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

Please do not distribute without authors' permission.

Andres Almazan† Nathan Swem‡ Sheridan Titman§ Gregory Weitzner¶

November 2024

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 IPO. 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. Finally, firms borrow from an expanded pool of lenders at more attractive rates after going public. Overall, our evidence is consistent with firms going public to improve their access to both equity and debt capital to fund new investments.

*We thank Jay Ritter for sharing his data on IPOs. We thank Jason Abrevaya, Adolfo De Motta, Paolo Fulghieri, Charlie Hadlock, Steve Kaplan, Borja Larrain, 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.

†University of Texas at Austin. Email: andres.almazan@mccombs.utexas.edu.

‡Federal Reserve Board. Email: nathan.f.swem@frb.gov.

§University of Texas Austin. Email: sheridan.titman@mccombs.utexas.edu.

¶McGill University. Email: gregory.weitzner@mcgill.ca.

1 Introduction

One of the most cited reasons firms go public is to gain improved access to capital. While this rationale seems natural, empirical support for this motive is mixed.[1] Moreover, even if access to capital was a key 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 still exists.[2] While the importance of this question is clear,[3] the limited availability of detailed data on private firms has been a challenge for this line of research.

This paper provides a comprehensive analysis of both the ex-ante determinants and the ex-post implications of firms' IPO decisions. Our analysis uses Federal Reserve Y-14Q data, which includes all corporate loans over one million dollars extended by large US bank holding companies from 2012 onward. Importantly, the data contains extensive financial information on private firms, many of which eventually go public. This includes balance sheet and income statement information, e.g., revenue, EBITDA, assets, and leverage, as well as granular information on firms' bank loans, e.g., the terms of these loans, the number of lending relationships and banks' internal risk assessments. The use of detailed information on a broad sample of US private firms distinguishes this study from the existing literature and, as discussed below, our analysis provides substantial evidence that access to capital is a key motive for firms going public.

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

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

[2]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.

[3]One of the express goals of the 2012 JOBS Act was to spur IPO activity, thereby improving the allocative efficiency of capital.

also because information is revealed during the security trading process.[4] Based on these ideas, we investigate two related issues. The first is whether private firms with greater needs for external capital are more likely to go public and the second is whether firms have improved access to financing and invest more after going public.

Our first tests show that firms with higher external capital needs, as proxied by ex-ante investment, i.e, CapEx/Assets, and profitability, i.e., EBITDA/Assets, are more likely to go public in the future. Specifically, we find that a one standard deviation increase in ex-ante investment (profitability) increases the likelihood of a firm going public by almost 50% (90%). This relationship between ex-ante investment and the going public decision is stronger for low profitability firms, which are likely to have greater external capital needs.[5]

We next compare the investment choices of firms before and after they go public. To do so, we estimate propensity scores based on the previously described ex-ante regressions and match firms one quarter prior to their IPO to the three closest control firms in the same industry. We then analyze differences between IPO firms and matched control firms along various dimensions over a window of 3 years prior to their IPO to 4 years after. Compared to matched control firms, IPO firms substantially increase investment spending: CapEx and total assets increase by 40% and 50% respectively, with growth observed for both tangible and intangible assets.

In addition to the influx of equity capital from the IPO, we find that the post-IPO growth is funded by increased bank debt, which is obtained from an expanded pool of lenders. Moreover, although the leverage ratios of newly public firms initially drop after their IPOs, IPO firms leverage ratios are not significantly different than control firms four years later. These results suggest that going public facilitates the issuance of bank

[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).

debt, not just equity, and are consistent with anecdotal evidence of IPO activity being an important determinant of aggregate bank lending.[6]

Our next set of tests asks whether the increase in the number of lenders following the IPO improves the bargaining power of newly public firms, thereby lowering their borrowing costs. To test this hypothesis, we analyze the change in borrowing costs after the IPO. Importantly, our regressions include banks' loan-level perceived risk assessments (i.e., the probability of default and loss given default) as controls.[7] Consistent with an improvement in bank loan terms, we find that *conditional on their risk*, firms' borrowing costs decline almost 45bps after their IPOs.[8]

While we have established that newly public firms invest and borrow more, these differences can arise from both selection and treatment effects. To estimate the causal effect of the IPO, we adopt an instrumental variable approach similar to Larrain et al. (2022), which is a refinement of the approach developed by Bernstein (2015). Specifically, we examine a sample of private firms that file to do an IPO in the near future, and instrument for whether they indeed complete the IPO using stock market returns prior to when the IPO is either completed or withdrawn. Using this approach, we find results that are qualitatively similar to our matched time-series results. In particular, our IV results are consistent with a causal increase in assets, bank debt and the number of lenders after going public.

Our final set of tests examine the firms in our sample that have VC-backing. This subsample is particularly interesting for a few reasons. First, these firms have better access to private capital than other firms, and are thus better able to time when they go public, i.e., having a large financing deficit does not force these firms to go public. On the other hand, these firms may be particularly difficult to value, and may thus benefit more from the information revealed in public markets. Our ex-ante estimates indicate that the going public choice of VC-backed private firms are more sensitive to investment expenditures and profitability than non-VC backed private firms, which is consistent with

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

[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.

the latter channel. Consistent with this interpretation, we also find stronger effects in a subsample of firms in technology related industries.

The analysis in this paper builds on a literature that uses data on private firms to analyze the ex-ante determinants as well as 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.[9] More recently, several papers (e.g., Babina, Ouimet, and Zarutskie (2020), Maksimovic, Phillips, and Yang (2020) and Chemmanur et al. (2022)), use the Census Longitudinal Business Database (LBD) to analyze the going public choice of US private firms.[10] The Census data contains information on total employment, total payroll, firm age, industry and location, but does not have information about the balance sheets or income statements of private firms, that are central to our analysis on firms' access to capital.[11]

Another related literature compares the behavior and outcomes of public and private firms separately.[12] 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 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'

[9]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).

[10]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)).

[11]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.

[12]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.

risk.[13]

The ex-post part of our analysis relates to another set of papers which focuses the causal impact of the IPO on ex-post outcomes. This literature uses data available for firms that file to go public but may ultimately withdrawal, instrumenting for the completion decision with market-wide returns.[14] Compared to this literature, our paper is the first to analyze how US firms' financing choices and borrowing rates change after going public.

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[15] and they find a reduction in both investment and leverage after the IPO.[16] 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.[17] More recently, Larrain et al. (2022) instrument for IPO completion and shows that firms in Europe expand their subsidiaries and make acquisitions after IPO, but do not find a statistically significant increase in assets.

Our paper provides evidence from many different angles, using comprehensive data

[13]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 the remain private.

[14]e.g., Bernstein (2015), Babina, Ouimet, and Zarutskie (2020), Borisov, Ellul, and Sevilir (2021), Cornaggia et al. (2021), Cornaggia et al. (2022) and Larrain et al. (2022).

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

[16]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.

[17]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.

on private firms in the US, that both ex-ante investment needs predict IPOs and that access to capital improves after the IPO. By doing so, we also provide several entirely new results to the literature. Furthermore, the sample we analyze is in a period in which private capital is abundant. We show that access to public capital is important even for VC backed firms, which arguably have ample access to private capital.

2 Data

Our analysis uses the Federal Reserve's Y-14Q data to assemble financial and bank loan information for a large panel of over 98,000 unique private firms. Within this set, we identify 318 firms that go public and obtain financial information in the years before and after their IPO choice.

Our analysis also involves data that identify firms that have received venture capital financing before the IPO, and firms that are acquired. Finally, our analysis involves data that identify firms that file with the SEC to go public, but withdraw prior to their IPO.

Below we outline each of these data sources and describe our methods for assembling the required samples. We describe additional details in Appendix A.

2.1 IPO Data

To identify which of the firms in the Y-14Q panel go public we assemble an initial set of IPOs in the 2012-2022 period from Jay Ritter's website. We merge this data to Compustat data to obtain tax IDs (TINs) for each IPO firm. Then, we remove IPOs from financial firms (i.e., SIC codes between 6000-6999) and roll-ups. After these filters, we are left with 1294 IPOs.

For our instrumental variable analysis we obtain data on withdrawn IPOs from the SDC Platinum database (now owned by Refinitiv). We consider acquisitions as an alternative form of exit and obtain data on acquisitions from SDC Platinum. Over the same period of 2012 - 2022 we identify 533 firms in the SDC Platinum database that file to go public but withdraw their IPO.

2.2 Sample of private firms

Our main source of data for private firms is the Schedule H.1 of the Federal Reserve's Y-14Q data. The Federal Reserve began collecting this data in 2011 to support the Dodd-Frank mandated stress tests and the Comprehensive Capital Analysis and Review (CCAR).[18] Our sample starts in 2012 as the data appear fully populated starting with the observations in this year.

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). 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.

We apply several filtering measures to the raw data: we drop firms missing TINs, firms headquartered outside the US, loans denominated in foreign currencies, loans to individuals, financials firms (NAICS code 52), real estate firms (NAICS code 92), and public administration and government entities (NAICS code 53). Some financials and non-profits have different industry classifications and are not dropped after this first pass. Hence, we drop any firms that have phrases in the firm names that appear relate to these, e.g., "School of", "CLO", and similar.[19] These filters reduce the sample to roughly 7.3 million loan-level records for loans that appeared on the balance sheets of the various reporting BHCs from 2012-2022.

We identify public firms in the Y-14Q data in a similar manner as Beyhaghi et al. (2024) by a multi-step process. 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

[18]Other papers that use Y-14Q data include: Bidder, Krainer, and Shapiro (2020), Brown, Gustafson, and Ivanov (2017), Ivanov, Pettit, and Whited (2020), Abdymomunov, Curti, and Mihov (2020), Greenwald, Krainer, and Paul (2020), Beyhaghi, Fracassi, and Weitzner (2022), Weitzner and Howes (2021) and Weitzner, Beyhaghi, and Howes (2022).

[19]See Appendix A for additional details.

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 private firms as a check to ensure that we exclude any large subsidiaries of public firms that may not have been properly identified in the cleaning process.

We supplement the Y-14Q data with additional information regarding firm location and venture capital financing. For firm location we merge the zip code fields in the Y-14Q data using the HUD crosswalk to identify each borrower firm's CBSA. To obtain data on VC-backing of private firms, we name match the borrower firms in the Y-14Q data to the Preqin VC funding database using the FedMatch algorithm (Cohen et al. (2021)).[20] 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 5,000 unique 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.

2.3 Merging the Y-14Q Data and IPO Firm Sample

We execute a two-stage merge process to identify which of the private firms in the Y-14Q data correspond to our sample of 1294 IPO firms that we outline above. First, we merge 478 of the IPO firms with the Y-14Q firms using TINs. However, we are missing a few TIN records among the IPO data and the TIN records in Y-14Q sometimes change when a firm goes public or plans to go public. Therefore to expand the number of matches, we do an additional merge and match an additional 435 IPO firms using the FEDMATCH string-match engine we well as the each firm's state and industry. We describe additional details in Appendix A

As a result of our two merges we match 913 of our sample of 1294 firms derived from Jay Ritter's IPO data to the Y-14Q data, which results in a match rate of 70.5%. Our

[20]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 VC in Prequin the investing firm must take a minority stake in the target firm. We refer to all of these deals as "VC investments".

matching rate compares well with 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 obtain a 48% match rate. We drop all private firms with less than $10 million in assets in order to eliminate the over one million very small private firms that unlikely to ever go public from our analysis. However, in dropping these one million small private firms we also drop 141 small IPO firms.

