NBER WORKING PAPER SERIES

WHY DO STARTUPS BECOME UNICORNS INSTEAD OF GOING PUBLIC?

Daria Davydova
Rüdiger Fahlenbrach
Leandro Sanz
René M. Stulz

Working Paper 30604
http://www.nber.org/papers/w30604

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
October 2022, Revised July 2024

We thank Harry DeAngelo, Michael Ewens, Josh Lerner, Vojislav Maksimovic, Ludovic Phalippou, Jay Ritter, Tereza Tykvová (discussant), Richard Thakor (discussant), Mike Weisbach, Karen Wruck, and participants at the IPCC conference at the University of North Carolina, the 6th Private Market Conference in Lausanne, the University of Minnesota Corporate Finance Conference, as well as seminar participants at Brigham Young University, the University of Florida, Harvard University, the Ohio State University, the University of Georgia, and the University of Utah for comments. Fahlenbrach gratefully acknowledges financial support from the Swiss Finance Institute. Please send correspondence to René M. Stulz, stulz.1@osu.edu. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Why Do Startups Become Unicorns Instead of Going Public?
Daria Davydova, Rüdiger Fahlenbrach, Leandro Sanz, and René M. Stulz
NBER Working Paper No. 30604
October 2022, Revised July 2024
JEL No. G24,G32,G34

ABSTRACT

Unicorns are startups that choose to stay private even though they are large enough to go public. We propose an efficiency explanation for their existence. Startups relying highly on organization capital are more vulnerable to expropriation of their organization capital if they go public before their position is sufficiently secure. Our main empirical findings are that shocks to the fragility of organization capital decrease the IPO likelihood, unicorn status enables startups to stay private longer by giving them access to new sources of capital, and unicorns and their industries have higher organization capital intensity than other startups.

Daria Davydova
Ecole Polytechnique Fédérale de Lausanne,
daria.davydova@epfl.ch

Rüdiger Fahlenbrach
Swiss Finance Institute @ EPFL
Quartier UNIL-Dorigny, Extranef 211
CH – 1015 Lausanne
Switzerland
ruediger.fahlenbrach@epfl.ch

Leandro Sanz
The Ohio State University
810 Fisher Hall
2100 Neil Avenue
Columbus, OH 43210
sanz.8@osu.edu

René M. Stulz
The Ohio State University
Fisher College of Business
806A Fisher Hall
Columbus, OH 43210-1144
and NBER
stulz@cob.osu.edu

Much evidence shows that startups go public later, if at all, than the typical startup that went public before the 2000s. Some of the startups eventually obtain a headline valuation of at least $1 billion and achieve unicorn status. Before the 2000s, founders would just have taken their startups public by issuing common shares before they reached unicorn status. These founders generally did not have the option of staying private longer. However, just because a startup can secure adequate funding to achieve unicorn status does not guarantee that its investors will benefit. We propose an efficiency reason for why some startups stay private long enough to reach unicorn status and show that unicorn status helps them stay private even longer. The efficiency reason is that joining the public markets can be especially costly for firms in the early stages of building organization capital. As a result, firms relying highly on organization capital and network effects maximize their value by building their organization capital privately. These firms stay private until they are robust enough that going public will not endanger their organization capital or hinder their growth.

To investigate why some startups stay private long enough to achieve unicorn status, we create a new comprehensive database of U.S. unicorns. We find that 639 U.S. startups achieved unicorn status since the beginning of the 2000s until the end of Q3 2021. The number of active unicorns increases steadily throughout our sample period. We have 427 active unicorns at the end of our sample period and observe 212 unicorn exits. By ending in Q3 2021, we essentially cover the whole bull market that followed the global financial crisis (GFC). Though our sample ends at the peak of the bull market and the rate of unicorn births falls afterwards, many unicorns have been created since.[1] We also collect information on 5,070 startups that received at least $50 million of VC funding from 2010 to Q3 2021. Lastly, we collect information on 3,369 IPOs from 2010 to Q3 2021. We create matched samples from these two databases to draw inferences about business models, funding structures, and exits of unicorns.

[1] As an example, there were more unicorn births in June 2022, after stock market valuations had fallen substantially, than in any quarter in our sample except the first three quarters of 2021. See "Meet the 32 new unicorns that joined the board in June 2022," by Gené Teare, Crunchbase.com.

Our proposed efficiency explanation for why some startups stay private long enough to achieve unicorn status is the growing importance of a new type of firm that relies heavily on organization capital to exploit economies of scale and scope based on network effects. Organization capital corresponds to “the knowledge used to combine human skills and physical capital into systems for producing and delivering (…) products” (Evenson and Westphal, 1995). It is more difficult to protect through patents, leading to high costs of public disclosure.[2] Broadly, spending on organization capital includes advertising, information technology, human capital, and customer relations (Corrado and Hulten, 2010). Another way to put it is that investing in organization capital involves investing “in certain business models, organization practices, and corporate culture” (Brynjolfsson, Hitt, and Yang, 2002). Firms with significant organization capital are highly valuable if they succeed but have little value if they fail.

For such startups, the cost of going public is high because it distracts them from their race to grow and reach scale before they become threatened by competition and because it is harder to build organization capital early on as a public firm. Going public slows the firm down, as management has to take time away from building the firm to deal with the IPO, thereby opening the door to competition and imitation, as well as making it less flexible. Once a firm is public, disclosure costs are high and management has to explain and justify itself publicly, which can make it hard to change the firm’s business model. Disclosure can also give information to potential competitors (e.g., Verrecchia, 1983; Bhattacharya and Ritter, 1983; Maksimovic and Pichler, 2001; Farre-Mensa, 2017; and Aghamolla and Thakor, 2022). Management of a public firm has to deal with disclosures, regulators, and investors in ways that it would not have to if the firm were private (Boot, Gopalan, and Thakor, 2006 and 2008; Bennett, Stulz, and Wang, 2024). These requirements can lead the firm to become less entrepreneurial and more bureaucratic. Consistently, existing evidence shows that public firms find it harder to innovate (Aghamolla and Thakor, 2022; Bernstein, 2015; and Tian and Wang, 2014) and that an IPO leads to substantial labor turnover (Babina, Ouimet, and

[2] Disclosure costs are high for firms that invest heavily in intangible assets because the limited excludability property of such assets makes it harder for firms to exert property rights on intangible assets (Haskel and Westlake, 2017; Crouzet, Eberly, Eisfeldt, and Papanikolaou, 2022).

Zarutskie, 2022). The pressures of being a public firm can also distract employees and even cause them to leave the firm. The changes that occur when a firm goes public also make it challenging for the startup to preserve its culture (Guiso, Sapienza, and Zingales, 2015). As a result, a firm that goes public before reaching scale may never reach scale.

We use our database of startups that have received at least $50 million of VC funding to show that there is a direct relation between the fragility of intangible capital that cannot be patented and the likelihood of an IPO exit for startups. For that purpose, we use the Supreme Court's decision in the matter of Alice Corp. vs. CLS Bank International in 2014. The decision revoked patent protection on a wide range of business methods patents, making it harder to patent business processes. Acikalin, Cakurlu, Hoberg, and Phillips (2022) investigate the impact of the Supreme Court's decision and show that the sectors most affected were those where innovation took the form of software or involved digital data processing. In these sectors, the decision made it easier for intangible capital to be expropriated as firms no longer had the same ability to patent as before. Using the decision to classify software startups as treated in a difference-in-differences model, we find that treated startups are less likely to IPO after the decision, which supports our theory that the costs of going public are high for firms relying heavily on intangible capital that cannot be protected through patents.

The scale and network effects that organization capital-intensive firms realize if they can execute their business model can justify high valuations. Private investors in these firms get access to material non-public information that they could not have accessed if they were public investors. Because they can overcome information asymmetries about the firm's business model and prospects by being inside investors, they can make funding available to firms at high private valuations. Without such funding, firms that rely heavily on organization capital and are made valuable by exploiting economies of scale and scope would either go public too fast, as many firms did in the internet boom, and then possibly fail, or not exist at all. What enables startups to stay private long enough to build the required organization capital is that, in the unicorn era, the funding and liquidity benefits associated with being a public firm are lower partly because of greater access to private funding. In the pre-unicorn era, private firms were funded by venture capitalists with a well-defined investment horizon and strict regulatory limitations on their ability to raise funds, which resulted in a limited supply of capital and pressure on startups to go public (de Fontenay, 2017; Ewens and Farre-Mensa, 2020). Though the provision of venture funding has a history of cyclicality (Gompers and Lerner, 2004), the ample availability of capital in much of this century has made it plausible to argue that "advances in the ease of capital raising in private markets have made it possible for firms to remain private indefinitely" (de Fontenay and Rauterberg, 2021).

We show that achieving unicorn status enables firms to access sources of finance other than traditional venture capital funding (see also Kwon, Lowry, and Qian, 2020).[3] We document that 27% of investors who invest in unicorn rounds do not invest in earlier rounds of the startups that become unicorns or comparable startups. Further, we find that VC firms are less likely to participate in post-unicorn rounds, but asset managers are more likely to do so. We show that the location of investors changes with unicorn status. The likelihood of an investor participating in a post-unicorn round increases with distance from San Francisco, while the likelihood of an investor participating in a pre-unicorn round decreases with distance from San Francisco. In addition, we document that the alternative sources of finance are willing to provide liquidity to founders and employees and, therefore, reduce the liquidity motive of going public. We argue that these benefits of unicorn status help explain why there is a discontinuity in the distribution of the value of startups at $1 billion. Such a discontinuity can arise if investors who do not normally invest in startups become interested in startups that have reached some scale threshold, i.e., $1 billion. Such a threshold may be justified as an indication that the startup has lower risk or that the scale of investments is appropriate for large non-VC institutional investors.

With our efficiency explanation for unicorns, only startups with characteristics that make them heavily reliant on organization capital should benefit from unicorn status. We conjecture that many industries may

[3] In a contemporaneous paper, Gahng (2022) argues that achieving unicorn status "makes employees more favorably assess the companies they work for," which leads firms to take steps to achieve unicorn status. The channel he focuses on is that the headline valuation increases as the firm increases authorized but not issued shares. He argues that firms use these shares to achieve unicorn status.

not have firms with those characteristics. Indeed, we find strong evidence of a very high industry concentration in unicorns. We show that 59% of unicorns have a business model that relies on the internet for distribution, where network and scale effects are particularly important. Since SG&A expenses are a well-known proxy for investment in organization capital (e.g., Eisfeldt and Papanikolaou, 2013, and Peters and Taylor, 2017), our explanation for unicorns implies that the fraction of startups that are unicorns should be higher in industries where young listed firms have high SG&A expenses than in other industries. We find support for that prediction. Finally, using a new measure of the importance of network effects in a startup's business model, we find that a firm for which network effects are important is more likely to be a unicorn.

Our database of startups that have received at least $50 million of VC funding allows us to measure the likelihood that a startup becomes a unicorn and to examine the determinants of that likelihood. As predicted, we find that unicorns and other startups differ in an important way in how they create intangible capital. With our database, we can match each unicorn that goes public with a startup that raised funds in the same year, at a similar valuation, with similar cumulative funding, and of similar age as the then future unicorn in its last pre-unicorn round. The logic of the match is that the matching firms have the same funding history up to and including the pre-unicorn round for the unicorn. This ensures that the startup that did not become a unicorn has a valuation similar to that of a firm that becomes a unicorn. We find that unicorn IPO firms spend much more on SG&A the year before the IPO. We also find that unicorns have fewer patents per dollar of VC funding than other IPO firms. In contrast, startup IPOs that did not become unicorns but are comparable to unicorn IPOs in valuation, cumulative funding, and age at their pre-unicorn round spend much more on R&D capital compared to organization capital the year before the IPO than unicorn IPOs do. This evidence is strongly supportive of our explanation for the existence of unicorns.

For startups to become unicorns, funding must be available to enable them to stay private and grow. The venture capital literature has studied the causes and consequences of fund inflows since Gompers and

Lerner (2000).[4] A perennial difficulty in examining the role of fund inflows on startups is the direction of causality. Do inflows merely reflect good opportunities, or do they cause startup creation? The issue is important for our explanation of the growth of unicorns since funding could respond to the investment opportunities of unicorns rather than being an independent cause for the growth in unicorns. We obtain sources of exogenous variation in capital flows using the investment plan at the inception of the Vision Fund of SoftBank and inflows into buyout funds. We find that an exogenous increase in the supply of funding increases the number of unicorn births.

