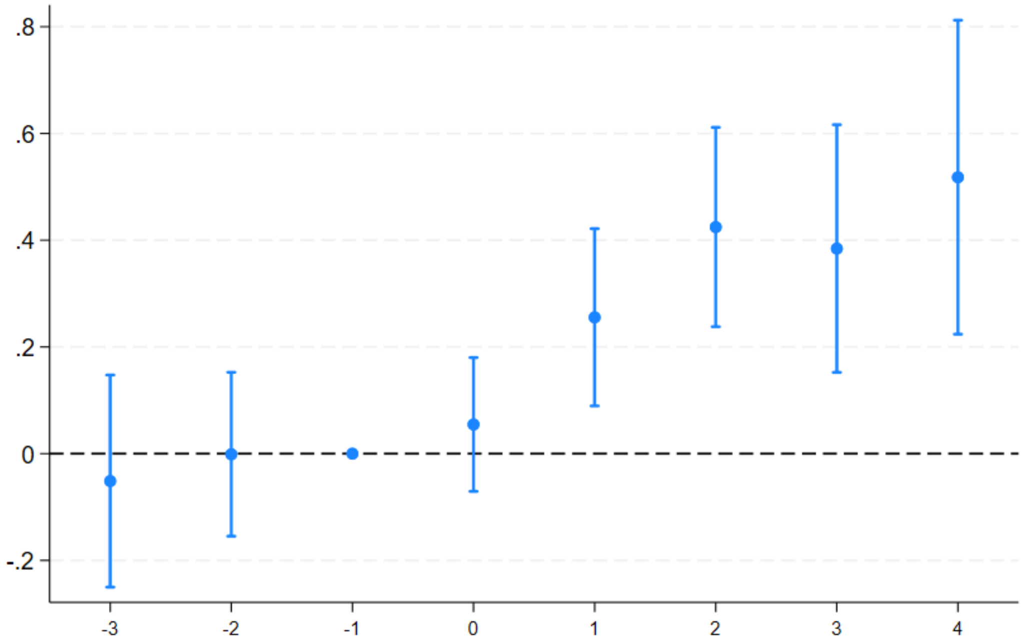
Figure 1: IPO Investment Dynamics

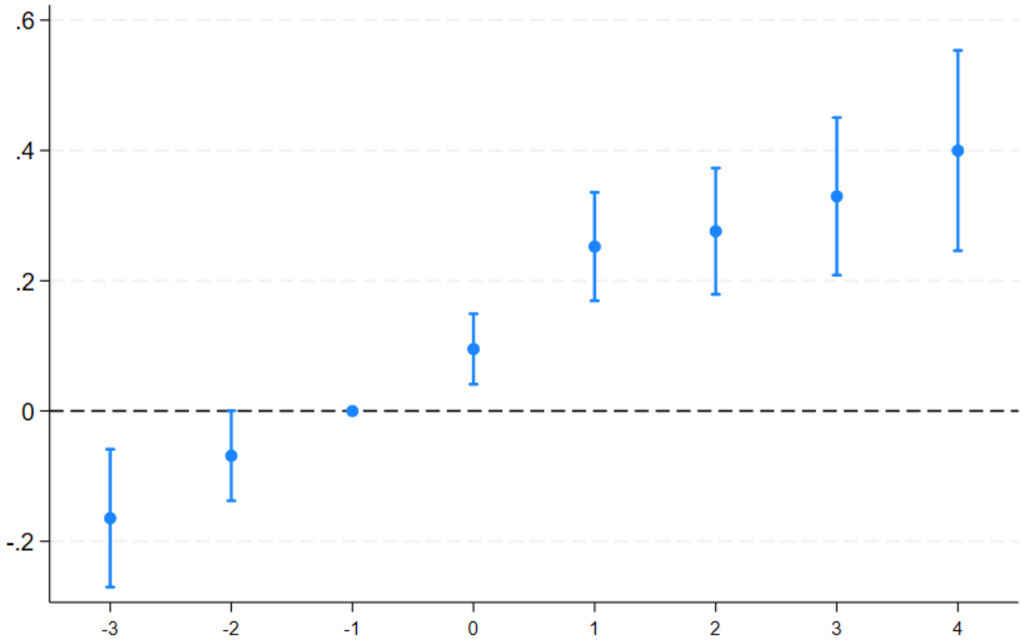


Note: In this figure, we analyze the dynamics of firm investment, i.e., log(CapEx), before and after the IPO using a matched sample. We form a matched sample by estimating propensity scores based on our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' last quarter in the year prior to the IPO. The matched sample includes the three closest firms in terms of propensity scores that are in the same two-digit NAICS industry. The dots are point estimates of the interaction coefficients between treated (IPO firms) and time dummies and the bars are the 90% confidence intervals from the following regression:

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

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

Figure 2: IPO Asset Dynamics

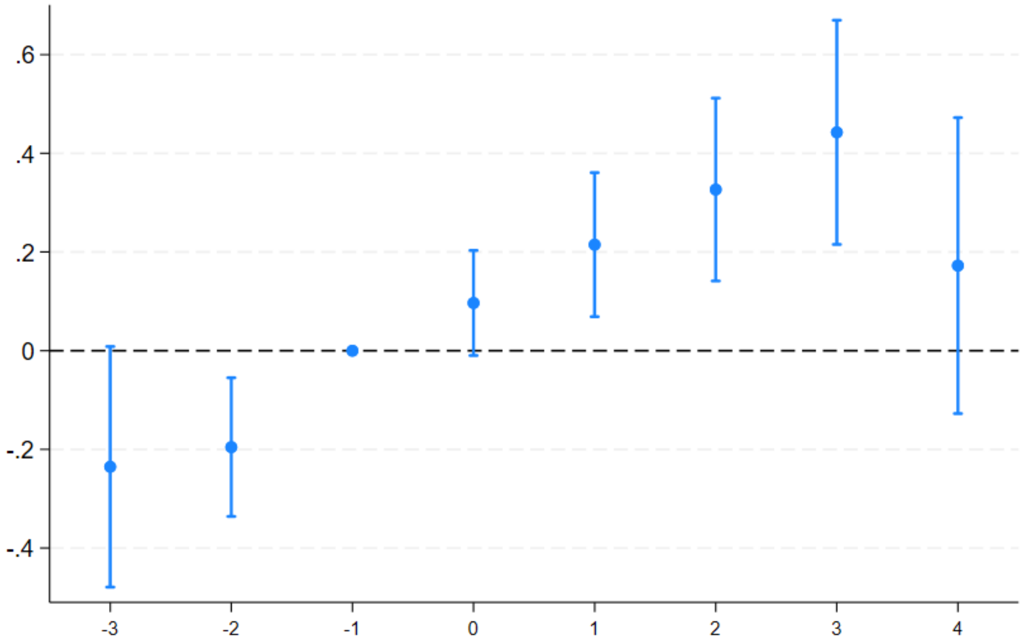


Note: In this figure, we analyze the dynamics of firm assets, i.e., log(assets), before and after the IPO using a matched sample. We form a matched sample by estimating propensity scores based on our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' last quarter in the year prior to the IPO. The matched sample includes the three closest firms in terms of propensity scores that are in the same two-digit NAICS industry. The dots are point estimates of the interaction coefficients between treated (IPO firms) and time dummies and the bars are the 90% confidence intervals from the following regression:

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

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

Figure 3: IPO Intangible Assets Dynamics

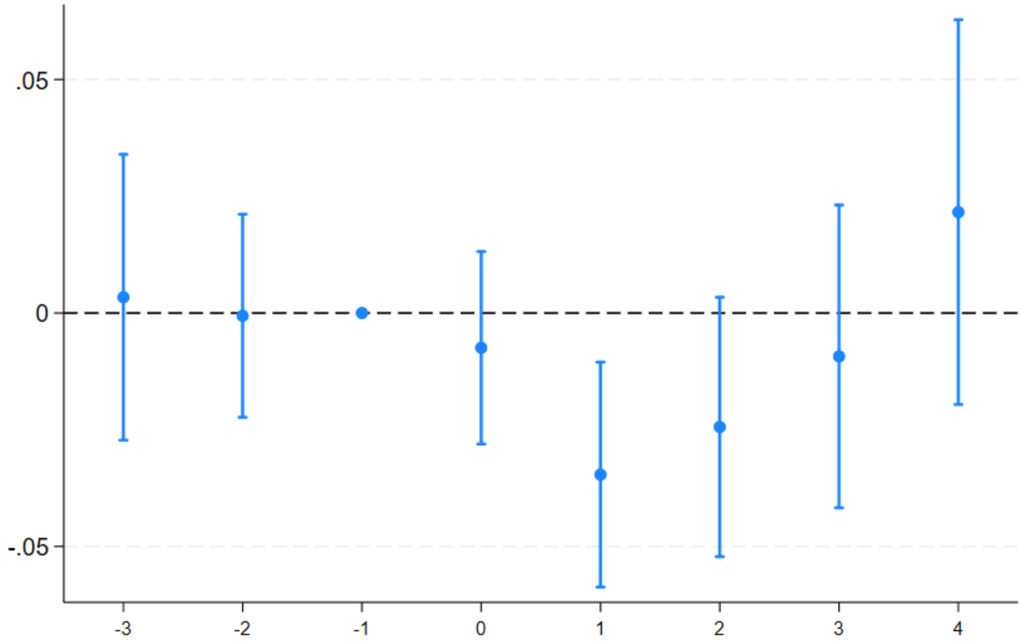


Note: In this figure, we analyze the dynamics of intangible assets, i.e., log(intangible assets), before and after the IPO using a matched sample. We form a matched sample by estimating propensity scores based on our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' last quarter in the year prior to the IPO. The matched sample includes the three closest firms in terms of propensity scores that are in the same two-digit NAICS industry. The dots are point estimates of the interaction coefficients between treated (IPO firms) and time dummies and the bars are the 90% confidence intervals from the following regression:

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

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

Figure 4: IPO Leverage Dynamics

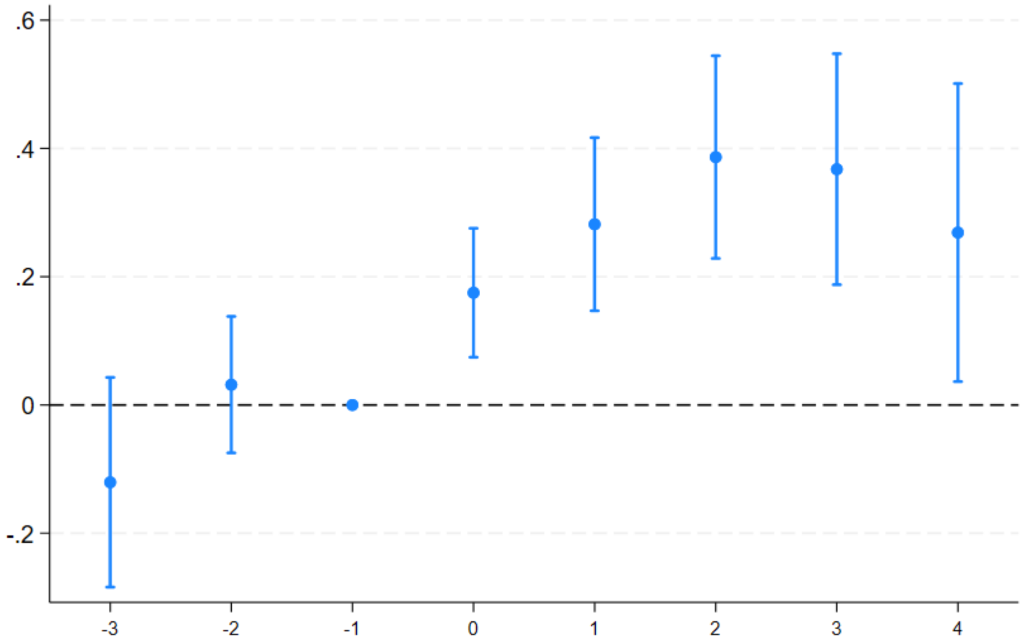


Note: In this figure, we analyze the dynamics of firm leverage, i.e., debt/assets, before and after the IPO using a matched sample. We form a matched sample by estimating propensity scores based on our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' last quarter in the year prior to the IPO. The matched sample includes the three closest firms in terms of propensity scores that are in the same two-digit NAICS industry. The dots are point estimates of the interaction coefficients between treated (IPO firms) and time dummies and the bars are the 90% confidence intervals from the following regression:

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

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

Figure 5: IPO Bank Debt Dynamics

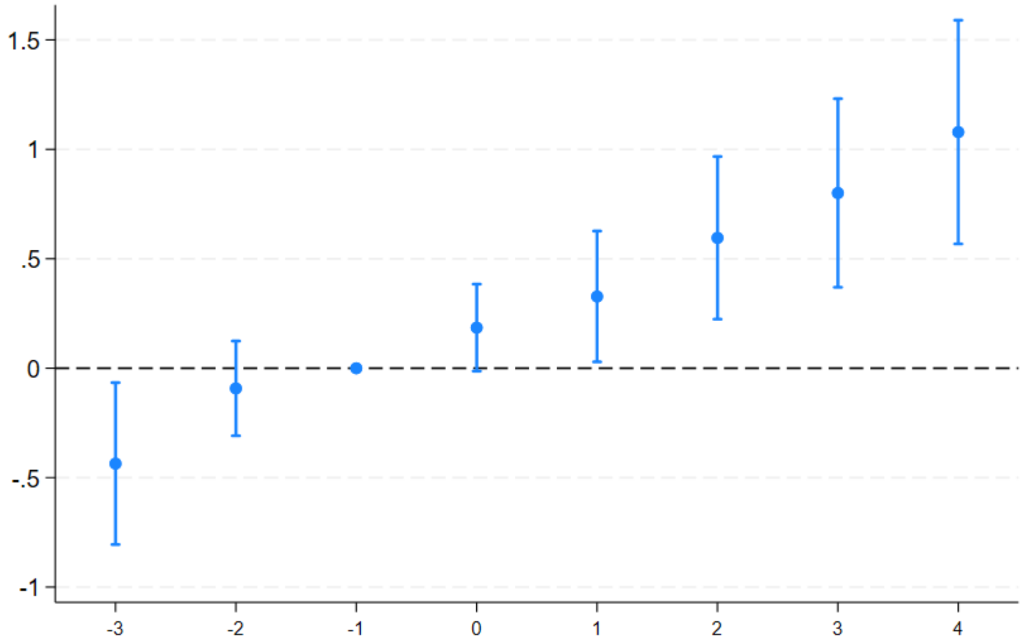


Note: In this figure, we analyze the dynamics of bank debt, i.e., log(bank debt), before and after the IPO using a matched sample. We form a matched sample by estimating propensity scores based on our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' last quarter in the year prior to the IPO. The matched sample includes the three closest firms in terms of propensity scores that are in the same two-digit NAICS industry. The dots are point estimates of the interaction coefficients between treated (IPO firms) and time dummies and the bars are the 90% confidence intervals from the following regression:

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

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

Figure 6: IPO Number of Banks Dynamics

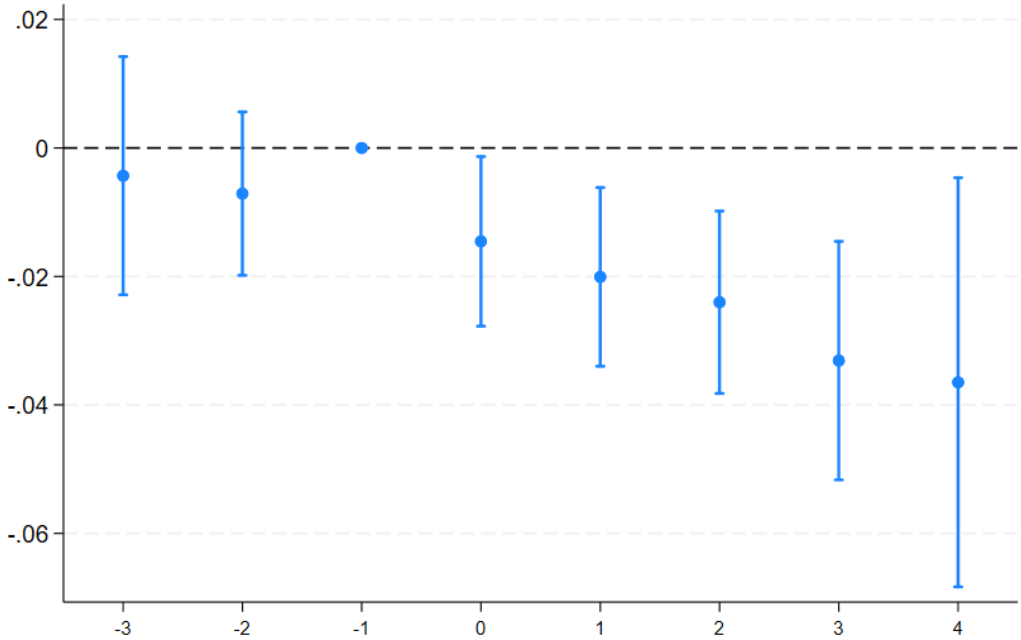


Note: In this figure, we analyze the dynamics of the number of banks the firm borrows from before and after the IPO using a matched sample. We form a matched sample by estimating propensity scores based on our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' last quarter in the year prior to the IPO. The matched sample includes the three closest firms in terms of propensity scores that are in the same two-digit NAICS industry. The dots are point estimates of the interaction coefficients between treated (IPO firms) and time dummies and the bars are the 90% confidence intervals from the following regression:

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

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

Figure 7: PD Dispersion



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

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

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

Table 1: 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 IPO.