After merging our IPO sample and private firm sample we are left with 318 unique IPO firms 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 595 IPO firms that we successfully match, but that do not appear in the data within the 3-year window prior to the IPO. We remove these firms to ensure that our analysis compares private firms that IPO firms to other private firms that to not IPO.

Tables 1 and 2 display the industry and location composition of IPO 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 perform a similar matching method for our sample of firms that file to go public but withdraw before the IPO. We are able to match 127 withdrawn IPOs in the Y-14Q Data for which we have complete data and have observations in the Y-14Q data that are within three years of the firm's IPO withdrawal.

2.4 Constructing the Firm-level Panel

After combining 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 2022. Tables 3 and 4 display the industry and location composition of the private firms in our sample.

We take several steps to mitigate the effect of outliers and data errors including dropping observations in which debt, cash, and tangible assets are greater than the firm's total assets, following Beyhaghi et al. (2024). 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. To maintain a sample of firms with the potential to go public, we also exclude a large number of borrower firms with under $10 million in assets.[21]

Table 5 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.

One shortcoming of our firm-level panel is our inability to distinguish between the various factors that might cause a private firm to exit our data. For example, a firm may exit our sample because the firm terminated their lending relationship with a Y-14Q bank, and initiated a lending relationship with a non-Y-14Q bank. While we can identify many firms that exit as a result of being acquired, we cannot distinguish exits for other reasons, such as switching to a non-Y-14Q bank.

2.5 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 Y14-Q firms above, with the respective firm's specific loan-level records that contain the terms of each loan at origination. As we show in Table 6, the Y14-Q 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).

[21] Our results are not sensitive to these size filters. For the bulk of our analysis, we drop firms that are publicly traded. However, for some aspects of our analysis we keep observations after companies IPO.

We follow several of the filters from Beyhaghi, Fracassi, and Weitzner (2022) which also examines loan-level data. Specifically, we observations in which the interest rates is zero or negative. We also drop observations in which the PDs and/or LGD is missing, zero, or greater than 1. Loan records can appear in the data for for multiple quarters, 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 conduct an instrumental variable analysis based exogenous variation in market conditions at the time of IPO filing. Finally, in Section 3.4 we show that firms' borrowing costs drop after the IPO.

3.1 Cross-Sectional Tests

Our first exercise is to 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 three years, which we multiply by 100.[22] 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.[23]

In 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' propen-

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

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

sity to IPO and their size (log(sales)). Specifically, a 10% increase in sales increases the likelihood of a firm IPOing by 64% from its base rate of 0.20%. 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 also positively related to their propensity to IPO. Specifically, a one-standard deviation increase in CapEx/Assets (10%), increases the likelihood of a firm IPOing by about 43%. 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 (0.43), increases the likelihood of a firm IPOing by about 77%. 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 are less able to generate cash flows internally, are more likely to go public. Taken in combination with our findings that firms with high capital investment intensity are more likely to IPO, our results relating to firm profitability suggest that firms with acute financing needs are more likely to IPO.

In the Appendix Table C2 we also show that we 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.

The negative and significant relationship between profitability and IPO propensity is also consistent with anecdotal evidence in which firms delay going public when they can generate cash flows internally. For example, John Collison, the Stripe Co-founder and President, recently stated that firms that more profitable firms do not need to go public because internally generated cash flows can fund their investments.[24]

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 to miss-pricing. The fact that we also find firms with lower ex-ante profitability and higher investment intensity suggests 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.[25] Across these alternative specifications with more restrictive fixed-effects, we find that the coefficients remain fairly similar, particularly for investment and profitability.

In Table 8 we re-estimate the same regressions from Table 7 except we include an additional interaction term between EBITDA/Assets and CapEx/Assets. If less profitable firms go public due to a lack of internal funds to finance investment, we would expect this effect to be stronger for firms with more investment needs to begin with. As we show across the columns of Table 8, for each of the specifications the coefficient for the interaction term is negative and statistically significant. These results suggest that the relationship between ex-ante profitability and IPOs is even stronger for firms with higher ex-ante investment needs. We argue that these results are perhaps surprising given the recent rapid growth in private capital markets. Could it be that the results are driven by firms that have limited or no access to these markets?

In Table 9 we re-estimate similar regressions from Table 7 but only include firms that we identify, using data from Prequin as we describe in Section 2.2, as having received venture capital funding.[26] The regressions that we present in the first four columns of Table 9 are similar to the regressions we show in Table 7.

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

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

[26]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.

The sign and significance of the coefficients for the first four columns of Table 9 are qualitatively consistent with the results we show in Table 7; however, much larger in magnitude. 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 of the results 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 with their external capital needs.

The Prequin data contains information regarding the year in which each firm was founded. 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 column (5) we show a similar regression as column (4) but with $YearFounded$ included as an additional interacted fixed effect. This specification has far fewer observations reflecting the relatively small number of private firms that share the same industry, location, and age among our sub-sample of venture-capital backed firms. However, we find very similar qualitative results when including this additional layer of fixed effects.

Although we control for industry with industry/date fixed effects, firms within industries may still not be completely comparable, particularly for very 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 10, we show that the main results are robust to excluding all tech/biotech firms and firms located in Silicon Valley.

Another concern could be that the types of firms in the Y-14Q data are fundamentally different than those that we do not 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 two years of pre-IPO financials for firms that ultimately IPO. In Table 11, 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.[27] Specifically, the point

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

estimates on profitability and investment are larger in magnitude than in Table 7.

Another concern is that some firms in our sample of firms that remain private are actually acquired. In Appendix Table C5 we show that our results are robust to excluding firms that exit via acquisition.

3.2 Time-Series Tests

In the previous section we analyze which firm characteristics predict firms' decisions to IPO in the future. In this section, we analyze 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 latest quarter available in the year prior to IPO. We form a matched sample by estimating propensity scores based on the our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' latest 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.

Throughout our analysis we estimate versions of 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 i, c and t index firm, cohort (matched group) and time respectively, $y_{i,c,t}$ is a firm-level outcome variable and $d_{i,c}$ 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 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 than in year one, in which all quarters are 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 40% 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 50% 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.[28] 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 50% 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 do 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 years 2 - 4 there is a positive, but not statistically different than 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.

Next, in Figure 5, we analyze how book equity, in logs, evolves before and after the IPO. Naturally, there is a large spike right after the IPO but remains relatively flat afterwards. This result is consistent with the infrequency of SEOs after the IPO first documented by Eckbo, Masulis, and Norli (2007). If firms leverage is not decreasing after the IPO and their book equity is increasing, it must be the case that firms are increasing their debt issuance after the IPO.

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

In Figure 6 we plot the coefficients for total bank debt (in logs). By year four, the amount of bank debt IPO firms use increases by around 40%. 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 7. IPO firms borrow from just under 1 more banks after four years starting from a baseline average of 3.5 banks. In the Appendix we also estimate the regression using a fixed-effects Poisson model (e.g., Cohn, Liu, and Wardlaw (2022)) and find very similar results.

Like our cross-section results above, we find similar time-series results when we restrict the sample to firms that are VC-backed.[29]

3.3 Instrumental Variable Approach

In the previous section we show that firms increase both their tangible and intangible investments after IPO and that they finance the increased investment not only with equity, but with bank debt sourced from a larger borrowing base. It is important to mention that these estimates inevitably include both selection and treatment effects. For example, it may be that the IPO *causes* firms to invest more, but it also could be that firms go public in *anticipation of* investing more. While we believe that both of these effects are interesting and likely present, it is useful to disentangle these two effects. To do this, we adopt a similar instrumental variable approach of Bernstein (2015) who instruments for firms' decisions to complete an IPO after filing using contemporaneous stock market returns. For this analysis, we only include firms in the sample that have filed for IPO and have either completed or withdrawn it.

Following Larrain et al. (2022), we estimate the following difference-in-differences regression:

$$y_{i,t} = \beta IPOCompleted_{i,t} + \alpha_i + \delta_\tau + \delta_{m,\tau} + \delta_{t,j}\epsilon_{i,t}, \quad (2)$$

[29] See the Appendix C for details.

where $y_{i,t}$ is a firm-level outcome variable which include log(CapEx), log(assets), debt/assets, log(bank debt), and number of banks. $IPOCompleted_{i,t}$ is a dummy variable that equals one if firm i has gone public in quarter t or earlier, and 0 if the firm withdraws the IPO and remains private. We include firm fixed effects (α_i), event-quarter fixed effects (δ_τ), IPO-month times Post fixed effects ($\delta_{m,\tau}$) as well as date by four-digit NAICS fixed effects ($\delta_{t,j}$). The inclusion of firm fixed effects makes it usch that we can interpret the coefficient β as the change in outcome variable for a completed IPO relative to a withdrawn IPO. Because $IPOCompleted_{i,t}$ is endogenous, we follow Larrain et al. (2022) and instrument for it using the the market returns over the two-months that precede the IPO completion or withdrawal date ($PreReturn_m$).[30] Specifically, the first stage of the regression is:

$$IPOCompleted_{i,t} = \gamma PreReturn_m \times Post_{i,t} + \alpha_i + \delta_\tau + \delta_{m,\tau} + \delta_{t,j}\epsilon_{i,t}, \qquad (3)$$

where $Post_{i,t}$ is a dummy variable that equals one if quarter t is in the post IPO decision period. $PreReturn_m$ is a market return variable. As in Larrain et al. (2022), we consider both the absolute level of returns and a dummy variable that equals one if the returns are greater than a specific threshold. However, while Larrain et al. (2022) construct a returns dummy to be one if the returns out positive, our returns dummy to equal one if the return is greater than -10%.

We first show the results of the first-stage in Table 12. In column (1) we include the continuous version of the IV. While the coefficient is positive and statistically significant, the F-stat is only 3.61, which is well below the standard rule of thumb for power in the first stage. However, in column (2) when we include a dummy variable that equals one when the market return is above -10%, the coefficient remains positive and large and the F-stat is over 20. The fact that this alternative instrument has more power than the continuous version is natural if there are non-linearities in the relationship between completing the IPO and market returns. For example, it probably makes little difference in terms of a firm deciding whether to complete an IPO if the market goes up 3% or 4%. However, a large negative downturn clearly has a big impact on whether a firm completes

[30]Specifically, we use the returns over the previous 40 trading days.

its IPO. Hence, throughout our analysis we use the dummy version of the instrument.

Table 13 shows the results from the second stage for assets, CapEx, leverage, bank debt and number of banks. All specifications are qualitatively consistent with our matched analysis; however, while assets, bank debt and number of banks are both positive and statistically significant, CapEx is positive but statistically insignificant.

Finally, it is worth making the following caveat regarding the IV analysis. While it is useful to understand the causal impact of IPOs on firm behavior, this is not the sole goal of this paper. We are also interested in understanding which ex-ante characteristics predict firms' *decisions to IPO*. Our analysis in Section 3.1 shows that the need of capital is related to the decision of firms to select to go public. The time series results provide further evidence for this story by showing that firms' indeed raise more capital after the IPO. In the next section we provide evidence that access to capital does indeed improve after the IPO.