In some theories of the timing of when firms go public (e.g., Pastor, Taylor, and Veronesi, 2009), founders trade off the loss of private benefits from joining the public markets, such as greater discretion in decision-making, against the benefits of being public, such as their ability to diversify their wealth. If the benefits of being public fall, startups will stay private longer (Ewens and Farre-Mensa, 2020). If startups stay private longer and funding is available, some will eventually become unicorns. Such an explanation for the emergence of unicorns is compatible with ours. Unless private benefits from controlling a private firm increased in the 2000s, the delay in going public must be explained by a change in the gain from going public, which is what we focus on. Our contribution is to show that there is an efficiency reason for unicorns to exist. We demonstrate that a surprisingly large fraction of unicorns that go public, namely 51%, have a dual class share structure that allows founders to retain control even after their firms become public. We also show that the likelihood of founders being CEOs at the IPO is higher for unicorns than other startups. This evidence weakens arguments that unicorns only stay private because of private benefits of control, although it could be that the greater monitoring from being public (Holmstrom and Tirole, 1993; Bolton and Von Thadden, 1998) reduces the benefits of control even when founders have majority control of a public company.

The paper proceeds as follows. In Section 1, we describe how we construct our sample and document the unicorn phenomenon by showing the evolution of the number of unicorns, the births and exits of

[4] Janeway, Nanda, and Rhodes-Kropf (2021) survey the subsequent literature.

unicorns, and the returns to unicorn round investors. In Section 2, we develop a framework to explain why we observe so many unicorns and provide a test showing that greater fragility of organization capital reduces the likelihood of an IPO. In Section 3, we ask whether unicorn status makes a difference to founders and firms. In Section 4, we investigate which private firms are more likely to become unicorns. In Section 5, we focus on startup exits and compare unicorns at the IPO exit to other startups that resemble them closely at the pre-unicorn stage. We conclude in Section 6.

1. Unicorn births and exits

In this section, we explain how we construct our sample of unicorns and then show how the number of unicorns evolves over time.

1.1. Sample construction

Our main data provider is CB Insights. CB Insights defines a unicorn as a VC-backed private company with a post-money headline valuation of $1 billion or more. Note that a company whose only valuation of $1 billion or more is the value at exit (either the IPO valuation or the M&A deal value) is not a unicorn under the CB Insights definition. We focus on U.S. unicorns, defined as unicorns with a registered office in the U.S.

The initial sample consists of 567 unicorns. We then add 72 unicorns from the sample of Gornall and Strebulaev (2020) to our initial sample. The Gornall and Strebulaev (2020) unicorn sample enables us to add unicorns to our sample that had an exit before the first CB Insights list was compiled in 2015. Our final sample consists of 639 unicorns, and the first unicorn in our sample was born in Q3 2005. Appendix A contains more details on the sample construction.

We obtain data for exits of unicorns from SDC Platinum, CB Insights, S&P Capital IQ, and individual web searches. We distinguish between five different types of exits – direct listings (DLs), initial public offerings (IPOs), reverse mergers through special purpose acquisition companies (SPACs), M&As, and failures. We classify a company as failed if it declares bankruptcy or is acquired for less than 25% of the unicorn round post-money headline valuation (which we call a rescue merger). For direct listings and IPOs, the exit date is the offer date. The exit date for reverse mergers and M&As is the deal completion date.

Of the 639 unicorns in our database, 427 are still unicorns at the end of our sample period (September 30, 2021).[5] An additional 10 unicorns are classified as alive but "down" if they had a final funding round with a post-money headline valuation of less than $1 billion or less than 25% of their peak valuation. The remaining 202 unicorns had an exit event.

In several of our tests, we compare unicorns to other startup companies that raised significant amounts of venture capital financing. We compile a list of U.S. startups that took money from VCs and raised at least $50 million of total funding (cumulatively across all available rounds) sometime between 2010 and Q3 2021 that do not become unicorns during our sample period. The data source is CB Insights. We track the startups through time.

For some of our analysis, we would like to compare unicorns to startups that could have become unicorns but did not. For that purpose, we use the list of U.S. startups that took money from VCs and raised at least $50 million of total funding just described and collect data to match startups to future unicorns in their last fund-raising prior to their unicorn fund-raising. For each future unicorn, we then identify a startup that 1) has the same valuation as the future unicorn, 2) raises funds in the same year as the year of the last pre-unicorn fund-raising round of the future unicorn, 3) raised a similar total amount as the future unicorn including that fund-raising, and 4) has a similar firm age at that fund-raising as the future unicorn. We use the Mahalanobis distance metric and match with replacement. We call the resulting sample the matched sample. We also create a smaller matched sample of startups that IPO. With this sample, we match a unicorn that has an IPO with a startup from the matched sample that has an IPO as well. Again, we use the Mahalanobis distance metric and match with replacement. We call this smaller sample the IPO-matched sample.

[5] Seventeen of those 427 companies had a pending M&A deal, but the deal was not consummated by the end of our sample period. We classified those as alive.

Finally, in some of our analyses, we compare the accounting characteristics and patents of unicorns and VC-backed startups around their IPO or use industry averages of accounting characteristics of young publicly listed firms as independent variables. These data come from Standard & Poor's Compustat database (accounting characteristics) and CB Insights (patents). We also use the list of venture-capital-backed IPOs compiled by Jay Ritter.[6]

1.2. Unicorn births and exits

Panel A of Figure 1 shows that until the third quarter of 2018, there were always less than 20 unicorns created per quarter. Until the end of the first quarter of 2021, there were always less than thirty unicorns created. During the last three quarters of our sample, the numbers increased markedly, with each quarter generating more than 60 new unicorns.

Panel B shows the number of unicorn exits (listings, M&A, or failure). No quarter until Q2 2020 featured more than ten unicorn exits. Exits increased markedly towards the end of our sample period. Panel C, however, shows that the exit rate, defined as the number of exits per quarter divided by the number of unicorns in existence in the previous quarter, was not particularly elevated toward the end of the sample period, although public companies had high valuations at that time. Panel D indicates that the number of unicorns in existence increased steadily through time as the number of births exceeded the number of exits.

Panel A of Table 1 shows summary statistics for the entire unicorn sample. The average firm took 6.9 years to reach unicorn status (median 6.3). The mean firm became a unicorn after 5.3 rounds of equity financing (median 5 rounds). The average post-money headline valuation of the unicorn round was $1.64 billion, and the median was $1.2 billion. The average post-money headline valuation of the last financing round (be it a private round or the exit valuation) was $4.07 billion (median $2.0 billion).

Unicorns raised on average $328 million in funding until they became unicorns, and a total of $708 million as a private company (medians are $253 and $383 million, respectively). Equity rounds were the

[6] Available for download free of charge from https://site.warrington.ufl.edu/ritter/ipo-data/.

dominant financing method, with the mean unicorn raising 95% of all funds through equity rounds and the median unicorn raising 100% through equity financing. We observe exits for 33.18% (or 212 unicorns) of the total sample. For the subset of firms that exit, the time between the unicorn round and exit was slightly more than three years, for a total average life as a private company of 10 years.

Panel B of Table 1 shows select summary statistics for exited unicorns during our sample period by type of exit.[7] Though a majority of unicorns in our sample did not exit during our sample period, 181 unicorns had successful exits, meaning that their value at exit exceeds their headline value at their last funding round. A unicorn exits the sample if its valuation falls below the threshold of $1 billion or if it has a valuation less than 25% of the peak post-money headline valuation (*down*). We consider a unicorn to have failed if it files for bankruptcy or is acquired for less than 25% of the unicorn round post-money headline valuation (*failed*). Such outcomes are exceedingly rare during our sample period. Ten firms had down-rounds. Twenty-one firms failed altogether. Unicorns that fail live 4.42 years on average as unicorns. The unicorns that fail have a median market value of zero after the last fundraising round, and, on average, 90% of the unicorns that fail have a PMV at exit of less than their total funding. The typical failure is not bankruptcy but an acquisition for less than 25% of the unicorn round post-money headline valuation.

Firms can become listed on public markets in three ways during our sample period: a) IPO (110 obs.); b) SPAC (18 obs.); and c) direct listing (9 obs.). Panel B of Table 1 shows that, on average, a unicorn that IPOs stays private for 2.79 years between achieving unicorn status and the IPO and has an additional 2.34 equity financing rounds as a private company. The average (median) PMV at exit for an IPO firm is 4.78

[7] We determine the valuation at exit for the different exit types as follows. For direct listings, the exit valuation is the number of shares outstanding (summed across all share classes for dual class companies) multiplied by the price per share at the end of the first listing day. For initial public offerings, it is the number of shares outstanding (summed across all classes) multiplied by the offer price. For dual class companies, we obtain the number of shares outstanding across all classes from the IPO prospectus's summary page of the offering. For reverse mergers, we equate the valuation at exit with the enterprise value at the time the reverse merger was announced. For M&A exits, we use the disclosed purchase price. For some M&A exits, no official purchase price is available. We classify these as M&A exits with an undisclosed purchase price unless the acquiring company mentions in its SEC filings that the purchase price was immaterial. Then we classify the M&A exit as a failure. For failures, we either assign the rescue merger consideration or the value, if any, disclosed in the press article describing the bankruptcy.

(2.57) times the average (median) PMV at the unicorn round.[8] On average (median), the IPO firm raises $1.03 billion ($483 million) of funding before the IPO. Firms that exit through a SPAC are unicorns on average 3.55 years when they exit, after 2.4 additional equity financing rounds as a private company. They raise on average (median) $914 million ($633 million). Their average (median) PMV at exit is 4.19 (2.89) the PMV at the unicorn round. The direct listing firms were, on average, unicorns for 4 years and raised an additional 3.22 equity financing rounds as private companies. They raise amounts comparable to the firms that exit through IPOs or SPACs. However, they have a much higher PMV at exit relative to the PMV at the unicorn round since it is 10.6 on average and 5.07 at the median. The last exit category is exit through an acquisition. The number of acquired unicorns is small at 44. The acquired unicorns have been unicorns for a similar number of years compared to those that exit through an IPO but have, on average, fewer additional equity financing rounds (1.07). The PMV at exit for the acquired unicorns relative to the PMV at the unicorn round is smaller than that of IPOs. The average is 3.2 compared to 4.8, and the median is 1.57 compared to 2.57.

Unicorn round investors in unicorns that exit during our sample period did extremely well. We show statistics on the performance of unicorn investors in Internet Appendix Table IA.B.1. The IPO price is, on average, 3.74 times the unicorn round share price. The median is 2.21. Both the mean and the median are statistically significantly different from the benchmark of one. We follow Kaplan and Schoar (2005) and compute the public market equivalent (PME) using the S&P 500, Russell 2000, and the S&P 500 Tech indices as benchmarks. The mean PME using the S&P 500 (Russell 2000) as benchmark is 2.62 (2.82); the median is 1.61 (1.65). The mean (median) PME using the S&P 500 Tech is lower at 2.04 (1.33), reflecting the strong performance of technology stocks during our sample period. All PMEs are statistically significantly different from one, which is the benchmark of equal performance of public and private markets. However, since the typical unicorn did not exit during our sample period, it is difficult to interpret

[8] In these comparisons, we use the traditional VC post-money headline valuation and do not price the special privileges as in Gornall and Strebulaev (2020). Hence, the reported ratios likely underestimate the true ratios.

the performance of the unicorns that exit.[9] It could be that the unicorns that exit had unusual performance or timed their exit well, but that other unicorns from our sample will not be able to exit on as favorable terms.

Our sample has 427 active unicorns at the end of our sample period in Q3 2021. A potential concern is that our sample period was a period of exuberance in the VC world. We seek to reduce concerns that many unicorns were created because of easy access to finance and unsubstantiated valuations rather than promising business models by following them through time until Q1 2024. Of the 427 active unicorns in Q3 2021, 15 exit through an IPO, 13 exit through a SPAC, and 16 exit through a M&A transaction. In other words, 10.55% of the unicorns have a successful exit. We found 14 unicorn failures, or 3.28% of the number of active unicorns at the end of our sample period. To summarize, 86.42% of the unicorns at the end of our sample period are still active unicorns at the end of Q1 2024.

2. Understanding the unicorn phenomenon

We develop our proposed explanation for why unicorns exist and why so many unicorns were created in the 2010s. This explanation relies on the argument that the fragility of organization capital leads firms to go public later. We provide evidence on this argument using a shock to the ability of firms to protect their intangible capital.