Industry	# of Firms	% of Total
Software Publishers	41	10.99
Computer Systems Design & Related Services	19	5.09
Data Processing, Hosting, & Related Service	16	4.29
Pharmaceutical & Medicine Manufacturing	15	4.02
Oil and Gas Extraction	13	3.49
Restaurants & Other Eating Places	11	2.95
Electronic Shopping	9	2.41
Support Activities for Mining	8	2.14
Lumber & Other Construction Materials Wholesalers	8	2.14
Other Information Services	7	1.88
Electric Power Gen, Transmission and Distribution	6	1.61
Miscellaneous Durable Goods Manufacturing	6	1.61
Scientific Research & Development Services	6	1.61
Traveler Accommodation	6	1.61
Navigation, Measuring, Electromed, & Control Instruments	5	1.34
Clothing Stores	5	1.34
Architectural, Engineering, & Related	5	1.34
Management, Scientific, & Technical Consulting	5	1.34
Other Amusement & Recreation Industries	5	1.34
Residential Building Construction	4	1.07
Semiconductor & Other Component Manufacturing	4	1.07
Professional & Commercial Equipment & Supplies Wholesalers	4	1.07
Grocery & Related Product Merchant Wholesalers	4	1.07
Advertising Agencies	4	1.07
Business Support Services	4	1.07
Investigation and Security Services	4	1.07
Other Wood Product Manufacturing	3	.8
Basic Chemical Manufacturing	3	.8
Soap, Cleaning Comp, and Toilet Prep Manufacturing	3	.8
Plastics Product Manufacturing	3	.8

Table 2: Location Composition of IPO Firms

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

CBSA	# of Firms	% of Total
San Francisco-Oakland-Hayward	43	11.53
New York-Newark-Jersey City	25	6.7
Boston-Cambridge-Newton	23	6.17
Los Angeles-Long Beach-Anaheim	22	5.9
Dallas-Fort Worth-Arlington	17	4.56
San Jose-Sunnyvale-Santa Clara	16	4.29
Chicago-Naperville-Elgin	15	4.02
Washington-Arlington-Alexandria	13	3.49
Philadelphia-Camden-Wilmington	12	3.22
Phoenix-Mesa-Scottsdale	11	2.95
Orlando-Kissimmee-Sanford	10	2.68
Indianapolis-Carmel-Anderson	9	2.41
Austin-Round Rock	8	2.14
Atlanta-Sandy Springs-Roswell	7	1.88
Minneapolis-St. Paul-Bloomington	6	1.61
Raleigh	6	1.61
Cleveland-Elyria	5	1.34
Detroit-Warren-Dearborn	5	1.34
Virginia Beach-Norfolk-Newport News	5	1.34
Bridgeport-Stamford-Norwalk	4	1.07
San Antonio-New Braunfels	4	1.07
Denver-Aurora-Lakewood	4	1.07
Las Vegas-Henderson-Paradise	4	1.07
Miami-Fort Lauderdale-West Palm Beach	4	1.07
Portland-Vancouver-Hillsboro	4	1.07
Salt Lake City	4	1.07
Riverside-San Bernardino-Ontario	4	1.07
Seattle-Tacoma-Bellevue	4	1.07
Midland	3	.8
Milwaukee-Waukesha-West Allis	3	.8

Table 3: 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	13501	13.32
Restaurants & Other Eating Places	2794	2.76
Wholesale Distribution	2423	2.39
Computer Systems Design & Related Services	1949	1.92
Grocery & Related Product Merchant Wholesalers	1692	1.67
Nonresidential Building Construction	1579	1.56
Building Equipment Contractors	1520	1.5
Architectural, Engineering, & Related	1481	1.46
General Freight Trucking	1472	1.45
Software Publishers	1407	1.39
Management, Scientific, & Technical Consulting	1377	1.36
Other Motor Vehicle Dealers	1303	1.29
Misc Durable Goods Merchant Wholesalers	1222	1.21
Plastics Product Manufacturing	1072	1.06
Offices of Physicians	1009	1
Electric Power Gen, Transmission and Distribution	1003	.99
Apparel & Accessories, Not Elsewhere	931	.92
Other Amusement & Recreation Industries	927	.91
General Medical & Surgical Hospitals	905	.89
Motor Vehicle Parts & Supplies Wholesalers	900	.89
Professional & Commercial Equipment & Supplies Wholesalers	881	.87
Lumber & Other Construction Materials Wholesalers	876	.86
Household Appliances & Electrical Goods Wholesalers	872	.86
Highway, Street, and Bridge Construction	861	.85
Legal Services	860	.85
Management of Companies and Enterprises	855	.84
Nursing Care Facilities	828	.82
Support Activities for Mining	782	.77
Oil and Gas Extraction	752	.74
Miscellaneous Nondurable Goods Wholesalers	748	.74

Table 4: Location Composition of Private Firm Sample

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

CBSA	# of Firms	% of Total
New York-Newark-Jersey City	9014	8.93
Los Angeles-Long Beach-Anaheim	4686	4.64
Chicago-Naperville-Elgin	4054	4.02
Philadelphia-Camden-Wilmington	2706	2.68
Indianapolis-Carmel-Anderson	2617	2.59
Non-Metro Area	2435	2.41
Dallas-Fort Worth-Arlington	2326	2.3
Washington-Arlington-Alexandria	2275	2.25
San Francisco-Oakland-Hayward	2230	2.21
Miami-Fort Lauderdale-West Palm Beach	2197	2.18
Boston-Cambridge-Newton	2179	2.16
Detroit-Warren-Dearborn	2129	2.11
Atlanta-Sandy Springs-Roswell	1978	1.96
Seattle-Tacoma-Bellevue	1459	1.45
Minneapolis-St. Paul-Bloomington	1359	1.35
Cleveland-Elyria	1255	1.24
Phoenix-Mesa-Scottsdale	1208	1.2
Denver-Aurora-Lakewood	1128	1.12
Charlotte-Concord-Gastonia	1123	1.11
Portland-Vancouver-Hillsboro	1044	1.03
Orlando-Kissimmee-Sanford	1041	1.03
Sacramento-Roseville-Arden-Arcade	962	.95
San Antonio-New Braunfels	960	.95
Riverside-San Bernardino-Ontario	930	.92
Tampa-St. Petersburg-Clearwater	910	.9
Columbus, OH	897	.89
Milwaukee-Waukesha-West Allis	840	.83
Indianapolis-Carmel-Greenwood	827	.82
San Jose-Sunnyvale-Santa Clara	809	.8
St. Louis	760	.75

Table 5: Firm Level Summary Statistics: IPO vs. Non-IPO Firms

This table contains summary statistics comparing IPO firm-quarters to non-IPO firm-quarters. Appendix B contains variable definitions.

	IPO Firms				Non-IPO Firms				
	N	Mean	Median	SD	N	Mean	Median	SD	Diff w.r.t. IPO firms
Sales	2755	1515.39	404.63	5554.86	1467963	429.02	66.45	4589.29	-1086.370***
Assets	2755	2136.27	607.87	6471.07	1467963	298.37	31.46	2753.83	-1837.894***
Capex/Assets	2579	0.08	0.03	0.13	1272342	0.05	0.02	0.10	-0.026***
Sales Growth	2580	0.42	0.16	0.73	1394996	0.15	0.07	0.42	-0.266***
EBITDA/Assets	2627	0.09	0.09	0.26	1429358	0.16	0.12	0.22	0.071***
Positive Profits	2627	0.78	1.00	0.41	1429358	0.89	1.00	0.31	0.109***
Funding Surplus	2700	0.01	0.05	0.20	1293138	0.10	0.08	0.18	0.090***
Debt/Assets	2755	0.34	0.34	0.26	1467963	0.31	0.26	0.26	-0.032***
Cash/Assets	2751	0.14	0.05	0.19	1464194	0.12	0.07	0.15	-0.017***
VC-Backed	2755	0.26	0.00	0.44	1467963	0.02	0.00	0.12	-0.242***
Silicon Valley	2755	0.14	0.00	0.34	1467004	0.02	0.00	0.15	-0.115***
Tech Firm	2755	0.30	0.00	0.46	1467963	0.10	0.00	0.30	-0.206***
Std Deviation of PD	723	0.03	0.01	0.07	74530	0.02	0.00	0.06	-0.013***
Range of PD	723	0.07	0.03	0.14	74530	0.03	0.01	0.10	-0.036***

Table 6: Loan Level Summary Statistics: IPO vs. Non-IPO Firms

This table contains summary statistics comparing IPO firm-quarters to non-IPO firm-quarters. Appendix B contains variable definitions.