3.4 Going Public and Bank Borrowing Costs

In Section 3.2 we show that firms do not simply issue equity after they go public. They finance their asset growth and investments with debt such that their leverage is unchanged four years after the IPO. Why do firms increase their debt after the IPO? One possibility is that be increasing the number of informed investors adverse selection costs go down (e.g., Sharpe (1990) and Rajan (1992) and Beyhaghi, Fracassi, and Weitzner (2022)). This can result in improved borrowing terms after the IPO as existing banks cannot extract the same rents as before. We further explore this idea in this Section 3.4.

An empirical problem with testing changes in firms' borrowing terms after going public is that their risk is also clearly changing. This makes it difficult to infer whether the terms of their debt have improved after the IPO purely by analyzing changes in interest rates. However, one special aspect of the Y-14Q data is that it includes banks' internal risk assessments (PD and LGD). These risk assessments strongly predict default (Beyhaghi, Fracassi, and Weitzner (2022) and Weitzner and Howes (2021)) and predict public equity and bond returns (Weitzner, Beyhaghi, and Howes (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.*[31]

In this section we use loan-level data and restrict the sample to newly issued loans to examine how the terms of these loans change after the IPO.[32] We estimate the following regression:

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

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,[33] 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.

The results are displayed in Table 14. 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-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

[31] In principle, we could also use the instrumental variable approach as before. However, there are not enough new loans in the data for the tests to have any meaningful amount of power. Moreover, even if we have exogenous variation in the IPO, if the IPO itself causes the firm to become less risky, e.g., because it is now less levered, then we would still not be able to infer whether the risk-adjusted cost of borrowing has gone down.

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

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

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 43.6bp 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.

These results suggest that borrowing from banks becomes more attractive after firms go public. These results, combined with the results showing that the number of banks IPO firms borrow from increase, are consistent with IPOs enabling firms to increase the number of informed investors which reduces the amount of information rents they can extract.

4 Conclusion

The most obvious reason for a firm to go public is to improve its access to capital. However, in recent years private capital markets have expanded rapidly, casting doubt on this presumed key benefit of being publicly traded. In this paper, we provide evidence that despite this trend, improved access to capital is an extremely important motive for firms going public.

Our paper exploits a novel supervisory dataset with detailed balance sheet, income statement and banking lending information on both private and public US firms. 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. Importantly, they finance this increased investment not just through equity but also by raising more debt capital and expanding the number of banks they borrow from, suggesting the IPO facilitates their overall ability to raise funds. Finally, we show that firms' borrowing costs *conditional on their risk* drop after going public.

While there have been many papers analyzing firms' IPO decisions, we believe our analysis using the Y-14Q data is the most comprehensive, containing detailed balance sheet, income statement and bank lending information for a large swath of private firms in the US. Given the size and importance of the US IPO market, we argue that a more complete, comprehensive analysis of US private firms' IPO decisions is much needed to better understand firms' IPO motives.

Taken together, our results are consistent with the idea that going public reduces 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.

References

Abdymomunov, Azamat, Filippo Curti, and Atanas Mihov, 2020, Us banking sector operational losses and the macroeconomic environment, *Journal of Money, Credit and Banking* 52, 115–144.

Acharya, Viral and Zhaoxia Xu, 2017, Financial dependence and innovation: The case of public versus private firms, *Journal of Financial Economics* 124, 223–243.

Aghamolla, Cyrus and Richard T Thakor, 2022, Ipo peer effects, *Journal of Financial Economics* 144, 206–226.

Asker, John, Joan Farre-Mensa, and Alexander Ljungqvist, 2015, Corporate investment and stock market listing: A puzzle?, *The Review of Financial Studies* 28, 342–390.

Aslan, Hadiye and Praveen Kumar, 2011, Lemons or cherries? growth opportunities and market temptations in going public and private, *Journal of financial and Quantitative Analysis* 46, 489–526.

Babina, Tania, Paige Ouimet, and Rebecca Zarutskie, 2020, Ipos, human capital, and labor reallocation, *Available at SSRN 2692845* .

Badertscher, Brad A, Dan Givoly, Sharon P Katz, and Hanna Lee, 2019, Private ownership and the cost of public debt: Evidence from the bond market, *Management Science* 65, 301–326.

Bernstein, Shai, 2015, Does going public affect innovation?, *The Journal of finance* 70, 1365–1403.

Bernstein, Shai, 2022, The effects of public and private equity markets on firm behavior, *Annual Review of Financial Economics* 14, 295–318.

Beyhaghi, Mehdi, Cesare Fracassi, and Gregory Weitzner, 2022, Adverses selection in corporate loan markets, *Available at SSRN 3733932* .

Beyhaghi, Mehdi, Murray Z Frank, Ping McLemore, and Ali Sanati, 2024, Monetary policy and corporate investment: The equity financing channel, *Available at SSRN 4793393* .

Bidder, Rhys M, John R Krainer, and Adam Hale Shapiro, 2020, De-leveraging or de-risking? how banks cope with loss, *Review of Economic Dynamics* .

Borisov, Alexander, Andrew Ellul, and Merih Sevilir, 2021, Access to public capital markets and employment growth, *Journal of Financial Economics* 141, 896–918.

Brav, Omer, 2009, Access to capital, capital structure, and the funding of the firm, *The journal of finance* 64, 263–308.

Brown, James R, Matthew Gustafson, and Ivan Ivanov, 2017, Weathering cash flow shocks, *Available at SSRN 2963444* .

Chemmanur, Thomas J and Jie He, 2011, Ipo waves, product market competition, and the going public decision: Theory and evidence, *Journal of Financial Economics* 101, 382–412.

Chemmanur, Thomas J, Jie He, Shan He, and Debarshi Nandy, 2018, Product market characteristics and the choice between ipos and acquisitions, *Journal of Financial and Quantitative Analysis* 53, 681–721.

Chemmanur, Thomas J, Jie He, Xiao Ren, and Tao Shu, 2022, The disappearing ipo puzzle: New insights from proprietary us census data on private firms, *Available at SSRN 3556993* .

Chemmanur, Thomas J, Shan He, and Debarshi K Nandy, 2010, The going-public decision and the product market, *The Review of Financial Studies* 23, 1855–1908.

Cohen, Gregory J, Jacob Dice, Melanie Friedrichs, Kamran Gupta, William Hayes, Isabel Kitschelt, Seung Jung Lee, W Blake Marsh, Nathan Mislang, Maya Shaton et al., 2021, The us syndicated loan market: Matching data, *Journal of Financial Research* 44, 695–723.

Cohn, Jonathan B, Zack Liu, and Malcolm I Wardlaw, 2022, Count (and count-like) data in finance, *Journal of Financial Economics* 146, 529–551.

Cornaggia, Jess, Matthew Gustafson, Jason D Kotter, and Kevin Pisciotta, 2021, Does being private constrain geographic expansion?, *Available at SSRN 3756590* .

Cornaggia, Jess, Matthew Gustafson, Jason D Kotter, and Kevin Pisciotta, 2022, Initial public offerings and the local economy, *Available at SSRN 3036176* .

Dambra, Michael and Matthew Gustafson, 2021, Do the burdens to being public affect the investment and innovation of newly public firms?, *Management Science* 67, 594–616.

Eckbo, B Espen, Ronald W Masulis, and Øyvind Norli, 2007, Security offerings, *Handbook of empirical corporate finance* 233–373.

Ewens, Michael and Joan Farre-Mensa, 2020, The deregulation of the private equity markets and the decline in ipos, *The Review of Financial Studies* 33, 5463–5509.

Fischer, Christoph, 2000, Why do companies go public? empirical evidence from germany's neuer markt, *Empirical Evidence from Germany's Neuer Markt (May 2000)* .

Frame, W Scott, Ping McLemore, and Atanas Mihov, 2020, Haste makes waste: Banking organization growth and operational risk .

Gilje, Erik P and Jerome P Taillard, 2016, Do private firms invest differently than public firms? taking cues from the natural gas industry, *The Journal of Finance* 71, 1733–1778.

Gopalan, Radhakrishnan and Todd A Gormley, 2013, Do public equity markets matter in emerging economies? evidence from india, *Review of Finance* 17, 1571–1615.

Greenwald, Daniel L, John Krainer, and Pascal Paul, The credit line channel (Federal Reserve Bank of San Francisco 2020).

Gustafson, Matthew, Ivan Ivanov, and Ralf R Meisenzahl, 2020, Bank monitoring: Evidence from syndicated loans, *Available at SSRN 2831455* .

Helwege, Jean and Frank Packer, *The decision to go public: evidence from mandatory SEC filings of private firms* (Citeseer 2003).

Ivanov, Ivan, Luke Pettit, and Toni M Whited, 2020, Taxes depress corporate borrowing: Evidence from private firms, *Available at SSRN 3694869* .

Jain, Bharat A and Omesh Kini, 1994, The post-issue operating performance of ipo firms, *The journal of finance* 49, 1699–1726.

Kim, Woojin and Michael S Weisbach, 2008, Motivations for public equity offers: An international perspective, *Journal of Financial Economics* 87, 281–307.

Kovner, Anna and Chenyang Jason Wei, 2014, The private premium in public bonds, *FRB of New York Staff Report* .

Larrain, Borja, Gordon M Phillips, Giorgo Sertsios, and Francisco Urzúa, 2022, The effects of going public on firm profitability and commercialization strategy .

Larrain, Borja, Giorgo Sertsios, and Francisco Urzúa, 2021, The going public decision of business group firms, *Journal of Corporate Finance* 66, 101819.

Lerner, Joshua, 1994, Venture capitalists and the decision to go public, *Journal of financial Economics* 35, 293–316.

Lowry, Michelle, 2003, Why does ipo volume fluctuate so much?, *Journal of Financial economics* 67, 3–40.

Lowry, Michelle, Roni Michaely, Ekaterina Volkova et al., 2017, Initial public offerings: A synthesis of the literature and directions for future research, *Foundations and Trends® in Finance* 11, 154–320.

Maksimovic, Vojislav, Gordon M Phillips, and Liu Yang, 2017, Do public firms respond to investment opportunities more than private firms? the impact of initial firm quality, Working paper, National Bureau of Economic Research.

Maksimovic, Vojislav, Gordon M Phillips, and Liu Yang, 2020, Are public firms really myopic? evidence from matching ipo firms at birth, *Evidence from Matching IPO Firms at Birth (March 1, 2020). Tuck School of Business Working Paper* .

Mikkelson, Wayne H, M Megan Partch, and Kshitij Shah, 1997, Ownership and operating performance of companies that go public, *Journal of financial economics* 44, 281–307.

Myers, Stewart C and Nicholas S Majluf, 1984, Corporate financing and investment decisions when firms have information that investors do not have, *Journal of financial economics* 13, 187–221.

Pagano, Marco, Fabio Panetta, and Luigi Zingales, 1996, The stock market as a source of capital: Some lessons from initial public offerings in italy, *European Economic Review* 40, 1057–1069.

Pagano, Marco, Fabio Panetta, and Luigi Zingales, 1998, Why do companies go public? an empirical analysis, *The Journal of Finance* 53, 27–64.

Phillips, Gordon M and Giorgo Sertsios, 2017, Financing and new product decisions of private and publicly traded firms, *The Review of Financial Studies* 30, 1744–1789.