There is a considerable literature focused on explaining why firms go public (see, e.g., Pagano, Panetta, and Zingales, 1998; Chemmanur and Fulghieri, 1999; Boot, Gopalan, and Thakor, 2006; Brau and Fawcett, 2006; Pastor, Taylor, and Veronesi, 2009), and why the number of IPOs dropped after the 1990s (see, e.g., Gao, Ritter, and Zhu, 2013; Doidge, Karolyi, and Stulz, 2017; Stulz, 2020). The unicorn puzzle is related

[9] Of the 427 sample unicorns that do not exit during our sample period, 119 have a subsequent fundraising round with disclosed PMV after having reached unicorn status. Panel B of Internet Appendix Table IA.B.1 shows their intermediate performance.

to but distinct from the issue of why the yearly number of IPOs is low in the 2000s (with the exception of 2021, which ranks as the 11th year in the number of IPOs from 1980 to 2021).[10]

The literature suggests that there are many potential benefits for a startup to become a public firm. However, there is general agreement that going public has two main benefits. First, firms go public when they require funding that private markets cannot provide on acceptable terms, when they require a currency to make acquisitions, or when they need tradeable equity for performance-based compensation. We call this the funding motive. Second, insiders will want a firm to go public so that they can sell shares and diversify their wealth. We call this the liquidity motive.

Going public has important costs. There are obvious pecuniary costs arising from registration with the SEC, the floating of shares, and the listing of shares (Ritter, 1987). The non-pecuniary costs can be more important. It takes time for firms to go public, which diverts management's attention from running the firm. After the firm has joined public markets, it often experiences turnover in its workforce as early employees move on or are no longer good matches for the firm, and the organization has to evolve to meet the challenges of public markets (Babina, Ouimet, and Zarutskie, 2023; Bernstein, 2022; Bias, Lochner, Obernberger, and Sevilir, 2023). Public firms are the subject of more attention. For instance, the SEC monitors them and analysts follow them. They are subject to different laws and more regulations. They have to disclose much information about themselves regularly. The production of this information involves costs but, more importantly, can help competitors and draw the attention of regulators and politicians. For instance, existing evidence shows that public disclosures can attract the attention of antitrust authorities (Barrios and Wollmann, 2024). Being public can also make it difficult for management to make large changes to the business model, as management would have to spend time explaining these changes to various constituencies and might experience strong pushback from analysts, shareholders, and politicians. Finally, a cost of going public is that the startup loses the option of going public at a higher valuation. This cost explains that there can be waves of IPOs when valuations are especially high. Lowry (2003) finds that

[10] See Jay Ritter, Initial Public Offerings: Updated Statistics. Available for free at https://site.warrington.ufl.edu/ritter/files/IPO-Statistics.pdf.

the demand for funding and sentiment are important determinants of IPO volume. When sentiment is high, losing the option of going public is worth little, and more startups go public.

The traditional view is that, as a firm grows, the benefits of being public eventually outweigh the costs. Figure 2 shows the traditional view of the net benefit of being public as a function of the firm's private valuation using the framework of Doidge, Karolyi, and Stulz (2017). The net benefit is negative for low private valuations and increases with the level of the private valuation. Historically, the net benefit became positive and the firm went public much before its private firm valuation exceeded $1 billion (solid red line). The additional lines in Figure 2 show how the unicorn phenomenon could arise. With a uniform decrease in the net benefit, all firms go public at higher valuations (black dashed line). Alternatively, a new type of firm could emerge for which the net benefit of being public is lower (the flatter dotted green line). The net benefit of being public only becomes positive for valuations exceeding $1 billion by some amount. The increased availability of funding for firms with private valuations of at least $1 billion lowers the slope of the relation between the net benefit of being public and a firm's private valuation once a $1 billion valuation is achieved (solid green line).

We argue that the green line describes firms well for which organization capital to support a business model centered on network effects is especially important. These firms are expected to be highly valuable if they succeed in building their organization capital and reach scale, but they might never succeed if they go public early since doing so might slow down their progress and give a window of opportunity to potential competitors.

Intangible assets have become much more important over time (e.g., Haskel and Westlake, 2017; Kahle and Stulz, 2017; Falato, Kadyrzhanova, Sim, and Steri, 2022). Tangible assets cannot be expropriated easily. But the use of many intangible assets is not restricted to one firm; other firms can imitate what a firm is doing (Haskel and Westlake, 2017; Crouzet, Eberly, Eisfeldt, and Papanikolaou, 2022). The digital economy has led to business models that build on intangible capital to create network effects and economies of scale. Firms for which intangible assets are particularly important benefit from achieving scale while private because they face much less demanding public disclosure requirements, are better able to change plans, can better bind employees to the firm, and are less distracted by outside attention. Founders can be vocal about "the additional painful scrutiny that comes with being public." [11]

Firms invest in intangible capital in two main ways. First, they spend money on R&D. Second, they spend money on organization capital. A growing literature emphasizes the importance of organization capital (e.g., Lev and Radhakrishnan, 2005; Hulten and Hao, 2008; Eisfeldt and Papanikolaou, 2013; Peters and Taylor, 2017). GAP accounting generally treats investment in intangible capital as an expense that is not separately identified, in contrast to capital expenditures which are capitalized and separately identified. This asymmetry creates a bias against public companies that are accumulating intangible capital aggressively (Rajgopal, Basirian, Iqbal, Srivastava, 2024; Ayyagari, Demirgüç-Kunt, and Maksimovic, 2024), which may also make it harder for these companies to go public. Lev, Radhakrishnan, and Zhang (2009) argue that the expenses that firms incur to develop intangible organization capital are reported as sales, general, and administrative (SG&A) expenses and include "IT outlays, employee training costs, brand enhancement activities, payment to systems and strategy consultants, and the cost of setting up and maintaining Internet-based supply and distribution channels." Recent empirical evidence shows that for the typical firm, the capitalized value of organization capital is more than four times the capitalized value of R&D (Iqbal, Rajgopal, Srivastava, and Zhao, 2024).

Organization capital is fragile because it depends partly on the personnel in place and their training. As a result, the ownership of organization capital is more complex than the ownership of alienable assets (Rajan and Zingales, 2000; Eisfeldt and Papanikolaou, 2013). Employees that leave may take some organization capital with them. Since personnel is more tied to the firm while it is private, it is valuable for firms that rely on organization capital to stay private until the organization capital is sufficiently established and the firm can cope with personnel turnover (Rajan, 2012). For instance, employees of private firms may not be able to exercise options while the firm is private because of liquidity constraints, which give them incentives to stay with the firm until the IPO (Bias, 2021). Further, organization capital cannot be protected as easily

[11] See Vance (2015).

from expropriation as R&D intangible capital. Part of organization capital consists of business processes that have been developed.

From our discussion, we would expect that if it becomes harder for a startup to protect its organization capital, such as through patenting, the advantages of going public decrease. This is especially true before the startup has established a solid position in its market. We use a shock to firms' ability to protect their intangible capital to provide support for the predicted relation between the ability to defend organization capital and the likelihood of startups going public. In 2014, the Supreme Court's decision in Alice Corp. vs. CLS Bank International revoked patent protection for a wide range of business methods patents, making it harder to patent business processes. Acikalin, Cakurlu, Hoberg, and Phillips (2022) investigate the impact of the Supreme Court's decision and show that the sectors most affected were those where innovation took the form of software or involved digital data processing. Importantly, small public firms exposed to the decision experienced a loss in value while large firms benefited. The authors argue that large firms were better positioned to defend their product space. Their evidence supports our hypothesis that a firm whose business model relies primarily on intangible capital may want to build that capital before going public so that its products are robust and less at risk from competitors.

With our database of startups that received at least $50 million in investments from the VC industry, we can examine the impact of the Alice Corp v. CLS Bank International decision on the likelihood of startup IPO exits. We take the treatment quarter to be Q2 2014 and define a startup to be treated if it is in the CB Insights software industry or a CB Insights software subindustry. For example, a startup in the financial industry developing "accounting and finance software" is treated under our definition. We estimate difference-in-differences (DiD) regressions in a five-year symmetric window around Alice, from Q2 2009 to Q1 2019. Table 2 presents the DiD results from a linear probability model of IPO exits. Column (1) shows estimates of the treatment effect in a regression with no controls and no fixed effects. We find that treated firms are less likely to have an IPO exit. In column (2), we add time fixed effects. Our results do not change. In column (3), we add industry controls as of Q1 2014 as well as controls having to do with the state of the IPO market. All variables are defined in Appendix B. Industry controls are calculated as the average of all young public firms in an industry. Young firms are firms in the lowest quartile of firm age each year. We do not use contemporaneous industry controls because of the possibility that these controls would be affected by the treatment. Again, we find a significant negative treatment effect. In column (4), we include time fixed effects and find similar results. The estimates are also economically meaningful. The unconditional IPO rate per quarter is 0.5%. Hence, a coefficient of -0.003 indicates a 0.3% lower probability of going public after Alice, a reduction relative to the mean of 60%. It follows from these regression estimates that the Alice decision reduced the likelihood of an IPO exit for the startups most affected.

We have emphasized the importance of a new type of firm that relies heavily on organization capital. One might argue that such firms came into existence with the growth of the internet in the 1990s. An example of such a firm is TheGlobe.com.[12] Its business model was to create a virtual community on the internet. It was an attempt at what Facebook would become. TheGlobe.com had to IPO because, according to one of the founders, "We were running outta money." When it went public, it did so with a bang, as its first-day return was more than 600%, and its valuation came close to $1 billion. It eventually fell to almost nothing. Had the firm been able to raise more money while private, its evolution might have been different. The example demonstrates that for firms to stay private to build intangible capital, they have to be able to obtain funding. Agarwal, Barber, Cheng, Hameed, Shanker, and Yasuda (2023) compare the post-GFC surge of private startup investments to the surge of the internet bubble and conclude that the surges are similar "with one exception: the surge of non-traditional investors." When additional funding for startups with high private market valuations became available in the 2000s, startups could contemplate a path toward building their intangible capital to a level where they would be less vulnerable to competition and could benefit from network effects or economies of scale.

Unicorns can access funding sources that are not typically available to firms with lower valuations, partly because firms that have demonstrated success have lower risk and partly because larger firms raise larger amounts that make it worthwhile for more regulated asset managers to conduct due diligence. These

[12] See Joe Weisenthal and Tracy Alloway, Markets Odd Lots, "Transcript: The Globe.com co-founder on what a bubble bursting feels like." The above quote from the founder is from that transcript.

asset managers include mutual funds, hedge funds, and sovereign wealth funds. Historically, private firms faced severe limitations in raising funds from investors. Many investment managers were limited to investing in public firms, and most individual investors were generally restricted from investing in private firms. However, the restrictions that limited access to funding by private firms have been relaxed over time (de Fontenay, 2017; Ewens and Farre-Mensa, 2020). As a result of this evolution, funding for private firms is often abundant (see, for instance, de Fontenay, 2019).

Equity compensation is an important component of the compensation package of startup employees. If the firm remains a stand-alone private firm, employees may not be able to monetize the equity they have acquired. As a result, employees can be an important force pushing firms to go public unless firms find a way to provide some liquidity to them. As we will show, unicorn investors have been more willing to provide some liquidity to employees (and early-round investors) than traditional VC financiers.

The Jumpstart Our Business Startups (JOBS) Act relaxed another important limitation to firms staying private in 2012. Before April 5, 2012, the SEC required firms with more than $10 million of assets to register under the securities laws if they had a class of securities with more than 499 holders of record, basically forcing firms to go public. For instance, Facebook went public as it exceeded that threshold. Importantly, employees who exercised stock options to receive common shares were counted against the threshold. The JOBS Act increased the threshold to 1,999 holders and modified the definition of holders of record. Employees exercising stock options are no longer counted against the threshold (Rodrigues, 2015). Several firms that ultimately went public might have had to go public earlier or change their compensation practices without the JOBS Act changes (see Alon-Beck and Livingstone, 2023, Table 2).

In summary, our proposed explanation for the unicorn phenomenon is as follows. A new type of firm for which organization capital and network effects are key assets has become much more important. These firms benefit from building their organization capital and network effects as private firms as long as they are not sufficiently established to withstand the costs of public exposure. If they can execute their business model, scale and network effects can make them extremely valuable. To stay private, they require a sufficient supply of funding, which became available in the 2000s because of deregulation and developments in the asset management industry. Startups have access to a new set of investors once they become unicorns. Because the new unicorn investors are often willing to offer liquidity to early investors and insiders, they further reduce pressures for startups to go public.

3. Does unicorn status make a difference to founders and firms?

First, we show that some startups value unicorn status. Next, we show that firms with unicorn status have access to a larger set of investors. We then provide evidence that these investors enable liquidity rounds for earlier investors and insiders.