	IPO Firms				Non-IPO Firms				
	N	Mean	Median	SD	N	Mean	Median	SD	Diff w.r.t. IPO firms
Interest Rate	501	4.25	4.00	1.85	92281	3.88	3.50	1.92	-0.378***
PD (%)	542	2.86	1.28	4.08	78756	1.56	0.88	2.94	-1.296***
LGD (%)	536	35.63	38.00	13.62	76869	32.49	33.73	15.54	-3.142***
PD × LGD (%)	532	0.96	0.46	1.53	76328	0.49	0.24	1.01	-0.469***
Maturity	808	48.53	58.72	20.64	113988	47.92	51.80	42.41	-0.610
Loan Amount (million USD)	837	28.56	14.88	54.04	121294	9.84	3.68	26.97	-18.725***
Floating Rate	494	0.83	1.00	0.38	93072	0.69	1.00	0.46	-0.137***

Table 7: Cross-Sectional Determinants of Firms' IPO Decisions

This table tests which firm characteristics predict firms' going public within the next three years. The dependent variable *IPO* is a dummy that equals one if the firm IPOs in the next three years. 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(Sales)	0.233***	0.228***	0.243***	0.237***
	(0.019)	(0.017)	(0.020)	(0.022)
Capex/Assets	0.758***	0.494***	0.789***	0.453**
	(0.157)	(0.120)	(0.163)	(0.187)
Sales Growth	0.464***	0.294***	0.452***	0.274***
	(0.057)	(0.040)	(0.058)	(0.049)
EBITDA/Assets	-0.600***	-0.565***	-0.608***	-0.510***
	(0.078)	(0.072)	(0.080)	(0.093)
Debt/Assets	0.096	0.288***	0.137**	0.299***
	(0.060)	(0.061)	(0.063)	(0.081)
NAICS4 MTB	0.099***		0.100***	
	(0.014)		(0.014)	
Date FE	Y	N	N	N
Date × NAICS4 FE	N	Y	N	N
Date × CBSA FE	N	N	Y	N
Date × NAICS4 × CBSA FE	N	N	N	Y
N	988898	1249587	982095	935030
R2	0.007	0.031	0.020	0.257

Table 8: Cross-Sectional Determinants of Firms' IPO Decisions: Interactions Between Investment and Profitability

This table tests which firm characteristics predict firms' going public within the next three years. The dependent variable *IPO* is a dummy that equals one if the firm IPOs in the next three years. 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	-1.433***	-0.802***	-1.435***	-1.180***
	(0.352)	(0.261)	(0.368)	(0.375)
Capex/Assets	1.176***	0.730***	1.208***	0.799***
	(0.232)	(0.175)	(0.242)	(0.257)
EBITDA/Assets	-0.487***	-0.493***	-0.495***	-0.410***
	(0.073)	(0.070)	(0.076)	(0.093)
Log(Sales)	0.233***	0.229***	0.243***	0.237***
	(0.019)	(0.017)	(0.020)	(0.022)
Sales Growth	0.465***	0.294***	0.452***	0.273***
	(0.057)	(0.040)	(0.058)	(0.049)
Debt/Assets	0.103*	0.291***	0.145**	0.303***
	(0.059)	(0.061)	(0.062)	(0.081)
NAICS4 MTB	0.099***		0.099***	
	(0.014)		(0.014)	
Date FE	Y	N	N	N
Date × NAICS4 FE	N	Y	N	N
Date × CBSA FE	N	N	Y	N
Date × NAICS4 × CBSA FE	N	N	N	Y
N	988898	1249587	982095	935030
R2	0.007	0.031	0.020	0.257

Table 9: Cross-Sectional Determinants of Firms' IPO Decisions (VC-Backed Sample)

This table tests which firm characteristics predict firms' going 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 IPOs in the next three years. 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(Sales)	2.344***	2.593***	2.292***	2.787***
	(0.309)	(0.368)	(0.322)	(0.498)
Capex/Assets	7.984***	8.197***	7.806***	10.834***
	(2.486)	(2.626)	(2.648)	(3.127)
Sales Growth	1.234***	1.000***	1.104***	0.576**
	(0.315)	(0.287)	(0.332)	(0.260)
EBITDA/Assets	-4.648***	-4.920***	-2.146	-3.380**
	(1.255)	(1.379)	(1.427)	(1.723)
Debt/Assets	-2.813**	-2.347*	-3.072**	-3.036
	(1.348)	(1.415)	(1.434)	(1.992)
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	21141	18714	19325	11406
R2	0.073	0.216	0.183	0.363

Table 10: Cross-Sectional Determinants of Firms' IPO Decisions (Tech Firms Only)

This table tests which firm characteristics predict firms' going public within the next three years among technology firms (i.e., internet, software, computer equipment, data or biotech firm). The dependent variable IPO is a dummy that equals one if the firm IPOs in the next three years. 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(Sales)	0.795***	0.691***	0.835***	0.835***
	(0.102)	(0.088)	(0.108)	(0.122)
Capex/Assets	4.021***	2.724***	4.453***	3.694***
	(1.063)	(0.813)	(1.219)	(1.312)
Sales Growth	0.971***	0.609***	0.878***	0.554***
	(0.175)	(0.126)	(0.178)	(0.149)
EBITDA/Assets	-1.752***	-1.433***	-1.429***	-1.180***
	(0.353)	(0.299)	(0.365)	(0.401)
Debt/Assets	0.765**	0.227	0.732*	-0.282
	(0.368)	(0.317)	(0.381)	(0.459)
NAICS4 MTB	0.826***		0.795***	
	(0.130)		(0.139)	
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	111217	130823	105879	95558
R2	0.028	0.047	0.084	0.238

Table 11: Cross-Sectional Determinants of Firms' IPO Decisions (VC-Backed Tech Firms Only)

This table tests which firm characteristics predict firms' going public within the next three years among VC-backed, technology firms (i.e., internet, software, computer equipment, data or biotech firm). The dependent variable *IPO* is a dummy that equals one if the firm IPOs in the next three years. 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(Sales)	3.240***	3.384***	3.013***	3.629***
	(0.499)	(0.536)	(0.514)	(0.661)
Capex/Assets	10.394***	8.201**	13.828***	10.696**
	(3.847)	(3.820)	(4.625)	(4.382)
Sales Growth	1.345***	1.063***	1.119***	0.685**
	(0.368)	(0.319)	(0.370)	(0.339)
EBITDA/Assets	-4.999***	-5.690***	-1.381	-5.514**
	(1.866)	(1.813)	(2.276)	(2.155)
Debt/Assets	-2.864	-3.489**	-3.617*	-3.927
	(1.797)	(1.701)	(1.952)	(2.506)
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	10824	10405	9738	7616
R2	0.103	0.190	0.234	0.350

Table 12: Going Public and Firms' Borrowing Costs

This table tests whether firms' borrowing costs drop after the IPO. The sample includes only new loans. Standard errors are shown below the parameter estimates in parentheses and are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Interest Rate (%)			
	(1)	(2)	(3)	(4)
IPO Firm × Post	-0.503**	-0.425**	-0.429**	-0.413**
	(0.207)	(0.184)	(0.168)	(0.176)
Log(Assets)	-0.072***	-0.060**	-0.048**	-0.048**
	(0.026)	(0.024)	(0.023)	(0.024)
Capex/Assets	0.238**	0.185*	0.171*	0.208*
	(0.111)	(0.104)	(0.096)	(0.110)
Sales Growth	0.024	0.029	0.041	0.048
	(0.037)	(0.036)	(0.033)	(0.039)
EBITDA/Assets	-0.378***	-0.321***	-0.339***	-0.253***
	(0.100)	(0.079)	(0.077)	(0.073)
Debt/Assets	0.455***	0.478***	0.442***	0.414***
	(0.091)	(0.081)	(0.080)	(0.091)
PD (%)				0.044***
				(0.007)
LGD (%)				0.003***
				(0.001)
Date FE	Y	Y	Y	Y
Bank/Firm FE	Y	Y	Y	Y
Bank/Date FE	N	N	Y	Y
Loan Controls	N	Y	Y	Y
N	37316	35983	35931	29879
R2	0.804	0.865	0.876	0.878

Appendix A. Additional Data Details

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

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

We apply several filtering measures to the Y-14Q raw data, in addition to those described in Section 2.4. Specifically, we exclude firms with the following terms in their names: *real estate, subsidiary, properties, investment, newco, credit, family, acquisition, merger, series, holdco, finco, funding, trust, bank, banc mortgage, government, commonwealth, school, university, college, township, financing, finance, lease, leasing, foundation, insurance, retirement, church, temple, jewish, christian, muslim, bible, ymca, yeshiva, methodist, episcopalian, community, jesus, israel, redevelopment, partners, partnership, citigroup, citicorp, jpmorgan, metlife, airport, hathaway, museum, nonprofit, non-profit, public, china, usa, securitization, ubs ag, north america, receivables company, distribution company, client services inc., institutional fund, reit, clo, spv, iii, ii, iv, viii, vii, vi, county of, counties of, city of, town of, state of, board of, district of, borough of, society of, college of, council of, council for, center of, center for, educational estate, national association, non profit, indian tribe, development auth, development and auth, developmentauth, building auth, and housing dev.* We use the name-filters in order to exclude records in which industries are incorrectly classified or missing.

One challenge of the Y-14Q data that has been discussed in prior academic studies that use these data is the difficulties in distinguishing parent companies from subsidiaries. As discussed in Gustafson, Ivanov, and Meisenzahl (2020) the Y-14Q data often includes loans to subsidiaries of public companies, that are otherwise indistinguishable from independent private firms. Thankfully, our data has been cleaned by a team of economists working within the Financial Institution Risk Evaluation section within the Financial Stability Division of the Federal Reserve Board. These cleaning measures involve identifying loans to subsidiaries of public companies, and classifying these borrowers as publicly traded.