Rajan, Raghuram G, 1992, Insiders and outsiders: The choice between informed and arm's-length debt, *The Journal of finance* 47, 1367–1400.

Ritter, Jay R, 1987, The costs of going public, *Journal of financial economics* 19, 269–281.

Sanati, Ali and Ioannis Spyridopoulos, 2023, Comparing capital allocation efficiency in public and private equity markets, *Available at SSRN 4557395* .

Saunders, Anthony and Sascha Steffen, 2011, The costs of being private: Evidence from the loan market, *The Review of Financial Studies* 24, 4091–4122.

Schenone, Carola, 2010, Lending relationships and information rents: Do banks exploit their information advantages?, *The Review of Financial Studies* 23, 1149–1199.

Sharpe, Steven A, 1990, Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships, *The journal of finance* 45, 1069–1087.

Sheen, Albert, 2020, Do public and private firms behave differently? an examination of investment in the chemical industry, *Journal of Financial and Quantitative Analysis* 55, 2530–2554.

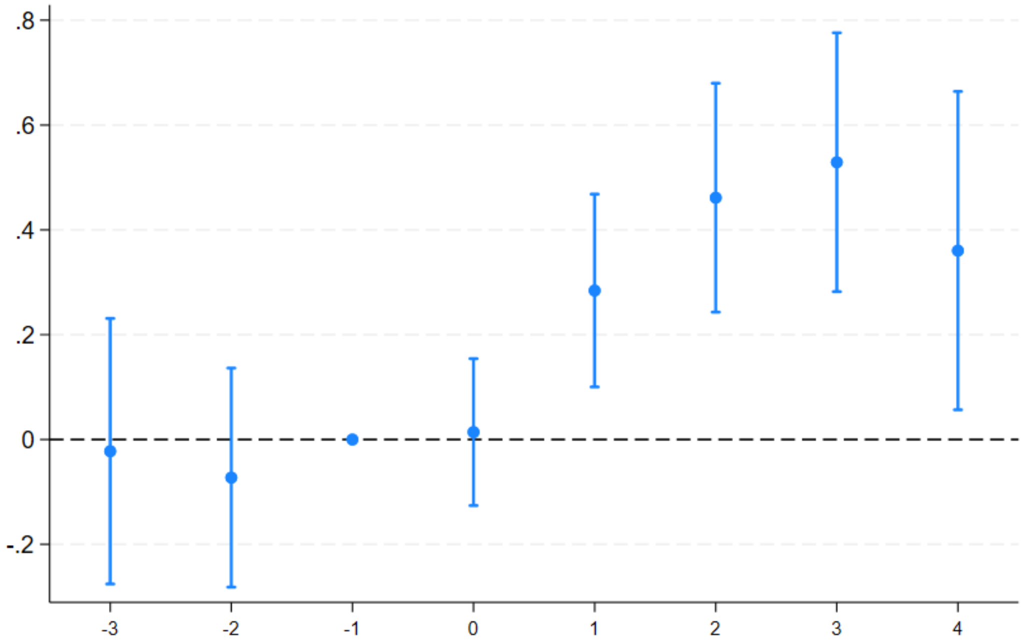
Stiglitz, Joseph E and Andrew Weiss, 1981, Credit rationing in markets with imperfect information, *The American economic review* 71, 393–410.

Subrahmanyam, Avanidhar and Sheridan Titman, 1999, The going-public decision and the development of financial markets, *The Journal of Finance* 54, 1045–1082.

Weitzner, Gregory, Mehdi Beyhaghi, and Cooper Howes, 2022, The information advantage of banks: Evidence from their private credit assessments, *Working Paper* .

Weitzner, Gregory and Cooper Howes, 2021, Bank information production over the business cycle, *Available at SSRN* .

Figure 1: IPO Investment Dynamics

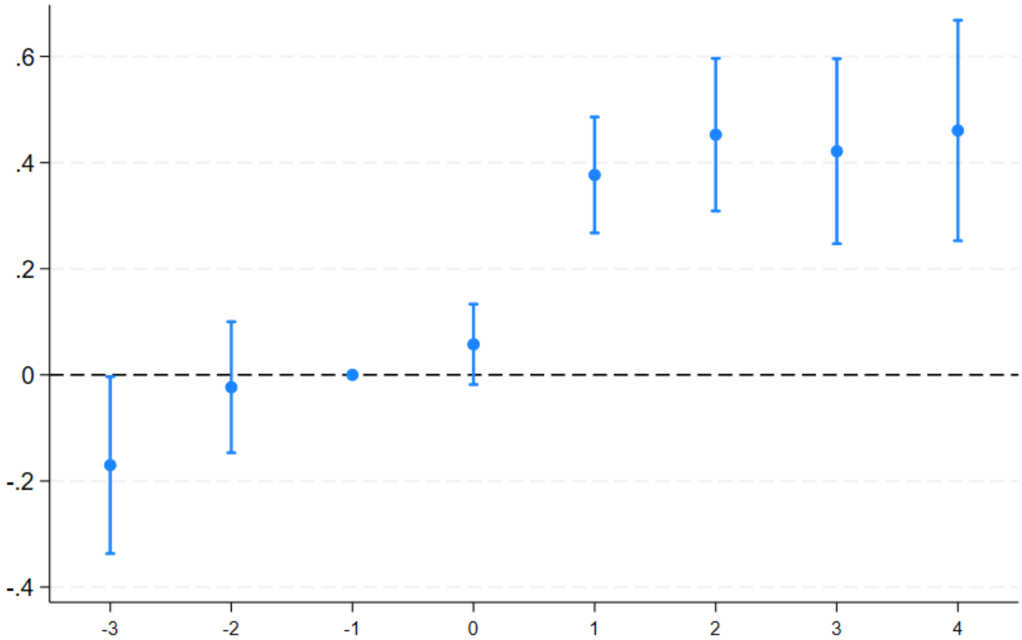


Note: In this figure, we analyze the dynamics of firm investment, i.e., log(CapEx), before and after IPO using a matched sample. We form a matched sample by estimating propensity scores based on the our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' latest 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 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

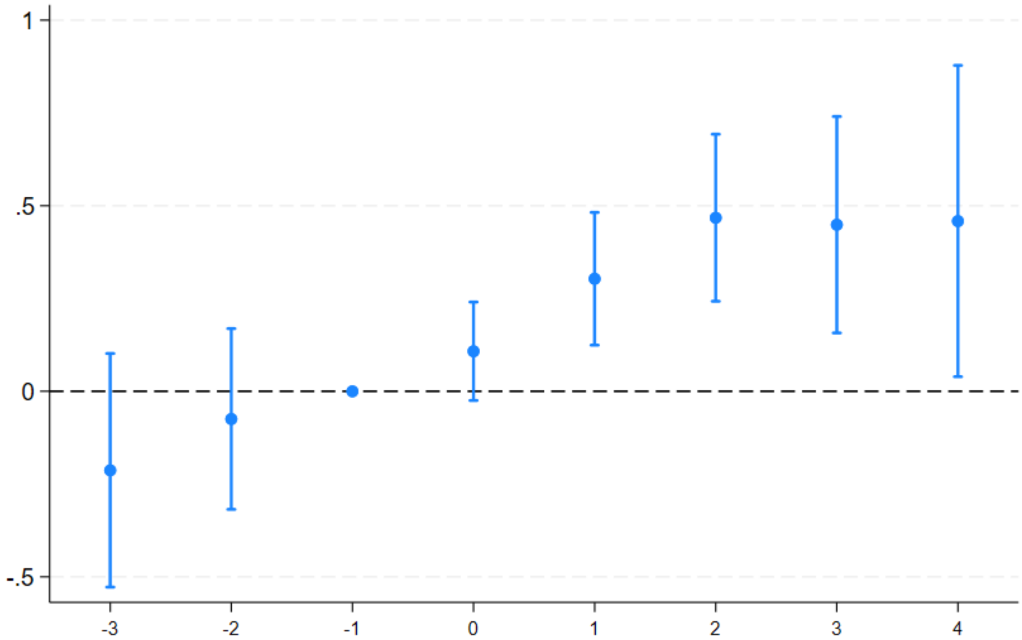


Note: In this figure, we analyze the dynamics of firm assets, i.e., log(assets), before and after IPO using a matched sample. We form a matched sample by estimating propensity scores based on the our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' latest 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 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

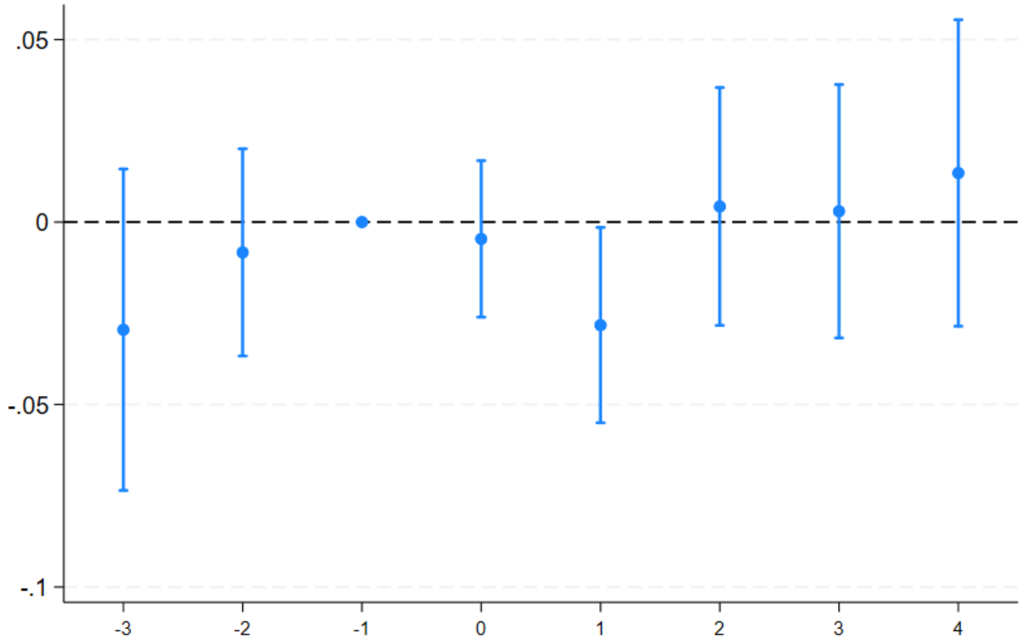


Note: In this figure, we analyze the dynamics of intangible assets, i.e., log(intangible assets), before and after IPO using a matched sample. We form a matched sample by estimating propensity scores based on the our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' latest 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 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