3.1. Founders' revealed preference

If founders did not care about unicorn status, we would expect the distribution of post-money valuation to be continuous at $1 billion. This is not the case. Panel A of Figure 3 shows that a large fraction of unicorns in our sample – more than 200 – had a headline valuation of exactly $1 billion at the unicorn round (see also Brown and Wiles, 2015; Brown and Wiles, 2020; Gahng, 2022). The median unicorn in our sample had a headline valuation of $1.2 billion. We obtain the headline valuations for all funding rounds of startups with at least $50 million of venture funding. The distribution of these headline valuations in the range of $500m to $1,500m is plotted in Panel B of Figure 3 and we observe a huge spike at $1 billion. Panel C shows the cumulative distribution function (CDF) of the empirically observed post-money headline valuations and the counterfactual CDF estimated without the window [$750 million, $1,100 million]. Clearly, the empirically observed CDF is strictly below the counterfactual CDF in the region just below the unicorn threshold. We follow Alvero and Xiao (2023) and Ewens, Xiao, and Xu (2024) and provide details on their fuzzy bunching estimator in the Internet Appendix. Using their estimator, we estimate the number of missing financing rounds between $750m and $999m to be 138. The hypothesis that M is equal to zero is rejected with a p-value less than 0.01 using bootstrapped standard errors.

Gornall and Strebulaev (2020) demonstrate that founders often grant unicorn (and later round) investors special privileges that make their preferred shares worth significantly more than the founder’s common shares. Their valuation model shows that the usual post-money headline valuation formula ($ investment/percentage ownership) often leads to inflated valuations.[13] If founders ascribe a large value to reaching unicorn status, we should observe them granting large privileges to investors in financing rounds that would have otherwise failed to reach the threshold of a $1 billion headline valuation. We examine this conjecture in Figure 4. To construct Figure 4, we start with Table 7 of Gornall and Strebulaev (2020). Their table lists the fair values, post-money headline valuations, and overvaluations derived from the most recent unicorn financing round before February 1, 2017. We focus on entries that correspond to the actual unicorn round and show in Figure 4 the distribution of fair market values and post-money headline valuations (Panel A), as well as the value of the special benefits granted relative to the fair market values (Panel B).

Figure 4, Panel A shows that the distribution of the fair market values around the $1 billion threshold is wider than that of the post-money headline valuations. Similarly, Panel B shows that the value of the benefits is higher the lower the fair market value.[14] This evidence supports the hypothesis that startups value unicorn status and are willing to grant new shareholders special benefits to inflate the price they pay for their shares. The evidence also helps explain the "missing" financing rounds just below the unicorn threshold in Panel C of Figure 3.

3.2. Does unicorn status expand access to investors?

Private firms have limited access to investors due to regulation and the nature of private markets. They are viewed as inherently riskier, so that there are legal and regulatory restrictions concerning who can invest in such firms and how they can raise funds.

Many promising startups receive funding from venture funds. The general partners of these funds have specific skills that help them assess the prospects of young firms and guide their growth. The vehicles for

---

[13] Gahng (2022) further argues that the denominator in the headline valuation formula is understated because the fully diluted number of shares used to calculate percentage ownership of the unicorn round investors includes shares reserved for the option pool that may never be issued or that may never vest.

[14] The average value of benefits as a fraction of fair value is positive, even for post-money headline valuation bins away from the threshold of $1 billion. It reflects the liquidation preference and seniority of the last round of preferred shares.

the investments made by VC firms, the VC funds, have a finite life of typically ten years, meaning they have to exit investments before the ten-year limit – though some exceptions can be allowed. As a firm grows and wants to stay private, it may have to access other investors than venture funds. To enable the firm to stay private, these investors may have to provide liquidity to early investors and perhaps even to early employees.

Unicorns can attract investors that typically do not invest in startups with lower valuations. These investors view investment opportunities in earlier rounds to be too risky, to require too much monitoring, or to be too small. It would seem useful for such investors to set a threshold valuation below which it is not worth it for them to be interested. It appears empirically that this threshold is $1 billion. It may be that there are other thresholds that are used by investors, but the unicorn threshold seems to be the most important one. In Table 3, we show that a large number of startup investors only invest in unicorns. Specifically, we consider all funding rounds of the unicorns and of the matching startups in our matched sample. We then count the number of investors who invest in the unicorn round but do not invest in pre-unicorn rounds of startups that become unicorns and do not invest in funding rounds of matched startups that do not become unicorns. Table 3 shows that 27% of unicorn-round investors do not invest in non-unicorn rounds for our sample of unicorns and matched startups. In contrast, only 11% of investors who invest in the pre-unicorn rounds do not invest in rounds before the pre-unicorn round or in matched startup rounds.

These investors who do not typically participate in earlier rounds include mutual funds, sovereign funds, hedge funds, private equity funds, and so on. It is already well known that mutual funds invest in unicorns (Chernenko, Lerner, and Zeng, 2021; Kwon, Lowry, and Qian, 2020; Imbierowicz and Rauch, 2024).[15] We build on this evidence in Table 4 by showing that the investor composition for the unicorn round is quite different from the investor composition of the early rounds. In Table 4, we list in Panel A the

[15] Huang, Mao, Wang, and Zhou (2021) show that "public market players" reduce underpricing at the IPO. They do not distinguish between unicorns and other startups. Their sample starts before the emergence of unicorns, so that "public market players" invest in startups that are not unicorns. In their sample, "public market players" are 13F filers, which include a wide range of institutional investors.

top 20 investors in B rounds of firms that eventually become unicorns.[16] We then show in Panel B the top 20 investors in unicorn rounds. Finally, in Panel C, we report the top 20 investors in unicorn rounds that are not in B rounds. Of the 20 top investors in unicorn rounds, 8 are not top 20 investors in B rounds.

The top investors that show up in unicorn rounds but not in B rounds are a mix of different types of investors. As expected, four mutual fund complexes, BlackRock, Fidelity, T. Rowe Price, and Wellington Management are active investors in unicorn rounds. The top investor is Tiger Global Management, an investment management firm with both public and private equity investment strategies. Though it invests in private businesses of all stages, its investment style makes it better suited to invest in more advanced rounds. Other investment firms in the list are growth-stage private equity investors. For instance, Meritech describes its objective to "invest in the best late-stage tech companies in the universe."[17] One of the most active investors in unicorn rounds is ICONIQ Capital, which is part family office to some billionaires (for instance, Mark Zuckerberg) and part private equity and venture capital general partner. Many investors that show up at the unicorn round are known for having a different degree of involvement in the companies in which they invest and different due diligence requirements than investors who participate in earlier rounds. For instance, they are unlikely to want board seats. Chernenko, Lerner, and Zeng (2021) show that rights granted to mutual fund companies typically differ from those granted to venture capital funds.

It is well-known that the VC industry is heavily concentrated geographically (see Chen, Gompers, Kovner, and Lerner, 2010) and that VC firms tend to invest in startups that are geographically close to facilitate monitoring (Lerner, 1995). Therefore, proximity to the San Francisco area makes access to funding through VC firms easier for startups in early stages. However, VC firms are often less willing or able to fund advance-stage startups. If a startup intends to stay private, it eventually has to find investors that are not VC firms. An advantage of unicorn status is access to a broader class of investors for whom location is not important as they do not monitor as actively as VC funds.

[16] By top 20 investors in B rounds, we mean the investors who participate the most often in B rounds in our data. We do not have the amounts invested and it would not be feasible to collect these amounts for all the B round investors across hundreds of unicorns.

[17] See https://www.meritechcapital.com/about-us.

Table 4 shows that unicorn rounds attract investors who differ substantially from traditional venture capitalists. Table 5 uses a regression framework to examine changes in the composition of unicorn investors and their distance from the unicorn's headquarters and San Francisco across funding rounds. In Panel A (Panel C), the regression sample consists of 16,221 (15,044) unicorn-funding round-investor observations, and in Panel B (Panel D), the regression sample consists of 3,924 (4,182) unicorn-funding round observations for 639 unicorns. In Panel A of Table 5, we show that the change in the composition of investors post-unicorn round shown in Table 4 is robust to controlling for the unicorn's industry and whether its headquarters are close to San Francisco. Venture firms are more likely to participate in pre-unicorn rounds and less likely to participate in post-unicorn rounds compared to the unicorn round. The opposite is the case for asset managers.[18]

We use an alternative approach in Panel B. We regress the fraction of investors of a given type on a unicorn fixed effect, a round fixed effect, and an indicator variable for the unicorn round. The round fixed effect controls for later-stage investors being different from early-stage investors. The unicorn fixed effect controls for time-invariant unobserved differences in interest from different types of investors across unicorns. We find strong evidence that the share of asset managers in a round, computed as the number of asset manager investors to the total number of investors, is significantly higher in the unicorn round, while the shares of angel investors and venture funds are significantly smaller. We also find that the share of growth funds is significantly higher.

In Panel C of Table 5, we show that the investors' distance from both the unicorn's headquarters and San Francisco changes with the unicorn round. Controlling for a unicorn's industry and its distance from San Francisco, we find in column (1) that investors in pre-unicorn rounds are closer to a unicorn's headquarters than unicorn-round investors, and investors in post-unicorn rounds are farther from a unicorn's headquarters than unicorn-round investors. Similarly, investors in pre-unicorn rounds are closer to San Francisco than unicorn-round investors, and investors in post-unicorn rounds are farther from San Francisco

[18] Note that the regression controls for funding round fixed effects, so the significance of the post-unicorn indicator is different from a late-stage financing effect.

than unicorn-round investors (column (2)). Using our alternative approach, we show in Panel D that the average investor distance from the unicorn's headquarters (column (1)) and from San Francisco (column (2)) increases in the unicorn round.

The evidence in this section shows that unicorn status allows startups to access different types of investors who are willing to invest in advanced-stage startups, enabling them to stay private longer.

3.3. Liquidity events for early-round investors and employees

An additional important characteristic of late-stage investors is that they frequently offer liquidity events to earlier-round investors, employees, and founders. Ample evidence for such liquidity events for our sample comes from IPO prospectuses because companies have to disclose in the related party transactions section any transaction that involved the purchase or sale of company stock by an executive officer, director, or existing large shareholder in the last three years prior to the IPO. For example, DoorDash (with IPO in December 2020) disclosed that in September 2018, three executive officers, among other parties, were allowed to sell stock in a liquidity event that totaled $62 million. Similarly, Lyft disclosed that a year prior to the IPO, several executive officers were allowed to sell stock for approximately $60 million in a tender offer to existing stockholders.

The *Wall Street Journal* published an article to discuss equity sales amounting to several hundred million dollars of the founder of WeWork in the years before it first attempted to go public. The article gives other examples of founders (including those of the sample unicorns Groupon, Snap, Slack, and Zynga) cashing out partially before the IPO and attributes this growing practice to the willingness of late-stage investors to allow founders and employees to cash out, a practice that is typically frowned upon by traditional venture investors.[19] The same article points out that late-stage investors have also let early venture investors cash out. Another example is the investment of Intel in Cloudera in 2014, where Intel

[19] "WeWork co-founder has cashed out at least $700 million via sales, loans," by Eliot Brown, Maureen Farrell, and Anupreeta Das, July 18, *The Wall Street Journal*.

obtained new shares for $371 million and then obtained additional shares for $371 million from employees and investors Accel Partners and Greylock Partners.[20]

Larcker, Tayan, and Watts (2018) discuss the emergence of exchanges that facilitate sales of shares by private market company insiders and early investors and report that over $4 billion in transaction volume was executed by only four private market liquidity providers in 2017. Large unicorns also can hold tender offers where investors can acquire shares from founders and employees.[21] SpaceX has held such tender offers twice annually (see, e.g., Vance, 2015). Uber and Airbnb had at least one such tender offer each before going public.[22] Lastly, there can be an active secondary market for unicorn shares. This was especially the case for Facebook before its IPO (see Rodrigues, 2015).

4. Which startups are more likely to become unicorns?

With the explanation for unicorns proposed in Section 2, unicorns are startups with high investment in organization capital relying on network effects that benefit from staying private longer. In this section, we provide support for our explanation. We first show that unicorns are concentrated in industries where organization capital appears more important. We also establish that ample funding results in more unicorn births.

The tests of the section are based on 5,070 startups with at least $50 million in funding between 2010 and 2021, 639 unicorns, and industry averages calculated from 3,096 young public firms.