The Y-14Q data include the date of each loan's record, a date of each loan's origination, as well as a date indicating the period-end for each corresponding borrower firm's latest financial data. To construct our panel of borrower financial data, we utilize the date that corresponds to the financial data. For smaller private firms the financial data are generally updated on an annual basis, while for larger public firms the financial data are generally updated quarterly. Throughout our analysis, we fill-down intra-year borrower financial data, by at most three quarters, for firms with financial data only reported at annual frequency. Our results are robust to removing the within-year fill-down process, but the fill-down increases the power of our time-series tests.

For the variables that relate to private firms' bank debt, we use the date that corresponds to the borrower firm's loan record. For example, for variables including the number of banks, the amount of bank debt, etc. We use the date that corresponds to the loan details, rather than the borrower financial details. Therefore, constructing a panel of private firms that contains both the private firm's financial data and the private firm's bank debt characteristics requires constructing two separate panels using the two sets of dates, and then merging these together. This process ensures that our panel of borrower financial data and bank debt characteristics are synced correctly.

Many of the private firms in the Y-14Q data borrow from multiple banks in a given quarter, and therefore the Y-14Q data include many duplicate records as the same borrower's financial data appears at different banks. Therefore, to transform the loanf-level Y-14Q data to our borrower-level panel we take the median financial record across each firm's lending banks within a quarter.

We make several cleaning adjustments to the data. For example, some banks record report borrower's capital expenditures as a negative number, while others record CapEx as positive. Therefore, we replace all CapEx all records with the record's absolute value, prior to taking the median across various bank loan records. In order to remove records that follow different units – for example some banks report in millions vs. others in thousands – we drop each observations if the firm's assets, which is the most populated borrower financial data field, are higher than 1.5 times the within-date median within or less than 0.5 times the within-date median. For categorical variables such as NAICS, zip code, borrower firm name, CUSIP, ticker, and year established, we take the mode across loan records within each quarterly date.

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

We are unable to match all IPOs in the SDC Platinum data to the private firms in Y-14Q for a few reasons. First, some Y-14Q firms may only borrow through subsidiaries rather than parent companies, and the subsidiary names and TINs do not match the SDC Platinum database. Second, some firms may not borrow from one of the Y-14Q banks at all, or only do so after the firm goes public. However, we infer that the larger IPO firms are more likely to borrow from the larger Y-14Q banks, because we successfully match the vast majority of the larger IPO firms but are less successful with merging the smaller IPO firms. As we show in Table C1 the sub-sample of IPO firms that we match with the Y-14Q data, just prior to the firm's IPO, average roughly $947 million in assets while the sub-sample of IPO firms that we do not match average $71 million in assets. Hence, our sample captures the largest and most important IPOs. Nonetheless, in Table C5 we find very similar results when we use Compustat data for the two years prior to IPO, suggesting our results are not being driven by sample selection effects.

Appendix B. Variable Definitions

Assets: Total assets, aggregated at the bank/firm level, from Y-14Q.

Amount: Committed loan amount, from Y-14Q

Bank Debt: Total amount of committed bank debt, aggregated at the firm level, from Y-14Q.

Book Equity: Total assets minus total liabilities, from Y-14Q.

CapEx: Funds used to acquire a long-term asset resulting in depreciation deductions over the life of the acquired asset, aggregated at the bank/firm level, from Y-14Q.

CapEx/Assets: Funds used to acquire a long-term asset resulting in depreciation deductions over the life of the acquired asset divided by total assets, aggregated at the firm level, winsorized at [1%, 99%], from Y-14.Q

Committed: Total loan commitment amount, in logs, aggregated at the bank/firm level, from Y-14Q.

EBITDA/Assets: EBITDA/assets, aggregated at the firm level, winsorized at [1%, 99%], from Y-14Q.

Funding Surplus: (EBITDA-Capex)/assets, aggregated at the firm level, winsorized at [1%, 99%], from Y-14Q.

Funding Deficit Dummy: Dummy variable that equals one if Funding Surplus is negative, aggregated at the firm level, from Y-14Q.

Intangible Assets: Total assets minus tangible assets, aggregated at the bank/firm level, from Y-14Q.

Interest Rate: Interest rate of the loan, multiplied by 100 and trimmed if negative, from Y-14Q.

IPO: Dummy variable that equals one if the firm IPOs within the next three years, multiplied by 100, from SDC.

IPOCompleted: Dummy variable that equals one if the firm completes its IPO, multiplied by 100, from SDC.

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

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

Loss Given Default (LGD): The bank's estimated loss given default per unit of loan weight by the committed dollar amount of each loan at the bank/firm/quarter level, from Y-14Q trimmed if $LGD = 0$ or $LGD = 1$.

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

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

NAICS4 MTB: The median market to book ratio of publicly traded companies for a given four digit NAICS industry within the given quarter, from Compustat.

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

Post: Dummy variable that equals one if the firm has IPOed as of the current quarter, from Y-14Q.

Probability of Default (PD): The bank's expected annual default rate over the life of the loan weight by the committed dollar amount of each loan at the bank/firm/quarter level, trimmed if $PD = 0$ or $PD = 1$, from Y-14Q.

Range of PD: The difference between the largest and smallest PD across banks within firm/time, from Y-14Q.

Sales Growth: Annual sales growth, aggregated at the bank/firm level, winsorized at [1%, 99%], from Y-14Q.

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-14Q and HUD.

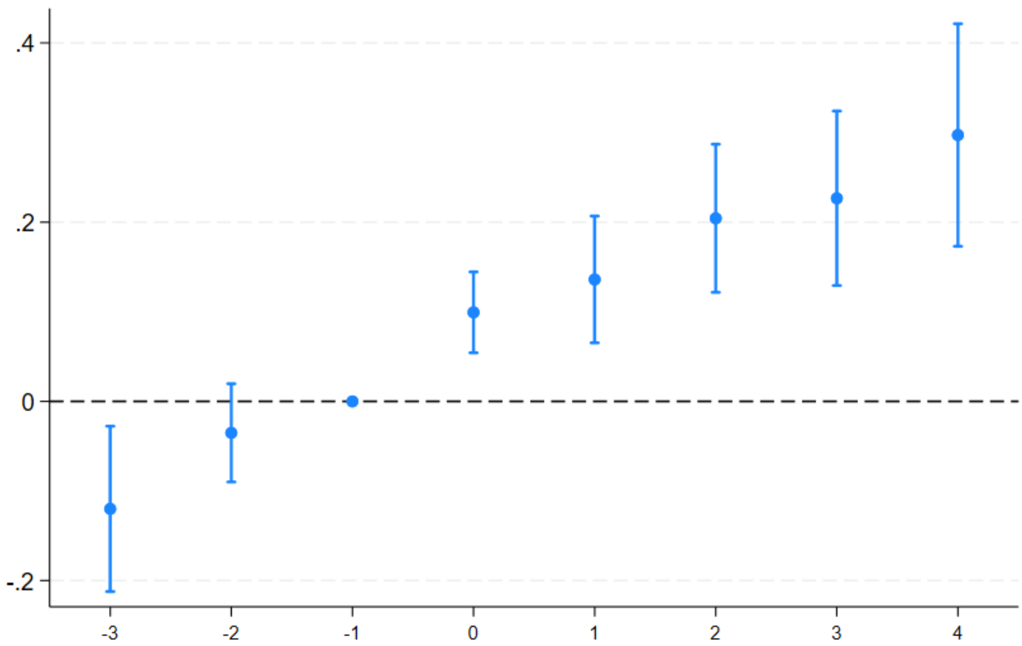
Standard Deviation of PD: The cross-sectional standard deviation of PD across banks within firm/time, from Y-14Q.

Tech Firm: Dummy variable that equals one if the firm is an internet, software, computer equipment, data or biotech firm, from Y-14Q.