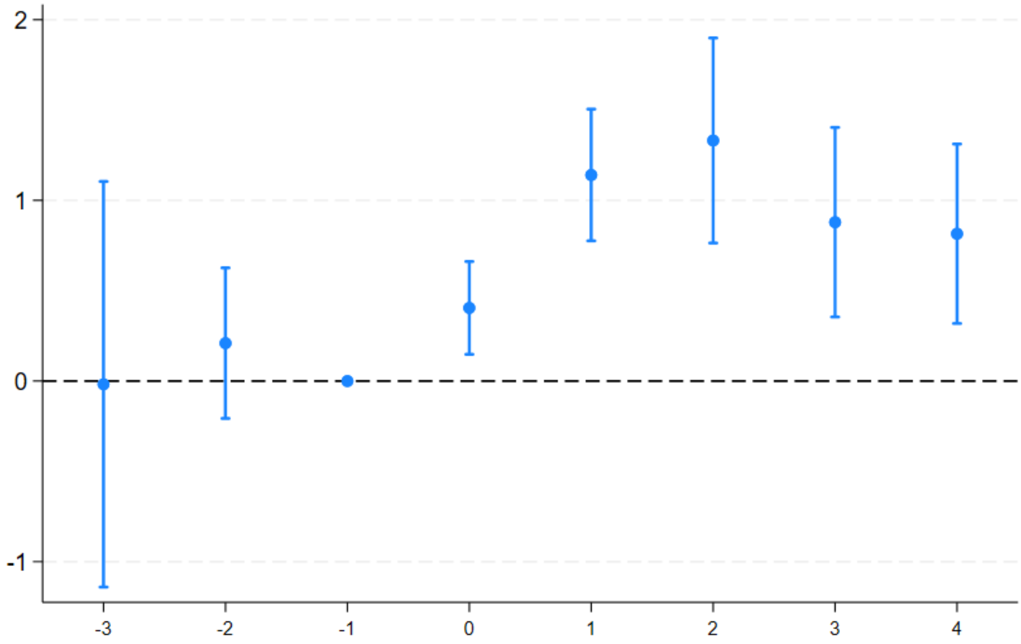


Note: In this figure, we analyze the dynamics of firm leverage, i.e., debt/assets, before and after IPO using a matched sample. We form a matched sample by estimating propensity scores based on the our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' latest 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 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 Book Equity Dynamics

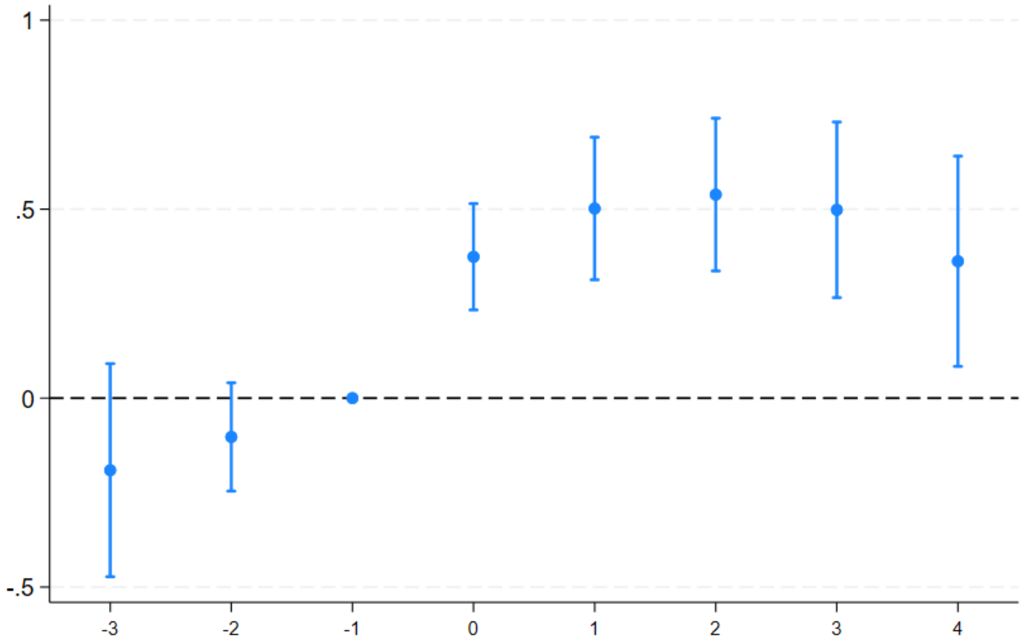


Note: In this figure, we analyze the dynamics of book equity before and after IPO using a matched sample. We form a matched sample by estimating propensity scores based on the our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' latest quarter in the year 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 the 90% confidence intervals from the following regression:

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

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 Bank Debt Dynamics

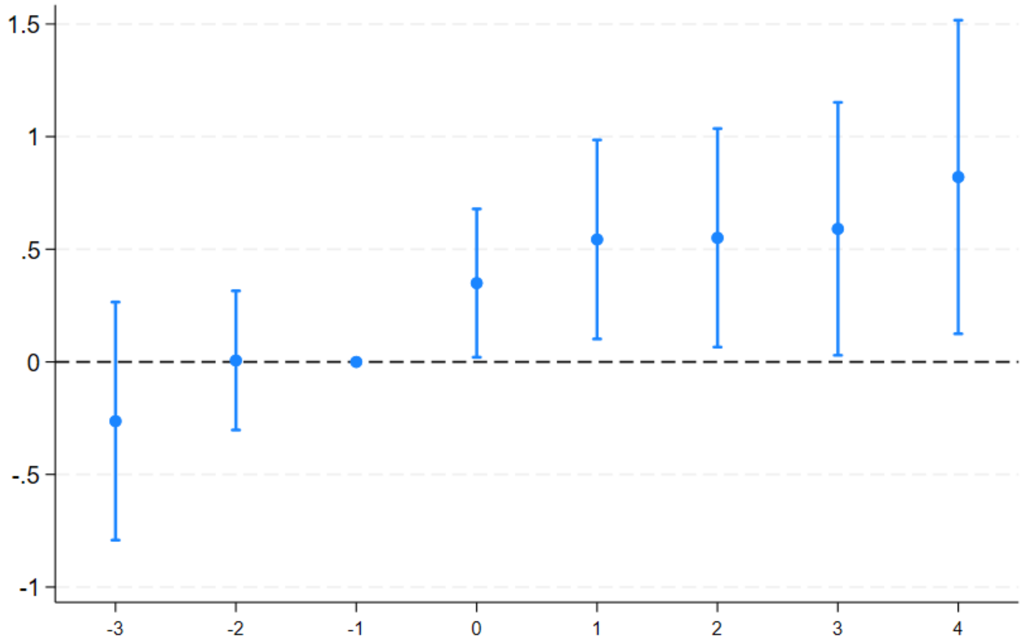


Note: In this figure, we analyze the dynamics of bank debt, i.e., log(bank debt), before and after IPO using a matched sample. We form a matched sample by estimating propensity scores based on the our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' latest 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 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 7: 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 IPO using a matched sample. We form a matched sample by estimating propensity scores based on the our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' latest 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 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.

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	34	12.88
Computer Systems Design & Related Services	22	8.33
Electronic Shopping	15	5.68
Other Information Services	14	5.3
Pharmaceutical & Medicine Manufacturing	13	4.92
Scientific Research & Development Services	11	4.17
Miscellaneous Durable Goods Manufacturing	10	3.79
Oil and Gas Extraction	8	3.03
Data Processing, Hosting, & Related Service	8	3.03
Support Activities for Mining	7	2.65
Electric Power Gen, Transmission and Distribution	6	2.27
Semiconductor & Other Component Manufacturing	4	1.52
Navigation, Measuring, Electromed, & Control Instruments	4	1.52
Management, Scientific, & Technical Consulting	4	1.52
Advertising Agencies	4	1.52
Restaurants & Other Eating Places	4	1.52
Residential Building Construction	3	1.14
Computer & Peripheral Equipment Manufacturing	3	1.14
Communications Equipment Manufacturing	3	1.14
Household Appliances & Electrical Goods Wholesalers	3	1.14
Architectural, Engineering, & Related	3	1.14
Home Health Care Services	3	1.14
Beverage Manufacturing	2	.76
Grocery & Related Product Merchant Wholesalers	2	.76
Miscellaneous Nondurable Goods Wholesalers	2	.76
Automobile Dealers	2	.76
Furniture Stores	2	.76

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	49	18.56
New York-Newark-Jersey City	22	8.33
Boston-Cambridge-Newton	21	7.95
Los Angeles-Long Beach-Anaheim	19	7.2
San Jose-Sunnyvale-Santa Clara	18	6.82
Dallas-Fort Worth-Arlington	13	4.92
Austin-Round Rock	8	3.03
Phoenix-Mesa-Scottsdale	8	3.03
Atlanta-Sandy Springs-Roswell	6	2.27
Indianapolis-Carmel-Anderson	6	2.27
Washington-Arlington-Alexandria	6	2.27
Philadelphia-Camden-Wilmington	5	1.89
Chicago-Naperville-Elgin	4	1.52
Miami-Fort Lauderdale-West Palm Beach	4	1.52
Raleigh	4	1.52
Virginia Beach-Norfolk-Newport News	4	1.52
Detroit-Warren-Dearborn	3	1.14
Minneapolis-St. Paul-Bloomington	3	1.14
Riverside-San Bernardino-Ontario	3	1.14
Seattle-Tacoma-Bellevue	3	1.14
Non-Metro Area	3	1.14
Boise City	2	.76
Denver-Aurora-Lakewood	2	.76
Orlando-Kissimmee-Sanford	2	.76
Cape Coral-Fort Myers	2	.76
Las Vegas-Henderson-Paradise	2	.76
Ogden-Clearfield	2	.76
St. Louis	2	.76
Salt Lake City	2	.76

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	17600	10.34
Restaurants & Other Eating Places	6197	3.64
Offices of Physicians	4379	2.57
Other Motor Vehicle Dealers	4127	2.42
Wholesale Distribution	3985	2.34
Computer Systems Design & Related Services	3695	2.17
Architectural, Engineering, & Related	2841	1.67
Grocery & Related Product Merchant Wholesalers	2762	1.62
Building Equipment Contractors	2746	1.61
Management, Scientific, & Technical Consulting	2641	1.55
Nonresidential Building Construction	2403	1.41
Misc Durable Goods Merchant Wholesalers	2332	1.37
General Freight Trucking	2231	1.31
Legal Services	2174	1.28
Other Amusement & Recreation Industries	2026	1.19
Apparel & Accessories, Not Elsewhere	1755	1.03
Software Publishers	1681	.99
Management of Companies and Enterprises	1521	.89
Professional & Commercial Equipment & Supplies Wholesalers	1499	.88
Lumber & Other Construction Materials Wholesalers	1484	.87
Plastics Product Manufacturing	1482	.87
Household Appliances & Electrical Goods Wholesalers	1445	.85
Miscellaneous Nondurable Goods Wholesalers	1434	.84
Motor Vehicle Parts & Supplies Wholesalers	1403	.82
Nursing Care Facilities	1236	.73

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	15066	8.86
Los Angeles-Long Beach-Anaheim	8732	5.14
Chicago-Naperville-Elgin	6281	3.69
Non-Metro Area	4498	2.65
Philadelphia-Camden-Wilmington	4383	2.58
Indianapolis-Carmel-Anderson	4195	2.47
Miami-Fort Lauderdale-West Palm Beach	4095	2.41
Washington-Arlington-Alexandria	3971	2.34
Dallas-Fort Worth-Arlington	3760	2.21
Detroit-Warren-Dearborn	3755	2.21
San Francisco-Oakland-Hayward	3581	2.11
Atlanta-Sandy Springs-Roswell	3384	1.99
Boston-Cambridge-Newton	3187	1.87
Seattle-Tacoma-Bellevue	2437	1.43
Phoenix-Mesa-Scottsdale	2329	1.37
Cleveland-Elyria	2151	1.27
Charlotte-Concord-Gastonia	2060	1.21
Minneapolis-St. Paul-Bloomington	1970	1.16
Denver-Aurora-Lakewood	1892	1.11
Orlando-Kissimmee-Sanford	1847	1.09
Riverside-San Bernardino-Ontario	1783	1.05
Sacramento-Roseville-Arden-Arcade	1688	.99
San Antonio-New Braunfels	1661	.98
Portland-Vancouver-Hillsboro	1621	.95
Columbus, OH	1464	.86
San Jose-Sunnyvale-Santa Clara	1427	.84
Indianapolis-Carmel-Greenwood	1383	.81
Orlando-Kissimmee-Sanford	1293	.76