4.1. The role of industry and location in the likelihood of achieving unicorn status

CB Insights classifies each venture-funded startup into one of 20 sectors. It classifies startups as belonging to the internet sector if their business depends on a delivery mode that uses the internet. With this CB Insights classification, 32% of startups and 59% of unicorns belong to the internet sector. We

[20] "Why Intel paid a premium for a stake in Cloudera," by Rachael King, Dow Jones Newswire, May 1, 2017.
[21] See, e.g., "Pre-IPO Liquidity for Late State Start-Ups" by Dawn Belt, Lexis Practice Advisor.
[22] "What Tesla Shareholders could learn from SpaceX," by Alfred Lee, The Information, August 8, 2018.

decided to reclassify startups that CB Insights classifies as belonging to the internet sector according to the type of goods or services they provide. We believe that it is more descriptive of the industry of startups than the original CB Insights classification. We describe the reclassification procedure in the Internet Appendix. After the reclassification, the number of unicorns in each sector is shown in column (1) of Table 6 and the percentage of unicorns in each sector is shown in column (2).

The sector with the largest number of unicorns is the business products and services sector (shortened to "business" in the tables), with 168 unicorns or 26% of unicorns. The internet sector has 111 (17%) unicorns, followed by the financial sector with 86 (14%) and the healthcare sector with 73 (11%) unicorns. Four sectors have more than 10% of unicorns each, and seven sectors have less than 1% each.

We compare the unicorn industry distribution with that of startups that raised more than $50 million. We show the distribution of startups across sectors in column (3) and the percentage of firms in each sector in column (4). The healthcare sector has the largest number of startups (1,427 firms, or 28% of startups). The next most important sector is the internet sector with 767 firms, or 15% of startups. Thirteen sectors have a higher percentage of startups than unicorns. The sector that is the most overweighted among startups compared to unicorns is the healthcare sector. It has 28% of startups, but only 11% of unicorns. In contrast, the business products and services sector is the most underweighted among startups compared to unicorns. It has 9% of startups but 26% of unicorns.

We then map the 20 CB Insights sectors to 4-digit NAICS codes so that we can make an industry comparison between unicorns, publicly listed firms, and IPOs. The mapping is described in the Internet Appendix. Column (5) in Table 6 shows the number of public firms for each sector in our sample and column (6) shows the percentage of public firms in each sector. We further show in columns (7) and (8) each sector's number and percentage of IPOs. The sector with the largest number of IPOs is healthcare, with 586 IPOs, followed by the business products and services sector, with 505 IPOs, and finally, the industrial sector, with 485 IPOs.[23]

[23] The large number of IPOs in the healthcare sector is likely, in part, the result of one of the few public disclosure requirements that apply to private companies. In 2007, Congress passed the Food and Drug Administration

We compare the percentage distribution of unicorns across sectors (column (2)) with the distribution of listed firms across sectors (column (6)). Two sectors stand out in having a large percentage of unicorns compared to their percentage of listed firms. The business products and services sector has 26% of unicorns but only 6% of listed firms. The internet sector has 17% of unicorns but only 4% of listed firms.

Lastly, we compare the distribution of unicorns across sectors (column (2)) to the distribution of IPOs across sectors (column (8)). We find that the business products and services sector and the internet sector are very much overrepresented among unicorns compared to these sectors' representation in the population of IPOs. While 26% of unicorns are in business products and services, only 14% of IPOs are in that sector. For the internet sector, 17% of unicorns are in that sector, but only 1% of IPOs.

Given our earlier discussion about the geographic concentration of the venture capital industry, proximity to the San Francisco area could make access to funding through VC firms easier. The San Francisco area is a hub for skills and services that may be particularly valuable to entrepreneurs with a business model involving network effects and the use of the internet as a tool for the distribution of products and services. Consequently, proximity to San Francisco could also help the development of startups, and make them more likely to succeed, because of agglomeration effects.

To explore the importance of the San Francisco area for unicorns, we compute the distance, as a straight line, from a firm's headquarters to central San Francisco. We find that unicorns are much closer to San Francisco than the typical startup with at least $50 million in funding or the typical listed firm. In Internet Appendix Figure IA.B.1, we show the geographic distribution of unicorns, startups, and young public firms. We report median distances from San Francisco for listed firms, startups, and unicorns by sector in Internet Appendix Table IA.B.2. The proximity to San Francisco is particularly pronounced for unicorns in the internet sector and the business products and services sector, which are the two sectors with an overrepresentation of unicorns compared to listed firms, IPOs, and VC-backed startups. For the internet

Amendments Act (FDAAA) that requires all companies (including private companies) to disclose publicly the results of Phase II trials or above. As a result, firms in the biopharmaceutical industry that were private lost a disclosure advantage of being private, which led to an increase in IPOs from these firms (see Aghamolla and Thakor, 2022).

sector, we find that the median distance of a unicorn from San Francisco is 33 miles. In contrast, the median distance for a listed firm is 1,581 miles and the median distance for a VC-backed startup is 447 miles. In five sectors, the median distance from San Francisco of unicorns is less than 50 miles.

We now turn to linear regressions to assess the relative importance of these factors for the likelihood that a startup becomes a unicorn. We report these cross-sectional regressions in Table 7. The dependent variable takes the value one if a startup that has obtained at least $50 million in financing is a unicorn and zero otherwise.[24]

Model (1) in Table 7 uses only indicator variables for a startup's sector, an indicator variable for whether the startup is located within 200 miles of San Francisco, and a variable that measures scale effects. We predict in Section 2 that startups for which scale effects and organization capital are more important are more likely to become unicorns. For each startup, we determine whether scale effects of the type associated with unicorns, namely network effects, are important. The variable *Scale* takes a value of one if the description of a startup's business in CB Insights includes one of the words "platform," "network," or "connect."

We see that the largest positive coefficients for the sector indicator variables (relative to the industrial sector) are for the business products and services, leisure, and internet sectors. Startups in electronics, metals and mining, and retail are least likely to become unicorns. Startups located within 200 miles of San Francisco are much more likely to be unicorns. *Scale* has a large and statistically significant positive effect on the likelihood of being a unicorn. Startups with a value of *Scale* equal to one have a 3.5% higher likelihood of achieving unicorn status, which is large relative to the 11.19% average unconditional probability of achieving unicorn status in the cross-section of startups that raise more than $50 million in funding. In Model (2), we include a firm's birth cohort to control for any effect of birth cohort on the likelihood that a startup becomes a unicorn. A startup's birth cohort is the year the firm raised more than $50m in funding (and thus enters the sample). The omitted birth cohort year is 2010. All indicator variables

[24] The total number of startups in the regressions presented in Table 7 decreases from 5,709 (5,070+639) to 5,690 because we require data on a startup's industry, the description of its business, and its zip code.

have positive and significant coefficients except for 2012 and 2021. Model (3) combines Models (1) and (2). The statistical and economic significance of the sector indicator variables does not change, but the magnitude of the birth cohort coefficients decreases. The birth cohort 2021 indicator variable is now significantly negative. Such a result is not surprising since one would expect startups to become unicorns sometime after having entered the sample.[25] Scale and proximity to San Francisco remain positively and statistically significantly related to the likelihood of being a unicorn.

4.2. Industry fundamentals and the fraction of startups in an industry that are unicorns

In Section 2, we conjecture that unicorns are more likely to be firms with high investment in organization capital. We do not observe accounting variables for unicorns that could be used to estimate their intangible investments unless unicorns go public. To investigate whether startups, in general, are more likely to become unicorns if they are firms that are more likely to be organization capital intensive, we use data from young publicly listed firms in the unicorn's industry. We therefore assume that if organization capital is more important for young public firms in the unicorn's industry, it will be more important for the unicorn. SG&A net of R&D expenditures is a widely used proxy for investment in organization capital. For simplicity, in the following, we use SG&A to denote SG&A net of R&D expenditures.[26]

Our proposed explanation has additional implications for the characteristics of industries where unicorns are more likely to be found. These industries should have lower fixed assets and lower capital expenditures. We expect an industry with more public firms that have losses to be in the process of being disrupted or ripe for disruption. Our regressions use Tobin's q as a measure of growth opportunities and

[25] We also estimate Model (3) using the logarithm of the distance from headquarters to San Francisco and show the results in the Internet Appendix. The coefficient on the distance measure is significantly negative, so that startups that are farther away from San Francisco are less likely to become unicorns.
[26] The literature differs in how to determine which part of SG&A corresponds to investment and which corresponds to expenses for current production. While Eisfeldt and Papanikolaou (2013) and Peters and Taylor (2017) attribute 30% of SG&A to investment, Lev and Radhakrishna (2005) and Falato, Kadyrzhanova, Sim, and Steri (2022) use, as we do, all of SG&A as a proxy for organization capital investment. For our purpose, all we need is that organization capital investment is proportional to SG&A. The Compustat variable SGA very often includes R&D expenditures so that R&D has to be subtracted to get to SG&A as a measure of organization capital (we follow the procedure of Peters and Taylor, 2017).

intangibles. We would expect firms in industries where Tobin's q is higher for public firms to be more likely to be unicorns.

In Table 8, we show the results of a regression of the fraction of startups in an industry that are unicorns on firm characteristics in that industry. The regression is at the industry-quarter level. Model (1) uses the entire sample, an industry-quarter panel running from Q1 2010 to Q3 2021. Model (2) uses an industry-quarter panel from Q1 2010 to Q4 2020 to address concerns that the large number of unicorn births and very favorable market conditions in 2021 drive our results.

Across both specifications, the fraction of unicorns is much higher in industries with high Tobin's q, i.e., industries with firms that have high growth opportunities and intangible assets. Our measure of organization capital, SG&A/total assets, has a positive and statistically significant coefficient in both specifications. The economic magnitude is large. A one standard deviation increase in organization capital increases the fraction of unicorns in an industry by 0.99 percentage points, corresponding to an 11.65% increase relative to the unconditional fraction of unicorns of 8% across industry-quarters. Industries with large cash reserves have fewer unicorns. The coefficient on R&D expenditures is negative but insignificant. We can reject the equality of the coefficients on SG&A/total assets and R&D/total assets at better than the 1% level (the F-statistic is 7.32 with a p-value of 0.007). As expected, the fraction of unicorns in an industry is negatively related to the importance of fixed assets for that industry. However, our predictions for capital expenditures and age are not borne out in the data. The coefficients on capital expenditures are negative and insignificant, and the coefficients on age are positive and insignificant in both models. To the extent one might have been concerned that 2021 reflects irrational exuberance in a way that earlier years do not, Model (2) indicates that our results supporting the role of organization capital do not depend on the unicorns created in 2021.

4.3. Industry fundamentals, VC fund flows, and the likelihood that a startup becomes a unicorn

We now turn to regressions examining the importance of VC fund flows for the likelihood that a startup becomes a unicorn. The regressions shown in Table 9 are estimated using 77,054 firm-quarter observations.

The dependent variable takes the value one if a VC-backed startup is a unicorn in quarter *t* and zero if it is not. In addition to the average industry characteristics from Table 8, we also include the indicator variables *Scale* and *Near San Francisco* in the regressions.

In Section 2, we conjecture that unicorns can only arise if sufficient funding is available to support private funding rounds. Hence, we would like to include lagged VC industry funding flows in our regressions. However, the venture capital funding variable is subject to an important endogeneity concern due to potentially omitted variables. Rather than ample available industry funding causing a higher likelihood of becoming a unicorn, it could be that funding in the prior quarter flows to the industries with the highest potential. To identify the effect of funding flows on the likelihood of being a unicorn, we need instruments that are correlated with industry fund flows in the prior quarter but are uncorrelated with the industry's potential. We use two instruments. First, we use the creation of the first SoftBank Vision Fund as an instrument for industry fund flows. SoftBank, at the announcement of the first closing of the fund in May 2017, committed to investing in only a subset of industries.[27] We create an indicator variable *Ex ante target SoftBank industry* equal to one if the respective industry was on the target list of industries in the announcement of the first closing and if the quarter is after Q2 2017.

Any instrument needs to satisfy the relevancy condition and exclusion restriction. SoftBank surprised the market with the size of the fund of almost $100 billion (in the press release of October 2016 on the establishment of the Vison Fund, SoftBank announced a size of approximately $25 billion). The National Venture Capital Association, in their annual yearbook, estimates that in all of 2016, the U.S. VC industry invested approximately $70 billion in startups. The relevancy condition is, therefore, likely fulfilled, as the Vision Fund is large relative to total VC funding. Regarding the exclusion restriction, one needs to maintain that SoftBank, in early 2017, could not predict the potential of specific industries. Wang (2020) examines

[27] See https://group.softbank/en/news/press/20170522. "The Fund and its associated vehicles are expected to be active across a wide range of technology sectors, including but not limited to: the Internet of Things, artificial intelligence, robotics, mobile applications and computing, communications infrastructure and telecoms, computational biology and other data-driven business models, cloud technologies and software, consumer internet businesses and financial technology."

the impact of what she calls the Softbank Vision Fund shock on the strategies of other VC funds. She finds that neither large established funds nor new funds moved investments toward Softbank Vision Fund industries, which suggests that these funds did not believe that Softbank had the ability to predict the potential of industries.