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: IPO Number of Banks Dynamics (Poisson Regression)

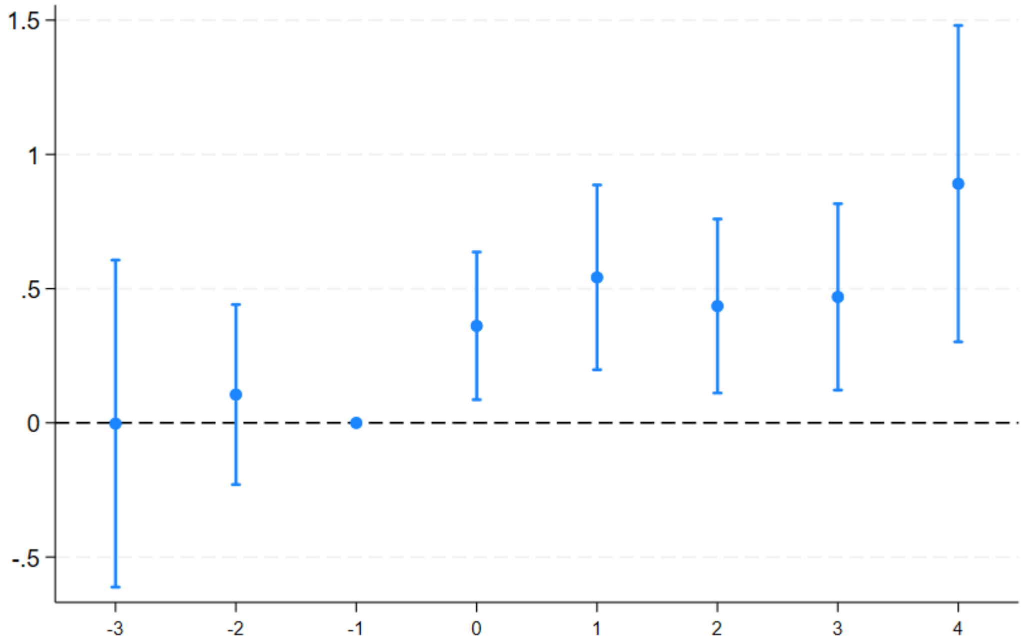


Note: In this figure, we analyze the dynamics of the number of banks firms borrow from before and after the IPO using a matched sample one quarter prior to IPO using a Poisson regression. We form a matched sample by estimating propensity scores based on our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' last quarter in the year prior to the IPO. The matched sample includes the three closest firms in terms of propensity scores that are in the same two-digit NAICS industry. The dots are point estimates of the interaction coefficients between treated (IPO firms) and time dummies and the bars are the 90% confidence intervals from the following regression:

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

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

Figure C2: IPO Investment Dynamics (VC-Backed Only)

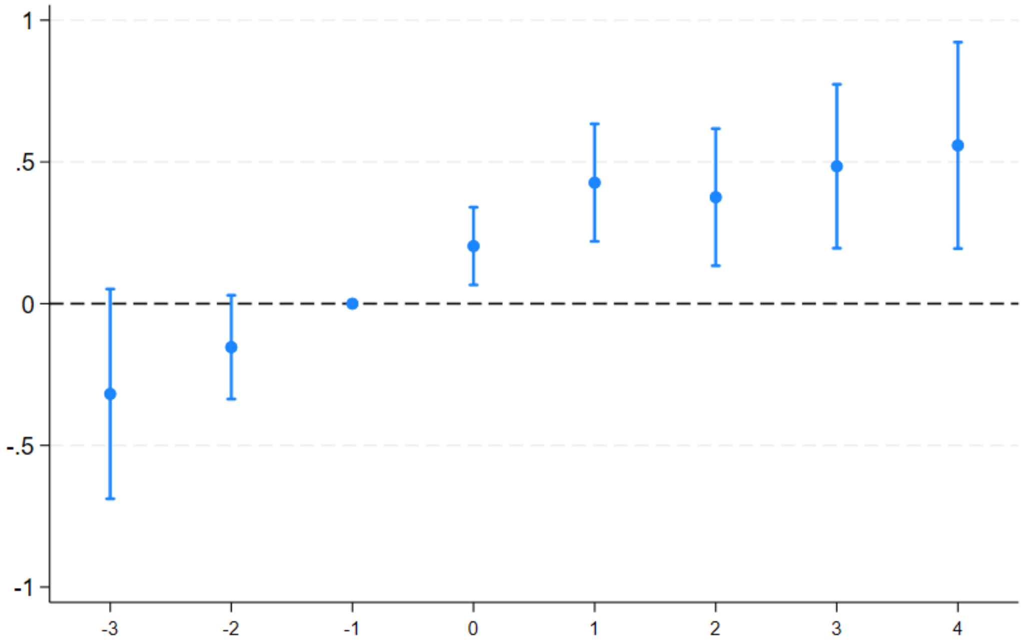


Note:: In this figure, we analyze the dynamics of firm investment, i.e., log(CapEx), before and after the IPO using a matched sample one quarter prior to IPO, restricting the sample to VC-backed firms. We form a matched sample by estimating propensity scores based on our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' last quarter in the year prior to the IPO. The matched sample includes the three closest firms in terms of propensity scores that are in the same two-digit NAICS industry. The dots are point estimates of the interaction coefficients between treated (IPO firms) and time dummies and the bars are the 90% confidence intervals from the following regression:

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

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

Figure C3: IPO Asset Dynamics (VC-Backed Only)

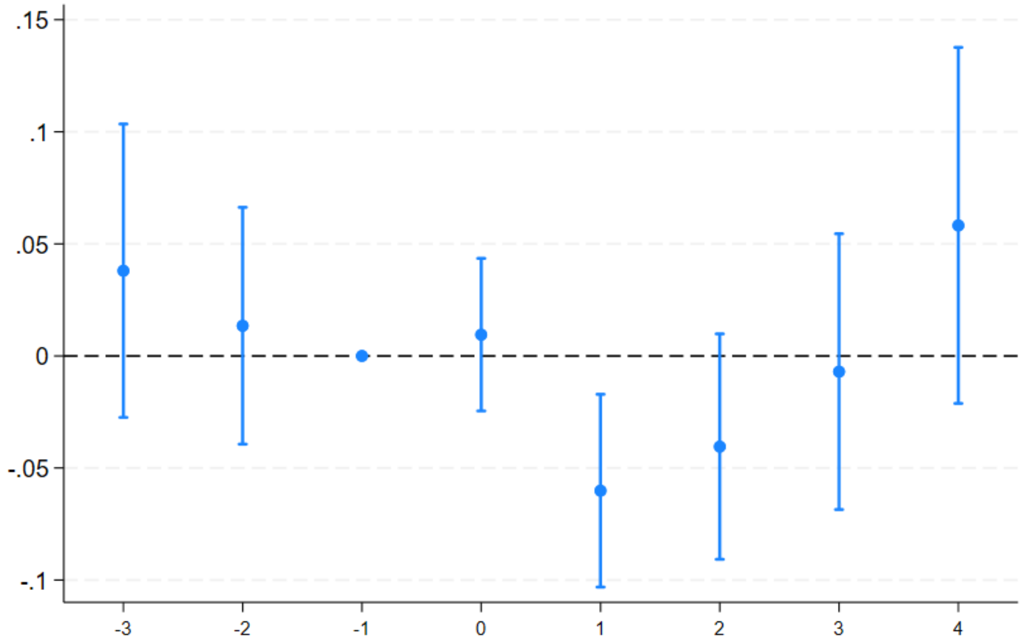


Note: In this figure, we analyze the dynamics of firm assets, i.e., log(assets), before and after the IPO using a matched sample one quarter prior to IPO, restricting the sample to VC-backed firms. We form a matched sample by estimating propensity scores based on our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' last quarter in the year prior to the IPO. The matched sample includes the three closest firms in terms of propensity scores that are in the same two-digit NAICS industry. The dots are point estimates of the interaction coefficients between treated (IPO firms) and time dummies and the bars are the 90% confidence intervals from the following regression:

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

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

Figure C4: IPO Leverage Dynamics (VC-Backed Only)

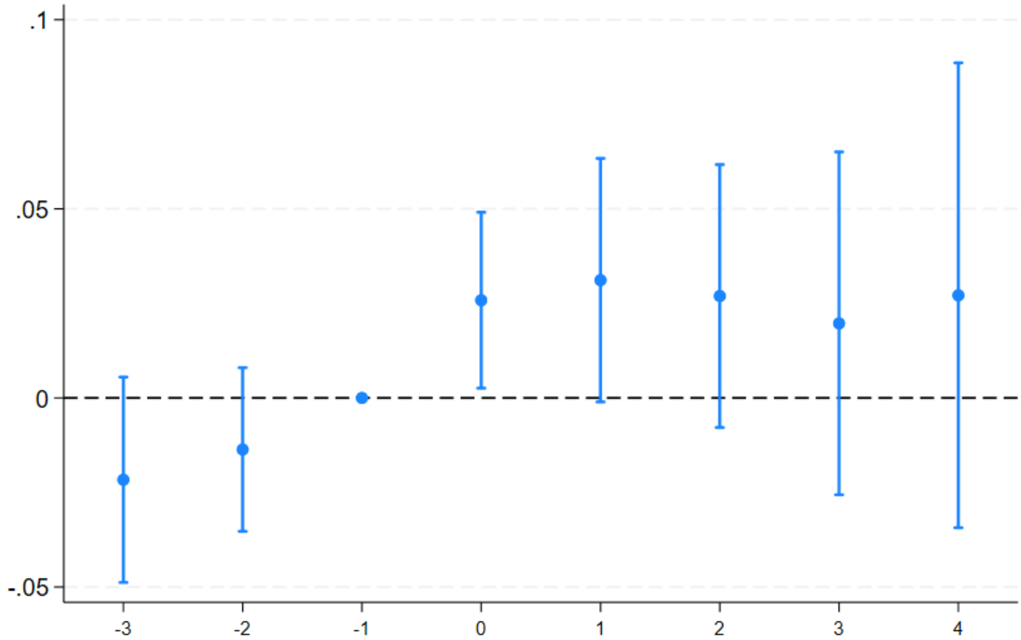


Note: In this figure, we analyze the dynamics of firm leverage, i.e., debt/assets, before and after the IPO using a matched sample one quarter prior to IPO, restricting the sample to VC-backed firms. We form a matched sample by estimating propensity scores based on our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' last quarter in the year prior to the IPO. The matched sample includes the three closest firms in terms of propensity scores that are in the same two-digit NAICS industry. The dots are point estimates of the interaction coefficients between treated (IPO firms) and time dummies and the bars are the 90% confidence intervals from the following regression:

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

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

Figure C5: IPO Bank Debt Dynamics (VC-Backed Only)

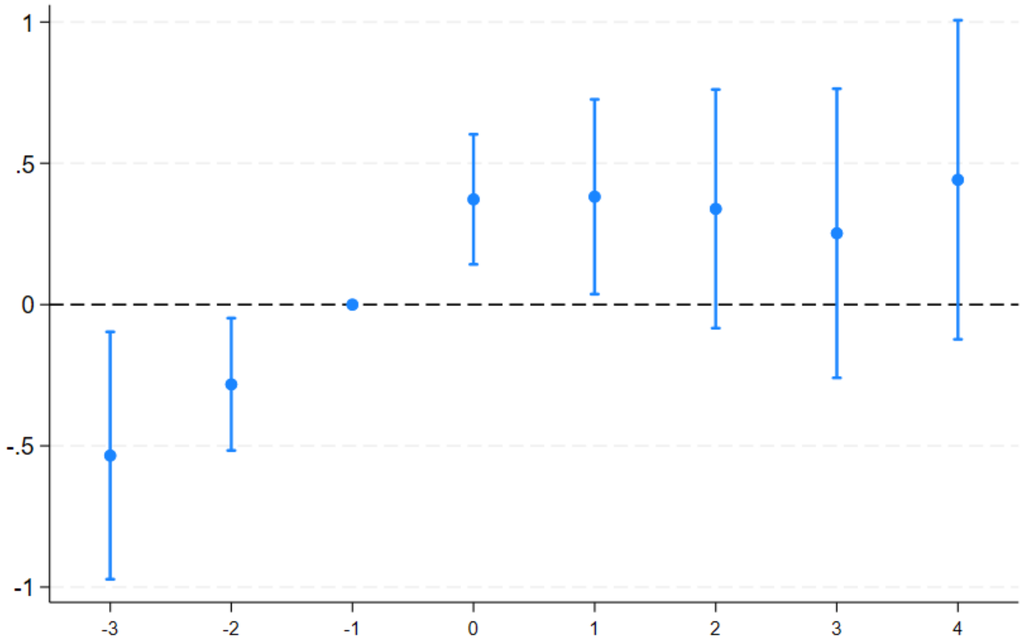


Note: In this figure, we analyze the dynamics of bank debt, i.e., log(bank debt), before and after the IPO using a matched sample one quarter prior to IPO, restricting the sample to VC-backed firms. We form a matched sample by estimating propensity scores based on our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' last quarter in the year prior to the IPO. The matched sample includes the three closest firms in terms of propensity scores that are in the same two-digit NAICS industry. The dots are point estimates of the interaction coefficients between treated (IPO firms) and time dummies and the bars are the 90% confidence intervals from the following regression:

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

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

Figure C6: IPO Number of Banks Dynamics (VC-Backed Only)

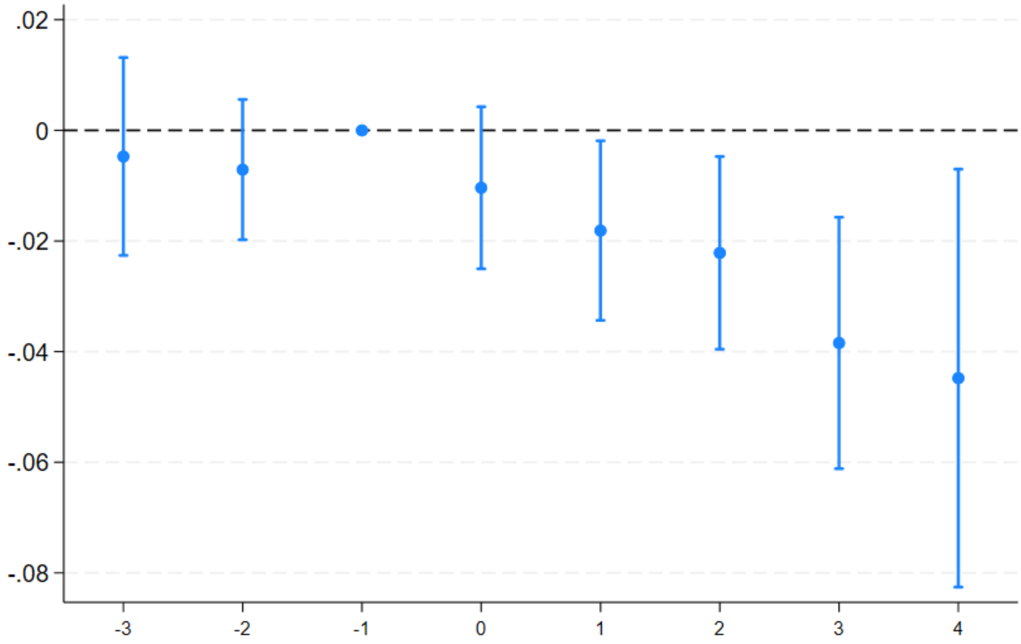


Note: In this figure, we analyze the dynamics of the number of banks the firm borrows from before and after the IPO using a matched sample one quarter prior to IPO, restricting the sample to VC-backed firms. We form a matched sample by estimating propensity scores based on our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' last quarter in the year prior to the IPO. The matched sample includes the three closest firms in terms of propensity scores that are in the same two-digit NAICS industry. The dots are point estimates of the interaction coefficients between treated (IPO firms) and time dummies and the bars are the 90% confidence intervals from the following regression:

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

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

Figure C7: PD Dispersion (Fixed Set of Banks)

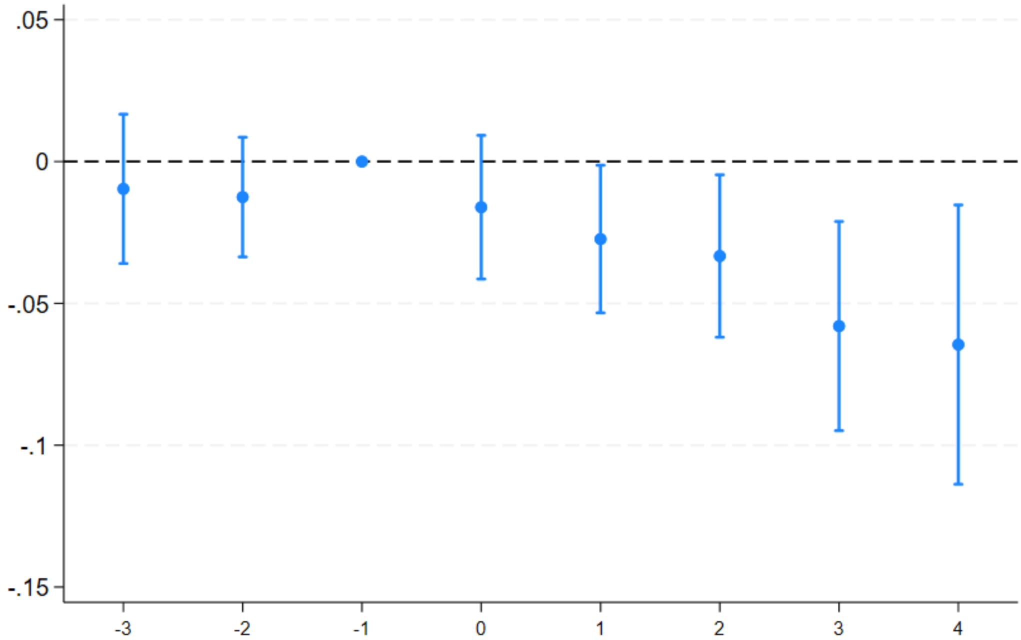


Note: In this figure, we analyze the dynamics of the dispersion in banks' probability of default (PD) estimates, measured as the cross-sectional standard deviation in PD within firm/time, using a matched sample which maintains a fixed set of banks for each firm throughout the analysis period. We form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

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

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

Figure C8: PD Dispersion (Range of PDs)



Note: In this figure, we analyze the dynamics of the dispersion in banks' probability of default (PD) estimates, measured as the difference between the highest and lowest PD within firm/time, using a matched sample which maintains a fixed set of banks for each firm throughout the analysis period. We form a matched sample based on the Mahalanobis distance measure using PD and the number of banks as non-exact matching variables. Each IPO firm is matched to three control firms that are in the same two-digit NAICS industry. The dots are point estimates of the interaction coefficients between treated (IPO firms) and time dummies and the bars are the 90% confidence intervals from the following regression:

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

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

Table C1: Summary Statistics: Merged IPO vs. Unmerged IPO Firms

This table contains summary statistics comparing merged IPO firm-quarters to unmerged IPO firm-quarters from Compustat. Appendix B contains variable definitions.