Table 5: 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	1911	652.84	253.65	1263.95	1350946	209.15	65.86	771.28	-443.691***
Assets	1911	811.67	333.65	1162.76	1350946	128.96	31.08	390.87	-682.702***
Capex/Assets	1777	0.10	0.04	0.15	1175461	0.05	0.02	0.10	-0.045***
Sales Growth	1775	0.54	0.26	0.80	1286597	0.14	0.07	0.40	-0.403***
EBITDA/Assets	1837	0.04	0.07	0.30	1316631	0.16	0.12	0.21	0.115***
Positive Profits	1837	0.64	1.00	0.48	1316631	0.89	1.00	0.31	0.257***
Funding Surplus	1834	-0.05	0.02	0.23	1193677	0.10	0.08	0.18	0.143***
Debt/Assets	1911	0.27	0.22	0.25	1350946	0.31	0.27	0.26	0.036***
Cash/Assets	1903	0.20	0.10	0.23	1347479	0.12	0.07	0.15	-0.081***
VC-Backed	1911	0.40	0.00	0.49	1350946	0.01	0.00	0.12	-0.384***
Silicon Valley	1911	0.16	0.00	0.36	1350156	0.02	0.00	0.14	-0.135***
Tech Firm	1911	0.35	0.00	0.48	1350946	0.10	0.00	0.30	-0.258***

Table 6: Summary Statistics: Loan Level Variables

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

	N	Mean	Median	SD	P5	P95
Interest Rate	146163	3.74	3.39	1.98	1.47	7.25
PD (%)	136557	1.42	0.67	2.95	0.09	4.44
LGD (%)	133722	33.97	35.00	15.21	8.00	55.00
PD $\times$ LGD (%)	132652	0.45	0.21	1.03	0.02	1.42
Maturity	196694	48.29	58.03	37.49	4.53	85.27
Loan Amount (million USD)	206347	22.81	6.00	75.84	1.03	89.78
Floating Rate	148131	0.70	1.00	0.46	0.00	1.00

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

This table tests which firm characteristics predict firms' IPOing 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 parenthesis and are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	IPO			
	(1)	(2)	(3)	(4)
Log(Sales)	0.133***	0.141***	0.141***	0.167***
	(0.015)	(0.014)	(0.015)	(0.020)
Capex/Assets	0.892***	0.688***	0.903***	0.689***
	(0.155)	(0.129)	(0.160)	(0.186)
Sales Growth	0.538***	0.373***	0.528***	0.403***
	(0.060)	(0.046)	(0.061)	(0.060)
EBITDA/Assets	-0.746***	-0.680***	-0.750***	-0.670***
	(0.085)	(0.082)	(0.086)	(0.105)
Debt/Assets	-0.190***	-0.024	-0.167***	-0.054
	(0.047)	(0.046)	(0.048)	(0.066)
NAICS4 MTB	0.084***		0.084***	
	(0.011)		(0.012)	
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	965447	1155105	958665	861560
R2	0.006	0.030	0.020	0.230

Table 8: Cross-Sectional Determinants of Firms' IPO Decisions: Interaction

This table tests which firm characteristics predict firms' IPOing 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 parenthesis 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	-1.686***	-1.111***	-1.680***	-1.171**
	(0.525)	(0.418)	(0.546)	(0.549)
Capex/Assets	1.374***	1.010***	1.383***	1.027***
	(0.258)	(0.212)	(0.266)	(0.275)
EBITDA/Assets	-0.612***	-0.582***	-0.618***	-0.572***
	(0.080)	(0.079)	(0.081)	(0.104)
Log(Sales)	0.134***	0.141***	0.141***	0.167***
	(0.015)	(0.014)	(0.015)	(0.020)
Sales Growth	0.539***	0.373***	0.529***	0.402***
	(0.060)	(0.046)	(0.061)	(0.060)
Debt/Assets	-0.180***	-0.020	-0.157***	-0.050
	(0.046)	(0.046)	(0.047)	(0.065)
NAICS4 MTB	0.084***		0.084***	
	(0.011)		(0.012)	
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	965447	1155105	958665	861560
R2	0.006	0.030	0.020	0.230

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

This table tests which firm characteristics predict firms' IPOing 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 parenthesis and are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	IPO				
	(1)	(2)	(3)	(4)	(5)
Log(Sales)	2.626***	3.176***	2.696***	3.370***	2.734***
	(0.346)	(0.425)	(0.370)	(0.564)	(0.981)
Capex/Assets	11.739***	13.445***	12.863***	14.054***	14.307**
	(3.248)	(3.585)	(3.454)	(4.055)	(6.247)
Sales Growth	1.742***	1.601***	1.526***	1.017***	0.242
	(0.421)	(0.415)	(0.440)	(0.381)	(0.615)
EBITDA/Assets	-6.646***	-7.408***	-3.664**	-3.154	-1.514
	(1.487)	(1.668)	(1.703)	(2.086)	(3.415)
Debt/Assets	-5.157***	-5.862***	-4.874***	-4.662*	-2.753
	(1.432)	(1.649)	(1.654)	(2.411)	(2.638)
Date FE	Y	N	N	N	N
Date × NAICS4 FE	N	Y	N	N	N
Date × CBSA FE	N	N	Y	N	N
Date × NAICS4 × CBSA FE	N	N	N	Y	N
Date × NAICS4 × CBSA × Yr Founded FE	N	N	N	N	Y
N	17485	15253	15798	8848	3164
R2	0.073	0.208	0.188	0.359	0.479

Table 10: Cross-Sectional Determinants of Firms' IPO Decisions (Excluding Tech/SV)

This table tests which firm characteristics predict firms' IPOing 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 parenthesis and are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	IPO			
	(1)	(2)	(3)	(4)
Log(Sales)	0.091***	0.094***	0.096***	0.103***
	(0.013)	(0.013)	(0.014)	(0.018)
Capex/Assets	0.491***	0.350***	0.481***	0.340**
	(0.121)	(0.102)	(0.123)	(0.154)
Sales Growth	0.292***	0.226***	0.300***	0.275***
	(0.052)	(0.041)	(0.054)	(0.057)
EBITDA/Assets	-0.361***	-0.379***	-0.384***	-0.456***
	(0.061)	(0.062)	(0.063)	(0.086)
Debt/Assets	-0.039	0.074*	-0.039	0.050
	(0.038)	(0.040)	(0.040)	(0.052)
NAICS4 MTB	0.027***		0.028***	
	(0.007)		(0.007)	
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	840865	1015025	834092	746788
R2	0.003	0.027	0.019	0.228

Table 11: Cross-Sectional Determinants of Firms' IPO Decisions (Including Unmerged Compustat Observations)

This table tests which firm characteristics predict firms' IPOing 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 parenthesis and are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	IPO			
	(1)	(2)	(3)	(4)
Log(Sales)	0.102***	0.120***	0.104***	0.151***
	(0.019)	(0.016)	(0.020)	(0.022)
Capex/Assets	1.867***	1.162***	1.838***	0.971***
	(0.182)	(0.136)	(0.187)	(0.196)
EBITDA/Assets	-1.775***	-1.493***	-1.769***	-1.180***
	(0.100)	(0.085)	(0.100)	(0.117)
Debt/Assets	-0.288***	0.037	-0.219***	0.072
	(0.062)	(0.059)	(0.064)	(0.081)
NAICS4 MTB	0.264***		0.266***	
	(0.016)		(0.016)	
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	1002932	1269250	995470	950863
R2	0.009	0.074	0.026	0.339

Table 12: First Stage Effect of Returns on IPO Completion

This table displays the first stage regression estimating (3), testing whether IPO completion is affected by returns one month prior to the completion/withdrawal date. $Post_{i,t}$ is a dummy variable that equals one if quarter t is in the post decision period. Standard errors are shown below the parameter estimates in parenthesis and are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	IPOCompleted (%)	
	(1)	(2)
Two Month Return × Post	1.281*	
	(0.675)	
Above -10% Two Month Return × Post		0.881***
		(0.181)
Firm FE	Y	Y
Date × NAICS4 FE	Y	Y
Event Quarter FE	Y	Y
IPO month × Post FE	Y	Y
N	8492	8799
R2	0.96	0.96
F-stat	3.61	23.55

Table 13: Instrumental Variable (2SLS) Results

This table displays the second stage results from the two-stage least-squares in (2). Columns (1) - (3) are estimated using the firm-level panel. Columns (4) and (5) are estimated based on the loan-level panel. Standard errors are shown below the parameter estimates in parenthesis and are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Log(Assets)	Log(CapEx)	Debt/Assets	Log(Bank Debt)	Number of Banks
	(1)	(2)	(3)	(4)	(5)
IPOCompleted	1.393***	0.503	0.043	2.184***	3.981***
	(0.446)	(0.675)	(0.142)	(0.715)	(1.521)
Firm FE	Y	Y	Y	Y	Y
Date × NAICS4 FE	Y	Y	Y	Y	Y
Event Quarter FE	Y	Y	Y	Y	Y
IPO month × Post FE	Y	Y	Y	Y	Y
N	8799	8582	8799	5880	5880
R2	23.56	23.16	23.56	20.90	20.90

Table 14: 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 parenthesis 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	-0.608***	-0.553**	-0.576***	-0.436**
	(0.233)	(0.227)	(0.203)	(0.219)
Log(Assets)	-0.047	-0.023	-0.016	-0.013
	(0.034)	(0.031)	(0.029)	(0.031)
Capex/Assets	0.240**	0.193*	0.207**	0.260**
	(0.111)	(0.104)	(0.098)	(0.111)
Sales Growth	0.003	0.011	0.019	0.032
	(0.037)	(0.036)	(0.032)	(0.037)
EBITDA/Assets	-0.457***	-0.466***	-0.491***	-0.419***
	(0.096)	(0.090)	(0.080)	(0.077)
Debt/Assets	0.356***	0.360***	0.352***	0.322***
	(0.093)	(0.083)	(0.078)	(0.087)
PD (%)				0.037***
				(0.008)
LGD (%)				0.003***
				(0.001)
Date FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Bank/Year FE	N	N	Y	Y
Loan Controls	N	Y	Y	Y
N	38279	35862	35857	29788
R2	0.695	0.780	0.791	0.798

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 2.5. 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 Jay Ritter list 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 Jay Ritter 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 most important IPOs. Nonetheless, in Table 11 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 Jay Ritter's website and 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.

One Month Return: Cumulative return over the 20 days prior to the IPO completion/withdrawal date of the value-weighted CRSP index, from CRSP and SDC.