Our second instrument consists of the inflows into leveraged buyout funds over the last four quarters, following Gompers and Lerner (2010). Flows into private equity funds are related to shifts in commitments to private markets (relevancy condition) more broadly, but should be unrelated to VC commitments to specific industries and their success, so that the exclusion restriction can be maintained.[28] We obtain information on capital raised by buyout funds from Prequin.

Lastly, we include variables capturing the state of the economy and financial markets that have been used in previous research concerning IPOs and funding conditions. These variables are the previous quarter's IPO volume, equal-weighted IPO first-day returns, real GDP growth, equal-weighted market returns, the aggregate market-to-book ratio, credit spread, and the federal funds rate. All variables we use are defined in detail in Appendix B. All the regressors are lagged by one quarter. We use year fixed effects since the variables capturing the state of the economy and financial markets are observed quarterly.

Table 9 shows the results. Column (1) shows OLS regression results for reference. Column (2) shows the first-stage results, and column (3) shows the second-stage result of the IV regression. The first stage results in column (2) demonstrate that the relevancy condition is fulfilled. The Softbank instrument and the buyout fund flow variable are strongly and positively correlated with VC industry fund flows. The second stage results using the instrumented fund flows are shown in column (3). We find that the higher instrumented industry fund flows are, the more likely it is that a startup is a unicorn. Our finding is therefore suggestive of ample available industry funding causing a higher likelihood of startups becoming unicorns. We continue to find strong support for the importance of organization capital as a determinant of the

[28] While we report results for using both instruments, we have estimated the regressions with each instrument separately and report these regressions in the Internet Appendix. The conclusions we draw from Table 9 do not depend on the choice of instrument.

likelihood that a startup is a unicorn since the coefficients on the industry ratio of SG&A to assets and on the scale variable are positive and significant. Further, we find that a startup is more likely to be a unicorn if its industry Tobin's q is high and the distance to San Francisco is low. These results support our proposed explanation.

Column (3) shows that a startup is more likely to be a unicorn if the first-day equally-weighted return of IPOs is high, the equal-weighted market returns are high, and the credit spread is high. The other variables are not significant. Except for the evidence on the credit spread, the macroeconomic variables are consistent with the view that unicorns are more likely to be created when IPO market conditions are good and when valuations in public markets are high.

Finally, in the OLS regression, the coefficient on R&D/total assets is significantly negative, while the coefficient on SG&A/total assets is significantly positive. In the 2SLS regression, the coefficient on R&D/total assets is negative but loses significance. Note that, except for R&D/total assets, the independent variables of particular interest, namely scale, operational capital as proxied by SG&A/total assets, fund flows, and proximity to San Francisco, have similar statistical and economic significance in the OLS regressions.

We also estimated these regressions omitting the three quarters of 2021 that are in our sample and in which many unicorns are born and report the results in the Internet Appendix Table IA.B.4. The results of the second-stage regression are quantitatively and qualitatively similar to those obtained for the whole sample. Lastly, we re-estimate the regressions adding industry fixed effects. The second-stage regression has a different interpretation from the regressions we just discussed in that it shows how changes in an industry are related to the probability that a startup in that industry is a unicorn. As we would expect, variation across industries is much more important than variation within industries in explaining whether a startup becomes a unicorn. The coefficient on R&D is positive in that regression and the coefficient on SG&A is insignificant. Tobin's q does not have a significant coefficient.

5. How do unicorns differ from close pre-unicorn matches?

In this section, we investigate how unicorns differ from other startups that resemble them closely at the pre-unicorn stage using the matched sample described in Section 1.1. Table 10 shows statistics for the matched sample. We do well on the matching criteria. The mean pre-unicorn valuation for a unicorn is $430 million, while the mean valuation of the matching startup is $420 million. The mean pre-unicorn round year is 2017, the same as for the matched sample. Both unicorns and matched sample firms have an average age since founding of 6.18 years.

However, the unicorn and the matching startup differ greatly in their evolution as private companies after the matching. The average post-money valuation after the last private funding round or exit for a unicorn during our sample period is $4.17 billion, while the average post-money valuation after the last private funding round or exit of the matching startup is $580 million. The unicorn will have raised more than three times as much funding as a private firm than the matching startup. Unicorns are less likely to have exited than the matching startups, as less than a third of unicorns exit, but almost half of the matching startups do so. There is no difference in the failure rate between unicorns and matching startups. As expected, the fraction of unicorns with a business description involving scale is higher than the fraction of matching startups (48% versus 39%). Unicorns are more likely to be located near San Francisco than the matching startups.

We use the matched sample to examine whether unicorns exit later than other matching startups and whether they exit differently. We use a firm-quarter panel. In column (1) of Table 11, we estimate a Cox proportional hazard regression model. We report hazard ratios so that a coefficient larger than one indicates that an increase in the independent variable makes it more likely that a startup exits the sample. The explanatory variables are constructed similarly to the explanatory variables in Table 9. We use industry characteristics based on the average characteristics of young public firms in the industry. We see in column (1) that unicorns exit later than matched startups, as predicted by our explanation. We also find that startups in industries with higher capex exit faster, but startups in industries with higher intangible investment do not. Startups in industries with higher R&D exit later. The coefficient on SG&A is lower than one but insignificant. Not surprisingly, favorable stock returns and macroeconomic conditions hasten exit. In columns (2) and (3) of Table 11, we estimate a multinomial logit regression of exits through listing and M&As. We find that unicorns are more likely to exit through a listing, while matching startups are more likely to exit through an M&A transaction.

We then focus on our matched IPO sample to compare IPO unicorns to matching IPO startups. To construct this sample, we additionally require the matching startup to have an IPO. The advantage of this sample is that we have company-specific accounting data from the IPO and do not have to rely on industry averages of young firms. We can, therefore, test whether unicorns spend more on organization capital relative to R&D compared to other exiting startups. Such an investigation is subject to an important caveat, which is that the exiting startups may differ from other startups for which we do not have the same data.

In Table 12, we compare the offer, accounting, and governance and control characteristics of unicorn IPOs to those of the matching startup IPOs. Panel A of the table shows offer characteristics. The valuation of unicorns is much larger than the valuation of the matching startups. Unicorns are less likely to price below the indicative range than matching startups and more likely to price above the indicative range than matching startups. Most of the proceeds from the IPO accrue to the company whether the startup is a unicorn or not. There is no difference in the first day return between unicorns and matching startups. Unicorns have significantly lower average three-month and six-month returns than matching startups.

We document the accounting characteristics in Panel B. We show the fundamental characteristics of firms the year before the IPO. Unicorn IPOs have more assets and sales than matching startups. Unicorns have less cash than other startups, but both unicorns and other startups have large ratios of cash to assets. There is no difference between unicorns and other startups with respect to plant, property, and equity or capital expenditures. However, R&D expenditures as a percentage of assets are almost half for unicorns compared to matching startups. In contrast, SG&A is 30% higher at the mean for unicorns than matching non-unicorn IPOs and twice as high at the median. There is no difference in leverage between unicorns and other startups. While unicorns have much higher gross profits to total assets than matching startups, almost 90% of unicorns and matching startups have negative net income. Panel B of Table 12 is highly supportive of our prediction that unicorns have more organization capital than other startups. Matching startups have higher R&D but lower SG&A, which proxies for organization capital, than unicorns.

Lastly, in Panel C of Table 12, we examine some data on governance and control. We first examine the frequency of offers with dual class shares. Unicorns are much more likely to have dual class shares when they become public compared to other firms. As far as we know, this result is new to the literature. We find that 52% of unicorns have dual class shares, but only 24% of matching startups have dual class shares. The sharp difference is consistent with the view that founders of startups that reach unicorn status have more power, but that may be optimal given our discussion of the type of startups that become unicorns. The importance of dual share structures for unicorns that go public also reduces the weight of the argument that founders want their firm to stay private for control benefits when their firm has achieved unicorn status.[29] However, recent evidence suggests that dual share structures may be value-creating for firms at the IPO by making it more likely that the founders can carry out their business strategy (Aggarwal, Eldar, Hochberg, and Litov, 2022; Fields and Lowry, 2022; Kim and Michaely, 2019). We then show that the founder is more likely to be CEO, to be chairman, and to be on the board at the IPO for unicorns than for non-unicorns. There is no evidence, therefore, that unicorns are more likely to go public when the founder has little or no power.

We highlighted in Section 2 that R&D often results in patents protecting the property rights of the innovating firm, while organization capital does not. We also mentioned the evidence of Acikalin, Cakurlu, Hoberg, and Phillips (2022) that the Alice decision had an adverse effect on the use of patents for software and related innovations. Since unicorns' business model is centered on developing organization capital rather than R&D, we expect them to be less patent-intensive. We provide supporting evidence for the relatively smaller role of patents for unicorns in Figure 5. For each company in our matched IPO sample,

[29] It could be that unicorns are more likely to exit with dual class shares because of their characteristics rather than because they are unicorns. We show in the Internet Appendix that startups with more organization capital investment are more likely to have dual class shares. However, the most important variable in explaining whether a startup has dual class shares when it exits through an IPO is whether it has unicorn status, so that even controlling for characteristics does not alter our conclusion.

we calculate the ratio of the total number of patents divided by the total amount of funding obtained (in $ millions) at a given point in time and plot medians for unicorn IPOs and other IPOs in the six quarters surrounding the IPO. Figure 5 shows that per dollar of funding raised, the number of patents is indeed much lower for unicorns than for non-unicorns, especially in the quarters prior to the IPO.

We next estimate regressions using the matched sample of IPO unicorns and matched startups. In these regressions, the left-hand side variable (unicorn status) is established before the accounting variables are measured. We think of the right-hand side accounting variables as proxies for the fundamental business model of the firms, and do not use them to predict unicorn status. Model (1) of Table 13 is similar to Model (1) of Table 9, except that now we use characteristics of the startups. Since we are using characteristics for the year before the IPO, we cannot compute Tobin's q. We winsorize the regressors at the 1% level. We find that unicorns have higher assets, higher cost of goods sold, higher SG&A, higher likelihood of being loss firms, and are closer to San Francisco. We do not find that scale has a significant coefficient. The strong positive coefficient for SG&A is supportive of our explanation for the existence of unicorns. Model (2) uses year- and industry-fixed effects. The results are quantitatively and qualitatively similar.

Overall, the evidence presented in this section supports our explanation for the existence of unicorns, that the importance of organization capital distinguishes unicorns from non-unicorns.

6. Conclusion

The existence of so many unicorns is a puzzling phenomenon. Before the 2000s, it was rare for firms to wait to go public until their private market headline valuation exceeded $1 billion. We develop an efficiency explanation for the unicorn phenomenon based on two developments: 1) the growing importance of a new type of firm that relies heavily on organization capital, especially organization capital involving network effects, and 2) the greater ability of startups with a headline valuation in excess of $1 billion to attract funding from different types of investors than startups with lower valuations.

Organization capital is fragile. It can be easily expropriated by competitors and employees can walk away with some of it. Firms for which organization capital is important benefit from staying private until this capital gives them a strong enough position in their industry that they can defend their product space effectively. We show a reduced likelihood of an IPO exit for firms affected by the Supreme Court's Alice decision that made it harder for firms to protect intangible capital through patents. We document that 27% of investors at the unicorn round are investors that have not invested in earlier rounds, so that unicorn status opens the doors to new investors that enable the startup to stay private longer. The easier availability of funding for unicorns made it possible for the new type of firm to grow and succeed in a way that would not have been possible without that funding. The success of early unicorns and the arrival of new types of private market investors with deep pockets were critical to the emergence and growth of the unicorn phenomenon. We show the importance of funding using unrelated flows to buyout funds and the surprise of the size of the Softbank Vision Fund and its business plan to create exogenous variation in funding and show that the likelihood of startups becoming unicorns increases with funding shocks.

In support of our explanation for the emergence of unicorns, we find that VC-backed firms are more likely to become unicorns if they are in industries where organization capital is more important. We construct a sample for which we match a unicorn that has an IPO with a non-unicorn startup that has an IPO as well. The matched startup raises funds in the same year as the year of the last pre-unicorn fund-raising round of the future unicorn, raises a similar total amount as the future unicorn including that fund-raising round, and has a similar firm age at that fund-raising as the future unicorn. We find that unicorns invest much more in organization capital than matching startups.