	Merged IPO Firms				Unmerged IPO Firms				
	N	Mean	Median	SD	N	Mean	Median	SD	Diff w.r.t. Merged IPO Fir
Sales	2755	1515.39	404.63	5554.86	2837	574.87	0.21	2898.73	-940.519***
Assets	2755	2136.27	607.87	6471.07	2837	944.67	71.28	3513.98	-1191.591***
Capex/Assets	2579	0.08	0.03	0.13	2795	0.07	0.02	0.13	-0.010***
Sales Growth	2580	0.42	0.16	0.73	556	0.27	0.18	0.51	-0.141***
EBITDA/Assets	2627	0.09	0.09	0.26	1605	-0.15	-0.17	0.31	-0.241***
Positive Profits	2627	0.78	1.00	0.41	1605	0.41	0.00	0.49	-0.371***
Funding Surplus	2700	0.01	0.05	0.20	1611	-0.21	-0.21	0.29	-0.219***
Debt/Assets	2755	0.34	0.34	0.26	2832	0.33	0.24	0.34	-0.008
Cash/Assets	2751	0.14	0.05	0.19	2830	0.39	0.33	0.33	0.254***
VC-Backed	2755	0.26	0.00	0.44	2837	0.06	0.00	0.23	-0.202***
Silicon Valley	2755	0.14	0.00	0.34	2837	0.16	0.00	0.37	0.026***
Tech Firm	2755	0.30	0.00	0.46	2837	0.24	0.00	0.43	-0.065***

Table C2: Firms' IPO Decisions: Funding Surpluses and Deficits

This table tests which firm characteristics predict firms' going public within the next three years. The dependent variable *IPO* is a dummy that equals one if the firm IPOs in the next three years. 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(Sales)	0.237***	0.241***	0.217***	0.238***
	(0.022)	(0.022)	(0.019)	(0.022)
Capex/Assets	0.453**			0.313*
	(0.187)			(0.189)
Sales Growth	0.274***	0.251***	0.231***	0.273***
	(0.049)	(0.048)	(0.043)	(0.049)
EBITDA/Assets	-0.510***			-0.456***
	(0.093)			(0.087)
Debt/Assets	0.299***	0.297***	0.331***	0.293***
	(0.081)	(0.082)	(0.069)	(0.082)
Funding Surplus		-0.635***		
		(0.114)		
Funding Deficit Dummy			0.180***	0.080**
			(0.041)	(0.039)
Date FE	N	N	N	N
Date × NAICS4 FE	N	N	N	N
Date × CBSA FE	N	N	N	N
Date × NAICS4 × CBSA FE	Y	Y	Y	Y
N	935030	936877	1072526	935030
R2	0.257	0.257	0.252	0.257

Table C3: Cross-Sectional Determinants of Firms' IPO Decisions (Excluding Tech/SV)

This table tests which firm characteristics predict firms' going public within the next three years, excluding tech firms and those from Silicon Valley. The dependent variable *IPO* is a dummy that equals one if the firm IPOs in the next three years. 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(Sales)	0.170***	0.170***	0.178***	0.156***
	(0.017)	(0.016)	(0.018)	(0.019)
Capex/Assets	0.408***	0.255**	0.428***	0.178
	(0.124)	(0.101)	(0.127)	(0.164)
Sales Growth	0.262***	0.192***	0.271***	0.215***
	(0.052)	(0.038)	(0.055)	(0.050)
EBITDA/Assets	-0.298***	-0.350***	-0.328***	-0.392***
	(0.061)	(0.059)	(0.064)	(0.079)
Debt/Assets	0.155***	0.302***	0.170***	0.303***
	(0.053)	(0.057)	(0.057)	(0.075)
NAICS4 MTB	0.036***		0.040***	
	(0.010)		(0.011)	
Date FE	Y	N	N	N
Date × NAICS4 FE	N	Y	N	N
Date × CBSA FE	N	N	Y	N
Date × NAICS4 × CBSA FE	N	N	N	Y
N	861872	1097740	855077	809858
R2	0.004	0.029	0.019	0.268

Table C4: Cross-Sectional Determinants of Firms' IPO Decisions (Firm Fixed Effects)

This table tests which firm characteristics predict firms' going public within the next three years, controlling for firm fixed effect. The dependent variable *IPO* is a dummy that equals one if the firm IPOs in the next three years. 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(Sales)	0.233***	0.228***	0.243***	0.237***
	(0.019)	(0.017)	(0.020)	(0.022)
Capex/Assets	0.758***	0.494***	0.789***	0.453**
	(0.157)	(0.120)	(0.163)	(0.187)
Sales Growth	0.464***	0.294***	0.452***	0.274***
	(0.057)	(0.040)	(0.058)	(0.049)
EBITDA/Assets	-0.600***	-0.565***	-0.608***	-0.510***
	(0.078)	(0.072)	(0.080)	(0.093)
Debt/Assets	0.096	0.288***	0.137**	0.299***
	(0.060)	(0.061)	(0.063)	(0.081)
NAICS4 MTB	0.099***		0.100***	
	(0.014)		(0.014)	
Date FE	Y	N	N	N
Firm FE				
Date × NAICS4 FE	N	Y	N	N
Date × CBSA FE	N	N	Y	N
Date × NAICS4 × CBSA FE	N	N	N	Y
N	988898	1249587	982095	935030
R2	0.007	0.031	0.020	0.257

Table C5: Cross-Sectional Determinants of Firms' IPO Decisions (Including Unmerged Compustat Observations)

This table tests which firm characteristics predict firms' going public within the next three years, including IPOs that were not merged into Y-14Q but have pre-IPO data from Compustat. The dependent variable *IPO* is a dummy that equals one if the firm IPOs in the next three years. 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(Sales)	0.157***	0.189***	0.160***	0.215***
	(0.022)	(0.019)	(0.023)	(0.025)
Capex/Assets	1.942***	1.179***	1.937***	0.905***
	(0.192)	(0.141)	(0.198)	(0.208)
EBITDA/Assets	-1.960***	-1.679***	-1.971***	-1.363***
	(0.099)	(0.085)	(0.100)	(0.119)
Debt/Assets	0.034	0.421***	0.130*	0.490***
	(0.075)	(0.074)	(0.079)	(0.101)
NAICS4 MTB	0.326***		0.331***	
	(0.019)		(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	1006196	1272558	998902	954579
R2	0.010	0.080	0.029	0.362

Table C6: Cross-Sectional Determinants of Firms' IPO Decisions (Excluding Merger Targets)

This table tests which firm characteristics predict firms' going public within the next three years, excluding firms that were acquired within the next three years. The dependent variable *IPO* is a dummy that equals one if the firm IPOs in the next three years. 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(Sales)	0.224***	0.218***	0.233***	0.224***
	(0.019)	(0.017)	(0.019)	(0.021)
Capex/Assets	0.777***	0.513***	0.806***	0.467**
	(0.158)	(0.120)	(0.164)	(0.186)
Sales Growth	0.469***	0.300***	0.460***	0.288***
	(0.057)	(0.041)	(0.059)	(0.049)
EBITDA/Assets	-0.601***	-0.563***	-0.613***	-0.529***
	(0.079)	(0.072)	(0.081)	(0.093)
Debt/Assets	0.065	0.251***	0.103*	0.257***
	(0.059)	(0.060)	(0.061)	(0.080)
NAICS4 MTB	0.099***		0.100***	
	(0.014)		(0.014)	
Date FE	Y	N	N	N
Date × NAICS4 FE	N	Y	N	N
Date × CBSA FE	N	N	Y	N
Date × NAICS4 × CBSA FE	N	N	N	Y
N	983133	1243052	976350	929467
R2	0.006	0.030	0.020	0.256

Table C7: Cross-Sectional Determinants of Firms' IPO Decisions (VC-Backed Sample)

This table tests which firm characteristics predict firms' going public within the next three years, restricting the sample to VC-backed firms and including year-founded fixed effects. The dependent variable *IPO* is a dummy that equals one if the firm IPOs in the next three years. 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(Sales)	2.582***	3.084***	2.355***	2.224***
	(0.344)	(0.499)	(0.414)	(0.648)
Capex/Assets	6.706***	3.036	7.096**	11.289**
	(2.544)	(2.555)	(3.198)	(4.518)
Sales Growth	1.177***	0.103	0.847**	-0.149
	(0.343)	(0.228)	(0.391)	(0.280)
EBITDA/Assets	-4.273***	-5.480***	-1.439	-1.796
	(1.347)	(1.624)	(1.846)	(2.297)
Debt/Assets	-2.457*	-3.129*	0.257	-4.532*
	(1.392)	(1.879)	(1.880)	(2.539)
Date × Year Founded FE	Y	N	N	N
Date × NAICS4 × Year Founded FE	N	Y	N	N
Date × CBSA × Year Founded FE	N	N	Y	N
Date × NAICS4 × CBSA × Year Founded FE	N	N	N	Y
N	19493	11308	11936	4306
R2	0.161	0.379	0.384	0.487