Positive One Month Returns: Dummy variable that equals one if the cumulative return over the 20 days prior to the IPO completion/withdrawal date of the value-weighted CRSP index is positive, from CRSP and SDC.

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.

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

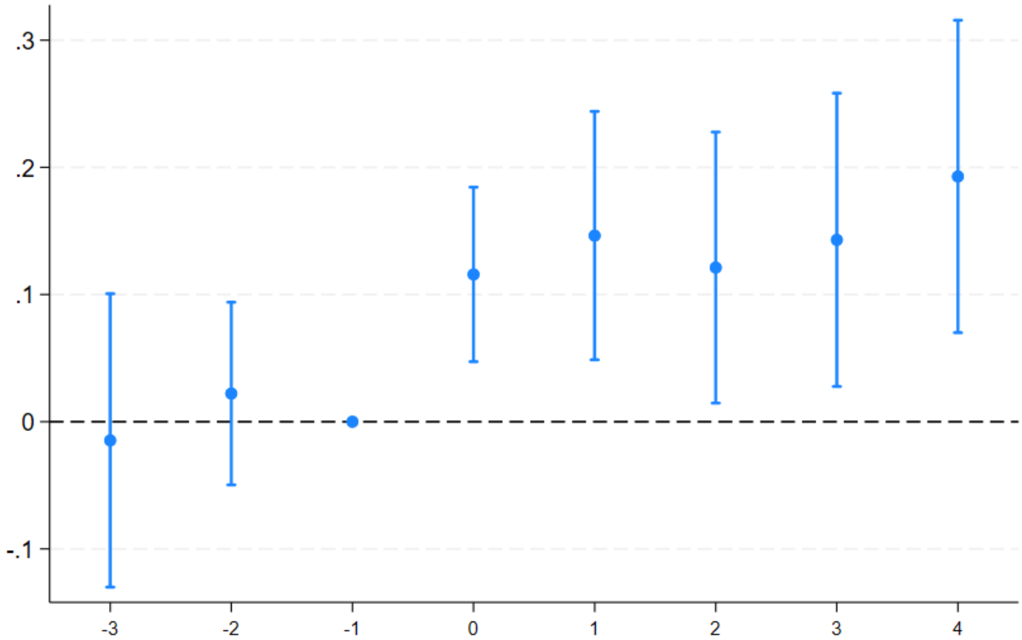
Silicon Valley: Dummy variable that equals one if the firm is located in Silicon Valley defined as CBSA San Francisco-Oakland-Hayward (code 41860) or San Jose-Sunnyvale-Santa Clara (code 41940), from Y-14Q and HUD.

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)

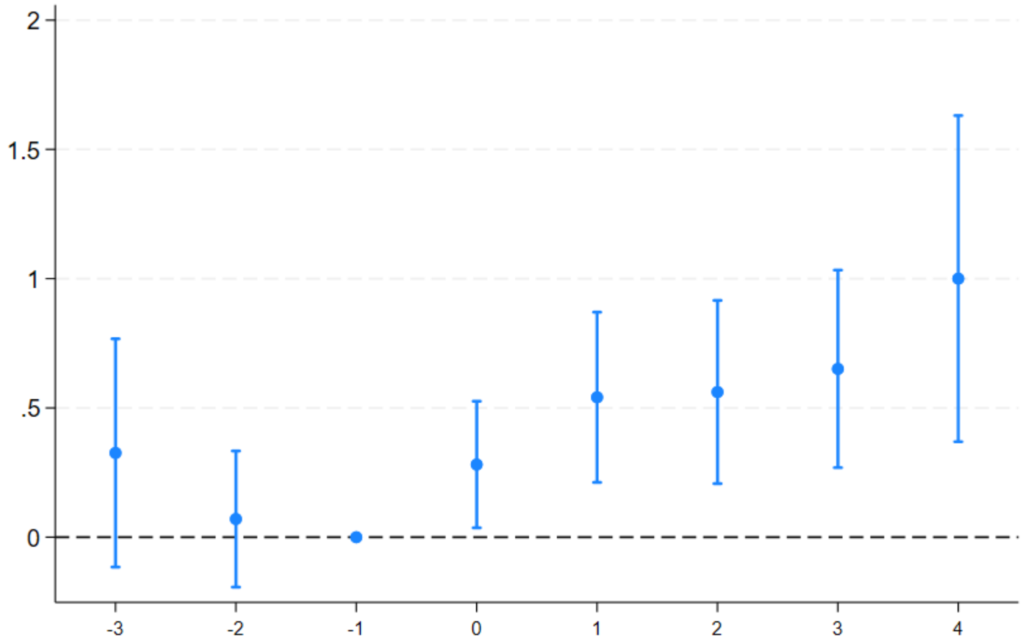


Note: In this figure, we analyze the dynamics of the number of banks firms borrow from before and after IPO using a matched sample one quarter prior to IPO using a Poisson regression. We form a matched sample by estimating propensity scores based on the our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' latest 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 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)

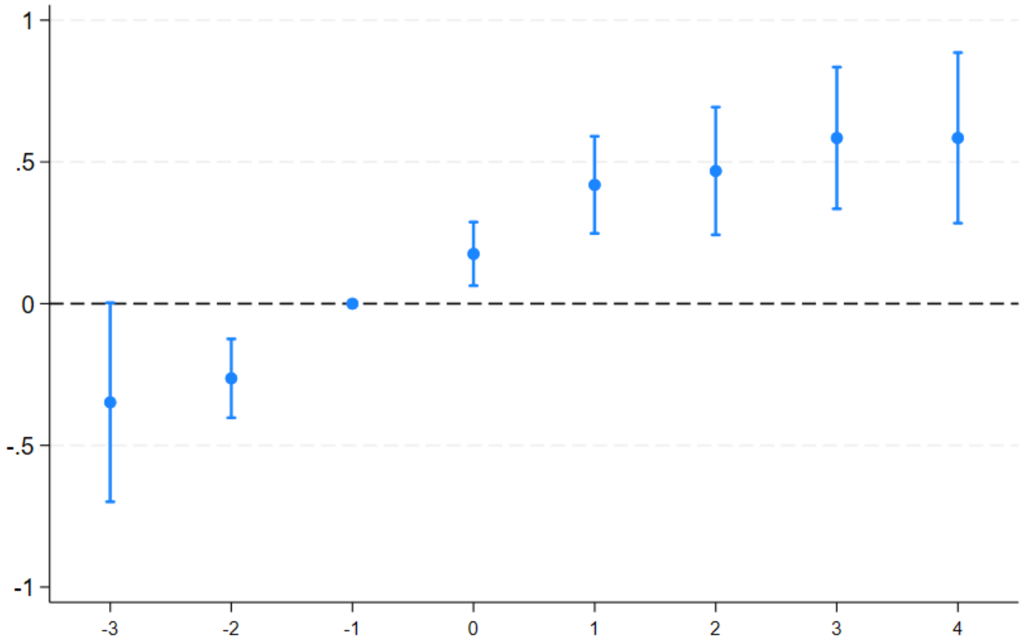


Note:: In this figure, we analyze the dynamics of firm investment, i.e., log(CapEx), before and after IPO using a matched sample one quarter prior to IPO, restricting the sample to VC-backed firms. We form a matched sample by estimating propensity scores based on the our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' latest 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 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)

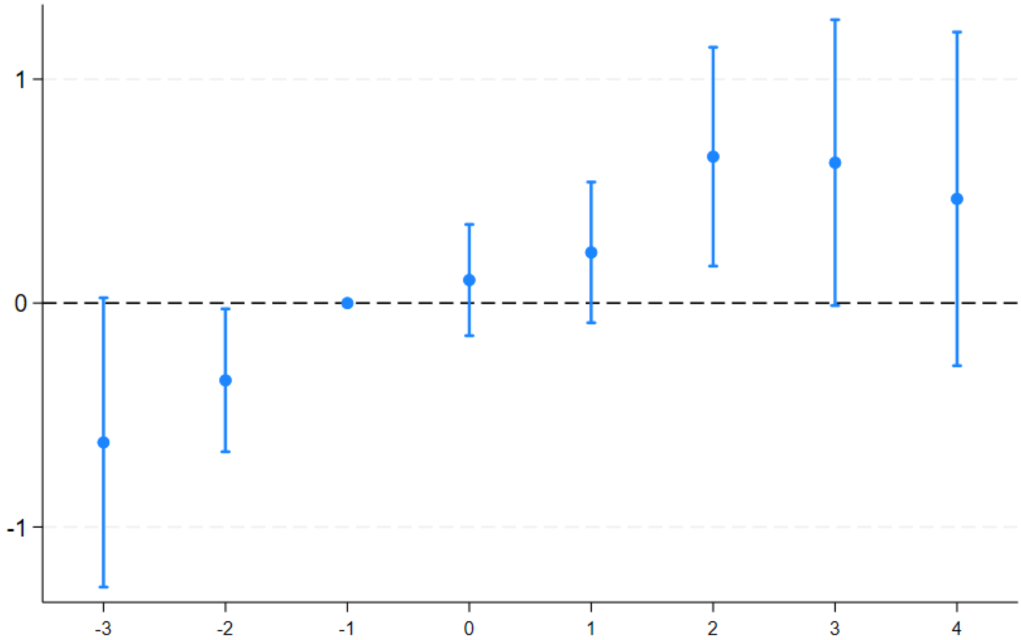


Note: In this figure, we analyze the dynamics of firm assets, i.e., log(assets), before and after IPO using a matched sample one quarter prior to IPO, restricting the sample to VC-backed firms. We form a matched sample by estimating propensity scores based on the our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' latest 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 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 Intangible Asset Dynamics (VC-Backed Only)

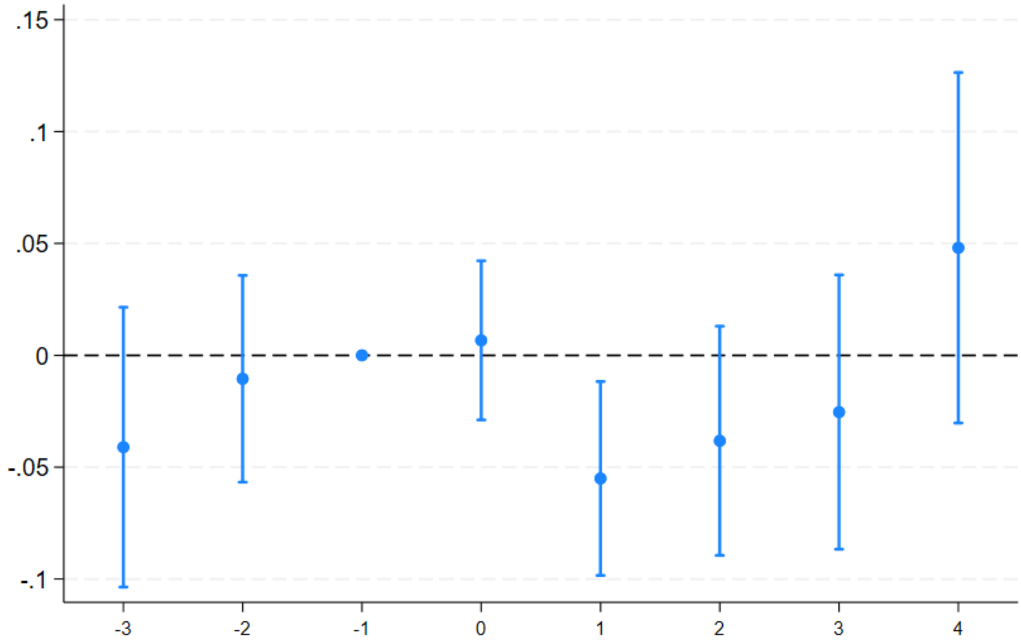


Note: In this figure, we analyze the dynamics of intangible assets, i.e., log(intangible assets), before and after IPO using a matched sample one quarter prior to IPO, restricting the sample to VC-backed firms. We form a matched sample by estimating propensity scores based on the our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' latest 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 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 C5: IPO Leverage Dynamics (VC-Backed Only)