The efficiency gains from building organization capital privately could not be obtained in the absence of ample capital for private firms that have high valuations. Further research should explore the implications of decreases in available funding for startups that rely heavily on organization capital, such as those that occurred in 2022 and 2023. Our explanation for unicorns would indicate that having less funding available makes it less likely that startups relying on organization capital will succeed in capturing the economies of scale and the network effects that make them especially valuable as public firms.

References

Acikalin, Utku U., Tolga Caskurlu, Gerard Hoberg, and Gordon M. Phillips. “Intellectual property protection lost and competition: An examination using machine learning.” Working Paper (2022).

Agarwal, Vikas, Brad Barber, Si Cheng, Allaudeen Hameed, Harshini Shanker, and Ayako Yasuda. “Do investors overvalue startups? Evidence from the junior stakes of mutual funds.” Working Paper (2023).

Aghamolla, Cyrus, and Richard T. Thakor. “Do mandatory disclosure requirements for private firms increase the propensity of going public?” *Journal of Accounting Research* 60, no. 3 (2022): 755-804.

Aggarwal, Dhruv, Eldar Ofer, Yael V. Hochberg, and Lubomir P. Litov. “The rise of dual-class stock IPOs.” *Journal of Financial Economics* 144, no. 1 (2022): 122-153.

Alon-Beck, Anat, and John Livingstone. “Mythical unicorns and how to find them: The disclosure revolution.” *Columbia Business Law Review*, no. 1 (2023): 69-114.

Alvero, Adrien, and Kairong Xiao. “Fuzzy Bunching.” Working Paper (2023).

Ayyagari, Meghana, Asli Demirgüç-Kunt, and Vojislav Maksimovic. “The rise of star firms: Intangible capital and competition.” *The Review of Financial Studies* 37, no. 3 (2024): 882-949.

Babina, Tania, Paige Ouimet, and Rebecca Zarutskie. “IPOs, human capital, and labor reallocation.” Working Paper (2023).

Barrios, John M., and Thomas G. Wollmann. “A new era of midnight mergers: Antitrust risk and investor disclosures.” *American Economic Journal: Microeconomics,* (2024), forthcoming.

Bennett, Benjamin, René M. Stulz, and Zexi Wang. “Public scrutiny, firm performance, and investment.” Working Paper (2024).

Bernstein, Shai. “Does going public affect innovation?” *The Journal of Finance* 70, no. 4 (2015): 1365-1403.

Bernstein, Shai. “The effects of public and private equity markets on firm behavior.” *Annual Review of Financial Economics* 14 (2022): 295-318.

Bhattacharya, Sudipto, and Jay R. Ritter. “Innovation and communication: Signalling with partial disclosure.” *The Review of Economic Studies* 50, no. 2 (1983): 331-346.

Bias, Daniel. “Illiquid equity, labor mobility, and talent allocation.” Working Paper (2021).

Bias, Daniel, Benjamin Lochner, Stefan Obernberger, and Merih Sevilir. “Going public and the internal organization of the firm.” Working Paper (2023).

Bolton, Patrick, and Ernst-Ludwig von Thadden. “Blocks, liquidity, and corporate control.” *The Journal of Finance* 53, no. 1 (1998): 1-25.

Boot, Arnoud W.A., Radhakrishnan Gopalan, and Anjan V. Thakor. “The entrepreneur's choice between private and public ownership.” *The Journal of Finance* 61, no. 2 (2006): 803-836.

Boot, Arnoud W.A., Radakrishnan Gopalan, and Anjan V. Thakor. “Market liquidity, investor participation, and managerial autonomy: Why do firms go private?” *The Journal of Finance* 63, no. 4 (2008): 2013-2059.

Brau, James C., and Stanley E. Fawcett. “Initial public offerings: An analysis of theory and practice.” *The Journal of Finance* 61, no. 1 (2006): 399-436.

Brown, Keith C., and Kenneth W. Wiles. “In search of unicorns: Private IPOs and the changing markets for private equity investments and corporate control.” *Journal of Applied Corporate Finance* 27, no. 3 (2015): 34-48.

Brown, Keith C., and Kenneth W. Wiles. “The growing blessing of unicorns: The changing nature of the market for privately funded companies.” *Journal of Applied Corporate Finance* 32, no. 3 (2020): 52-73.

Brynjolfsson, Erik, Lorin M. Hitt, and Shinkyu Yang. “Intangible assets: Computers and organization capital.” *Brookings Papers on Economic Activity*, no. 1 (2002):137-181.

Chen, Henry, Paul Gompers, Anna Kovner, and Josh Lerner. “Buy local? The geography of venture capital.” *Journal of Urban Economics* 67, no. 1 (2010): 90-102.

Chemmanur, Thomas J., and Paolo Fulghieri. “A theory of the going-public decision.” *The Review of Financial Studies* 12, no. 2 (1999): 249-279.

Chernenko, Sergey, Josh Lerner, and Yao Zeng. “Mutual funds as venture capitalists? Evidence from unicorns.” *The Review of Financial Studies* 34, no. 5 (2021): 2362-2410.

Corrado, Carol A., and Charles R. Hulten. “How do you measure a "technological revolution"?” *American Economic Review* 100, no. 2 (2010): 99-104.

Crouzet, Nicolas, Janice C. Eberly, Andrea L. Eisfeldt, and Dimitris Papanikolaou. “The economics of intangible capital.” *Journal of Economic Perspectives* 36, no 2 (2022): 29-52.

de Fontenay, Elisabeth. “The deregulation of private capital and the decline of the public company.” *Hastings Law Journal* 68, no. 3 (2017): 445-502.

de Fontenay, Elisabeth. “Examining private market exemptions as a barrier to IPOs and retail investment.” Testimony before House of Representatives Committee on Financial Services (2019).

de Fontenay, Elisabeth, and Gabriel Rauterberg. “The new public/private equilibrium and the regulation of public companies.” *Columbia Business Law Review*, no. 1 (2021): 1199-1243.

Doidge, Craig, G. Andrew Karolyi, and René M. Stulz. “The US listing gap.” *Journal of Financial Economics* 123, no. 3 (2017): 464-487.

Eisfeldt, Andrea L., and Dimitris Papanikolaou. “Organization capital and the cross-section of expected returns.” *The Journal of Finance* 68, no. 4 (2013): 1365-1406.

Evenson, Robert E., and Larry E. Westphal. “Technological change and technological strategy.” In *Handbook of development economics*, ed. J. Behrman and T. N. Srinivasan, Vol. 3, 2209-2299. Amsterdam: North-Holland (1995).

Ewens, Michael, and Joan Farre-Mensa. “The deregulation of the private equity markets and the decline in IPOs.” *The Review of Financial Studies* 33, no. 12 (2020): 5463-5509.

Ewens, Michael, Kairong Xiao, and Ting Xu. “Regulatory costs of being public: Evidence from bunching estimation.” *Journal of Financial Economics* (2024), forthcoming.

Falato, Antonio, Dalida Kadyrzhanova, Jae Sim, and Roberto Steri. “Rising intangible capital, shrinking debt capacity, and the US corporate savings glut.” *The Journal of Finance* 77, no. 5 (2022): 2799-2852.

Farre-Mensa, Joan. “The benefits of selective disclosure: Evidence from private firms.” Working Paper (2017).

Fields, Laura, and Michelle Lowry. “Bucking the trend: Why do IPO firms choose controversial governance structures and why do investors let them?” *Journal of Financial Economics* 146, no 1 (2022): 27-54.

Gao, Xiaohui, Jay R. Ritter, and Zhongyan Zhu. “Where have all the IPOs gone?” *Journal of Financial and Quantitative Analysis* 48, no. 6 (2013): 1663-1692.

Gahng, Minmo. “Create your own valuation.” Working Paper (2023).

Gompers, Paul A., and Josh Lerner. “Money chasing deals? The impact of fund inflows on private equity valuations.” *Journal of Financial Economics* 55, no. 2 (2000): 281-325.

Gompers, Paul A., and Josh Lerner. “The venture capital cycle.” MIT Press, 2004.

Gornall, Will, and Ilya A. Strebulaev. “Squaring venture capital valuations with reality.” *Journal of Financial Economics* 135, no. 1 (2020): 120-143.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales. “The value of corporate culture.” *Journal of Financial Economics* 117, no. 1(2015): 60-76.

Haskel, Jonathan, and Stian Westlake. “Capitalism without capital.” Princeton University Press (2017).

Holmström, Bengt and Jean Tirole. “Market liquidity and performance monitoring.” *Journal of Political Economy* 101, no. 4 (1993): 678-709.

Huang, Shiyang, Yifei Mao, Cong Wang, and Dexin Zhou. “Public market players in the private world: Implications for the going-public process.” *The Review of Financial Studies* 34, no. 5 (2021): 2411-2447.

Hulten, Charles R., and Xiaohui Hao. “What is a company really worth? Intangible capital and the ‘market to book value’ puzzle.” Working Paper (2008).

Imbierowicz, Björn, and Christian Rauch. “What drives startup valuations?” Working Paper (2024).

Iqbal, Aneel, Shivaram Rajgopal, Anup Srivastava, and Rong Zhao. “A better estimate of internally generated intangible capital.” *Management Science* (2024), forthcoming.

Janeway, William, Ramana Nanda, and Matthew Rhodes-Kropf. “Venture capital booms and startup financing.” *Annual Review of Financial Economics* 13, (2021): 111-127.

Kahle, Kathleen M., and René M. Stulz. “Is the US public corporation in trouble?” *Journal of Economic Perspectives* 31, no. 3 (2017): 67-88.

Kaplan, Steven N., and Antoinette Schoar. “Private equity performance: Returns, persistence, and capital flows.” *The Journal of Finance* 60, no. 4 (2005): 1791-1823.

Kim, Hyunseob, and Roni Michaely, “Sticking around too long? Dynamics of the benefits of dual-class voting.” Working paper (2019).

Kwon, Sungjoung, Michelle Lowry, and Yiming Qian. “Mutual fund investments in private firms.” *Journal of Financial Economics* 136, no. 2 (2020): 407-443.

Larcker, David F., Brian Tayan, and Edward Watts. “Cashing it in: Private-company exchanges and employee stock sales prior to IPO.” *Stanford Closer Look Series* (2018).

Lerner, Josh. “Venture capitalists and the oversight of private firms.” *The Journal of Finance* 50, no. 1 (1995): 301-318.

Lev, Baruch, and Suresh Radhakrishnan. “The valuation of organization capital.” In *Measuring capital in the new economy*, pp. 73-110. University of Chicago Press (2005).

Lev, Baruch, Suresh Radhakrishnan, and Weining Zhang. “Organization capital.” *Abacus* 45, no. 3 (2009): 275-298.

Lowry, Michelle. “Why does IPO volume fluctuate so much?” *Journal of Financial Economics* 67, no. 1 (2003): 3-40.

Maksimovic, Vojislav, and Pegaret Pichler. “Technological innovation and initial public offerings.” *The Review of Financial Studies* 14, no. 2 (2001): 459-494.

Pagano, Marco, Fabio Panetta, and Luigi Zingales. “Why do companies go public? An empirical analysis.” *The Journal of Finance* 53, no. 1 (1998): 27-64.

Pástor, Luboš, Lucian A. Taylor, and Pietro Veronesi. “Entrepreneurial learning, the IPO decision, and the post-IPO drop in firm profitability.” *The Review of Financial Studies* 22, no. 8 (2009): 3005-3046.

Pástor, Luboš, and Pietro Veronesi. “Technological revolutions and stock prices.” *American Economic Review*, 99 no. 4 (2009): 1451-83.

Peters, Ryan H., and Lucian A. Taylor. “Intangible capital and the investment-q relation.” *Journal of Financial Economics* 123, no. 2 (2017): 251-272.

Rajan, Raghuram G. “Presidential address: The corporation in finance.” *The Journal of Finance* 67, no. 4 (2012): 1173-1217.

Rajan, Raghuram G., and Luigi Zingales. “The governance of the new enterprise.” Working Paper (2000).

Rajgopal, Shivaram, Elnaz Basirian, Aneel Iqbal, and Anup Srivastava. “Reassessed earnings with capitalized intangibles.” Working paper (2024).

Ritter, Jay R. “The costs of going public.” *Journal of Financial Economics* 19, no. 2 (1987): 269-281.

Ritter, Jay R., and Ivo Welch. “A review of IPO activity, pricing, and allocations.” *The Journal of Finance* 57, no. 4 (2002): 1795-1828.

Rodrigues, Usha R. “The once and future irrelevancy of section 12 (g).” *University of Illinois Law Review* 2015, no. 4 (2015): 1529-1562.

Stulz, René M. “Public versus private equity.” *Oxford Review of Economic Policy* 36, no. 2 (2020): 275-290.