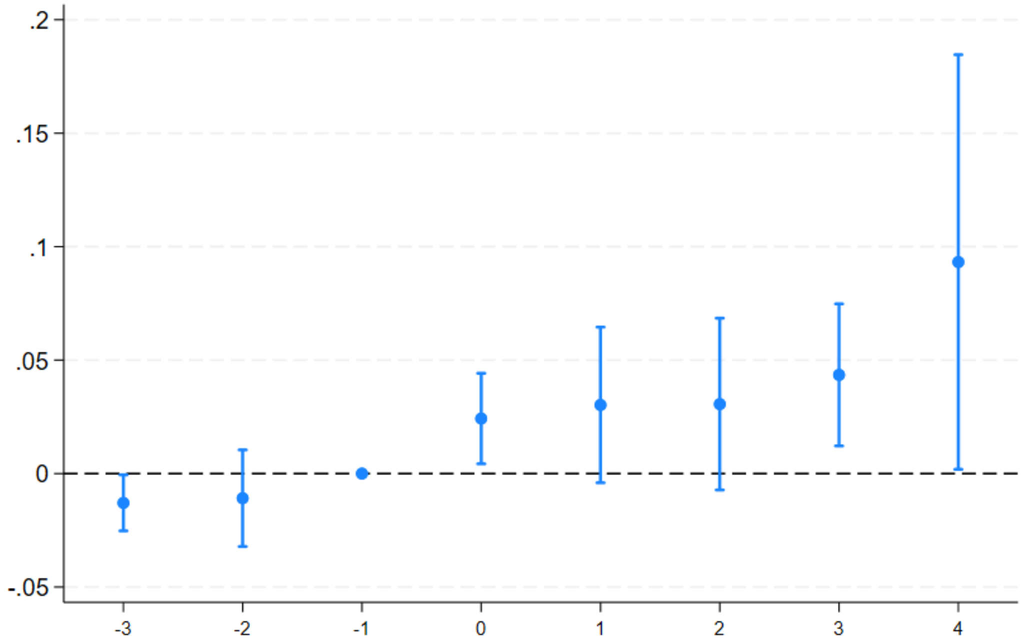


Note: In this figure, we analyze the dynamics of firm leverage, i.e., debt/assets, before and after IPO using a matched sample one quarter prior to IPO, restricting the sample to VC-backed firms. We form a matched sample by estimating propensity scores based on the our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' latest 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 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 C6: IPO Bank Debt Dynamics (VC-Backed Only)

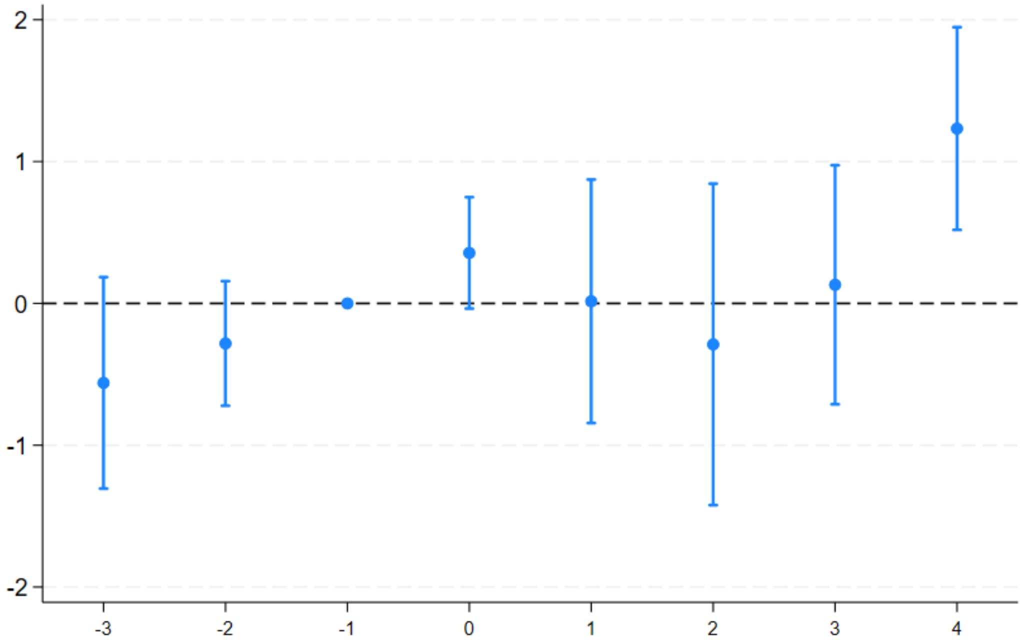


Note: In this figure, we analyze the dynamics of bank debt, i.e., log(bank debt), before and after IPO using a matched sample one quarter prior to IPO, restricting the sample to VC-backed firms. We form a matched sample by estimating propensity scores based on the our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' latest 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 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 C7: IPO Number of Banks Dynamics (VC-Backed Only)



Note: In this figure, we analyze the dynamics of of the number of banks the firm borrows from before and after 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 the our ex-ante regression (1) with date by industry by CBSA fixed effects, but only including IPO firms' latest 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 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.

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 Firms
Sales	1911	652.84	253.65	1263.95	2483	213.71	4.88	741.38	-439.130***
Assets	1911	811.67	333.65	1162.76	2483	370.04	80.08	799.21	-441.629***
Capex/Assets	1777	0.10	0.04	0.15	2470	0.07	0.03	0.11	-0.027***
Sales Growth	1775	0.54	0.26	0.80	523	0.35	0.28	0.48	-0.191***
EBITDA/Assets	1837	0.04	0.07	0.30	1466	-0.14	-0.19	0.29	-0.183***
Positive Profits	1837	0.64	1.00	0.48	1466	0.36	0.00	0.48	-0.271***
Funding Surplus	1834	-0.05	0.02	0.23	1467	-0.20	-0.22	0.27	-0.155***
Debt/Assets	1911	0.27	0.22	0.25	2483	0.26	0.12	0.30	-0.016*
Cash/Assets	1903	0.20	0.10	0.23	2482	0.44	0.47	0.32	0.234***
VC-Backed	1911	0.40	0.00	0.49	2483	0.01	0.00	0.10	-0.389***
Silicon Valley	1911	0.16	0.00	0.36	2483	0.23	0.00	0.42	0.073***
Tech Firm	1911	0.35	0.00	0.48	2483	0.27	0.00	0.44	-0.085***

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

This table tests which firm characteristics predict firms' IPOing 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 parenthesis and are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	IPO			
	(1)	(2)	(3)	(4)
Log(Sales)	0.153***	0.156***	0.136***	0.156***
	(0.018)	(0.018)	(0.016)	(0.018)
Capex/Assets	0.645***			0.443**
	(0.173)			(0.179)
Sales Growth	0.349***	0.321***	0.293***	0.348***
	(0.052)	(0.050)	(0.045)	(0.052)
EBITDA/Assets	-0.626***			-0.544***
	(0.099)			(0.091)
Debt/Assets	-0.060	-0.070	0.007	-0.067
	(0.061)	(0.061)	(0.051)	(0.062)
Funding Surplus		-0.761***		
		(0.111)		
Funding Deficit Dummy			0.225***	0.112***
			(0.039)	(0.036)
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	931860	933655	1065132	931860
R2	0.244	0.243	0.238	0.244

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

This table tests which firm characteristics predict firms' IPOing within the next three years among technology firms (e.g., 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 parenthesis and are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	IPO			
	(1)	(2)	(3)	(4)
Log(Sales)	0.563***	0.545***	0.596***	0.706***
	(0.082)	(0.078)	(0.090)	(0.112)
Capex/Assets	4.467***	3.665***	4.558***	4.378***
	(1.051)	(0.912)	(1.180)	(1.341)
Sales Growth	1.177***	0.816***	1.104***	0.870***
	(0.198)	(0.160)	(0.203)	(0.205)
EBITDA/Assets	-2.220***	-1.834***	-1.936***	-1.512***
	(0.396)	(0.357)	(0.412)	(0.462)
Debt/Assets	-0.340	-0.601**	-0.265	-0.926**
	(0.288)	(0.278)	(0.315)	(0.471)
NAICS4 MTB	0.752***		0.731***	
	(0.126)		(0.138)	
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	109255	121147	103930	87544
R2	0.025	0.045	0.073	0.238

Table C4 Cross-Sectional Determinants of Firms' IPO Decisions (Manufacturing Only)

This table tests which firm characteristics predict firms' IPOing within the next three years, including only manufacturing firms (NAICS 31 - 33). 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 parenthesis and are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	IPO			
	(1)	(2)	(3)	(4)
Log(Sales)	0.124***	0.123***	0.145***	0.113**
	(0.037)	(0.034)	(0.040)	(0.044)
Capex/Assets	0.393	0.493*	0.389	0.617*
	(0.284)	(0.253)	(0.284)	(0.344)
Sales Growth	0.541***	0.465***	0.550***	0.520**
	(0.148)	(0.125)	(0.158)	(0.209)
EBITDA/Assets	-0.655***	-0.552***	-0.595***	-0.462
	(0.224)	(0.193)	(0.231)	(0.283)
Debt/Assets	-0.038	-0.035	-0.059	-0.081
	(0.078)	(0.080)	(0.080)	(0.135)
NAICS4 MTB	0.091***		0.089**	
	(0.035)		(0.040)	
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	239554	268373	231822	171463
R2	0.005	0.032	0.078	0.334

Table C5: Cross-Sectional Determinants of Firms' IPO Decisions (Excluding Merger Targets)

This table tests which firm characteristics predict firms' IPOing 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 parenthesis and are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	IPO			
	(1)	(2)	(3)	(4)
Log(Sales)	0.127***	0.126***	0.133***	0.144***
	(0.015)	(0.014)	(0.016)	(0.017)
Capex/Assets	0.869***	0.640***	0.893***	0.670***
	(0.151)	(0.119)	(0.156)	(0.171)
Sales Growth	0.502***	0.317***	0.494***	0.344***
	(0.058)	(0.040)	(0.059)	(0.052)
EBITDA/Assets	-0.735***	-0.624***	-0.735***	-0.596***
	(0.087)	(0.077)	(0.088)	(0.098)
Debt/Assets	-0.200***	-0.052	-0.176***	-0.078
	(0.045)	(0.042)	(0.046)	(0.060)
NAICS4 MTB	0.080***		0.080***	
	(0.011)		(0.012)	
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	980163	1239930	973289	926205
R2	0.006	0.031	0.020	0.246