Tian, Xuan, and Tracy Yue Wang. “Tolerance for failure and corporate innovation.” *The Review of Financial Studies* 27, no. 1 (2014): 211-255.

Vance, Ashlee. “Elon Musk: Tesla, SpaceX, and the quest for a fantastic future.” Ecco (2015).

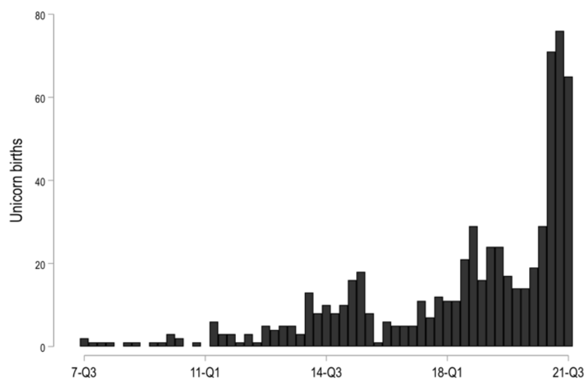
Verrecchia, Robert E. “Discretionary disclosure.” *Journal of Accounting and Economics* 5, (1983): 179-194.

Wang, Lydia. “The effect of SoftBank Vision Fund on venture capital cycles.” Bachelor’s thesis, Harvard College (2020).

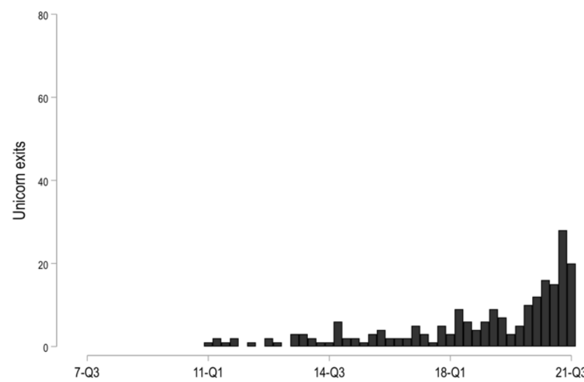
Figure 1. U.S. unicorn births, exits, and exit rate

The four panels of the figure show the number of new U.S. unicorns by quarter (Panel A), the number of unicorn exits by quarter (Panel B), the unicorn exit rate, defined as the number of exits per quarter divided by the number of unicorns in existence in the prior quarter (Panel C), and the cumulative number of U.S. unicorns born, exited, and in existence by quarter (Panel D). The sample consists of 639 U.S. unicorns, defined as private companies with a post-money headline valuation of at least $1 billion. The sample period is from Q3 2005 to Q3 2021. Data are from CB Insights, S&P's Capital IQ, Gornall and Strebulaev (2020), and Crunchbase.

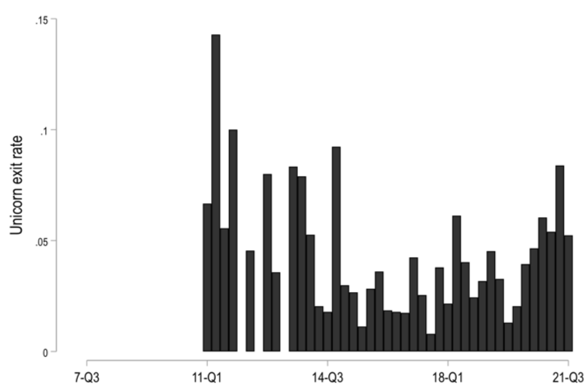
Panel A: Unicorn births



Panel B: Unicorn exits



Panel C: Unicorn exit rate



Panel D: Cumulative numbers

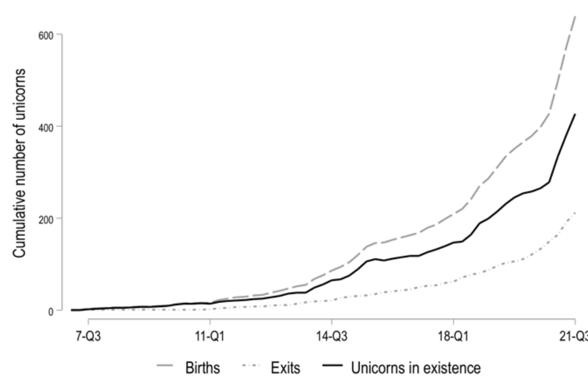


Figure 2. The net benefit of being public and private valuation

The figure shows the net benefit of being public as a function of a firm's private valuation. The continuous red line shows that it becomes advantageous for firms to go public when their valuation exceeds a threshold. The firm goes public when the net benefit is positive. A decrease in the net benefit of being public shifts the net benefit line to the right, so that firms go public at higher valuations (black dashed line). The green dotted line shows a new type of firm for which the net benefit of being public is lower than for existing firms and is decreased further through a funding advantage if they become unicorns (solid green line).

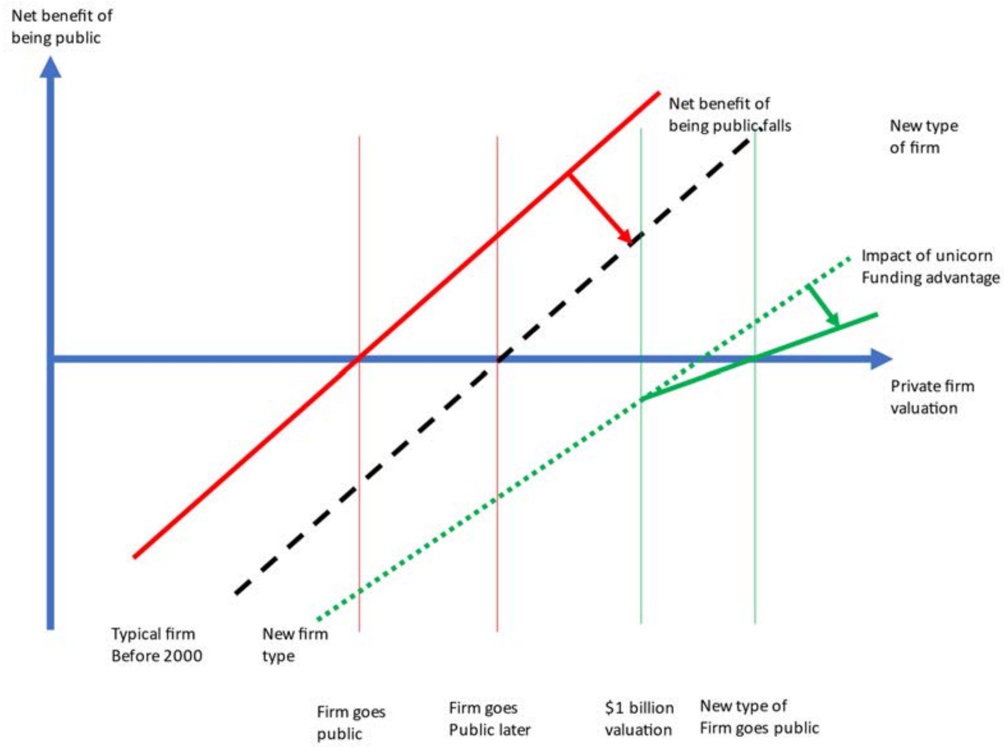
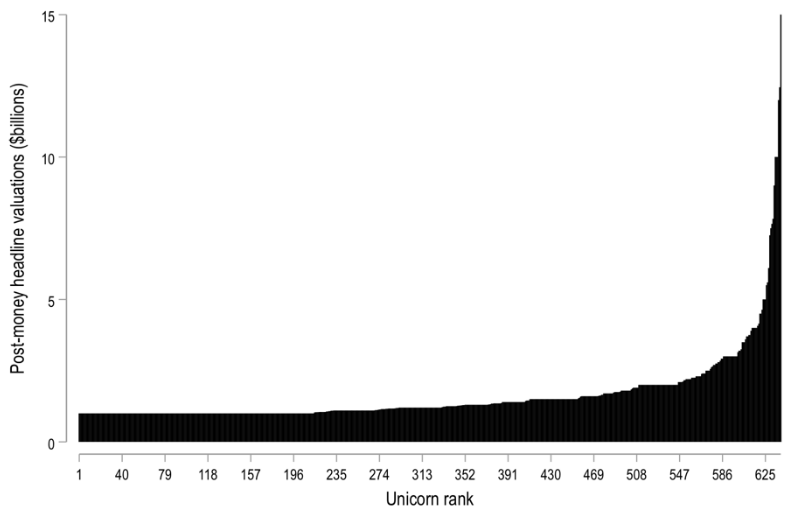


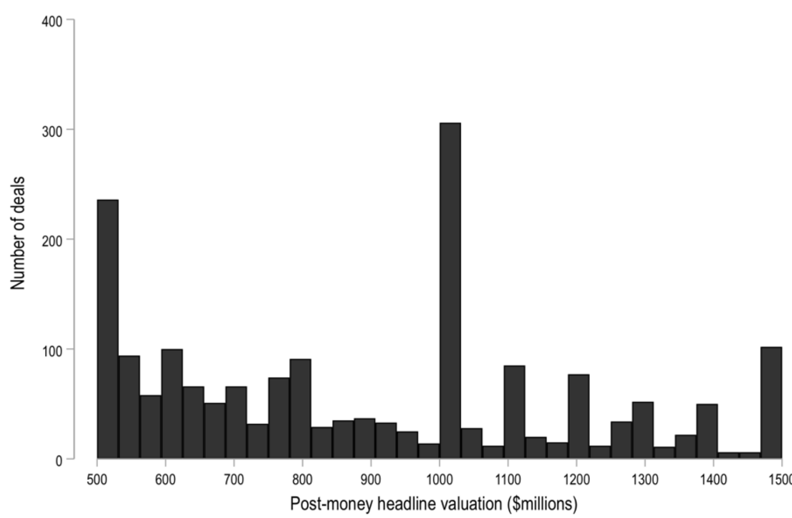
Figure 3. Distribution of headline valuations at unicorn and other financing rounds

Panel A of the figure shows the post-money headline valuations, defined as the product of the number of shares and the share price used in the unicorn fundraising round for the 639 sample unicorns. Unicorns are private companies with a post-money headline valuation of at least $1 billion. The sample period is from Q3 2005 to Q3 2021. Data are from CB Insights, S&P's Capital IQ, Gornall and Strebulaev (2020), and Crunchbase. Panel B shows the post-money valuations of all VC-backed startups in the CB Insights database that obtained more than $50 million in funding and had a post-money valuation between $500 million and $1,500 million. Panel C shows the cumulative distribution function (CDF) of the empirically observed post-money valuations and the counterfactual CDF estimated without the window [$750 million, $1,100 million]. Data for Panels B and C are from CB Insights.

Panel A: Post-money headline valuations of unicorns



Panel B: Distribution of post-money valuations between $500m and $1500m for a sample of large VC-backed startups



Panel C: Empirical and estimated counterfactual cumulative distribution functions of post-money valuations between \$500m and \$1,500m

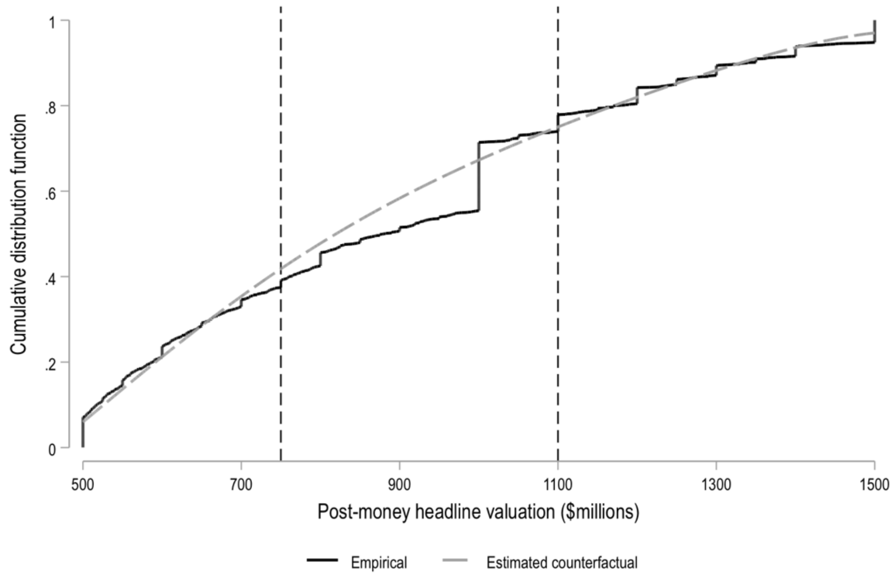
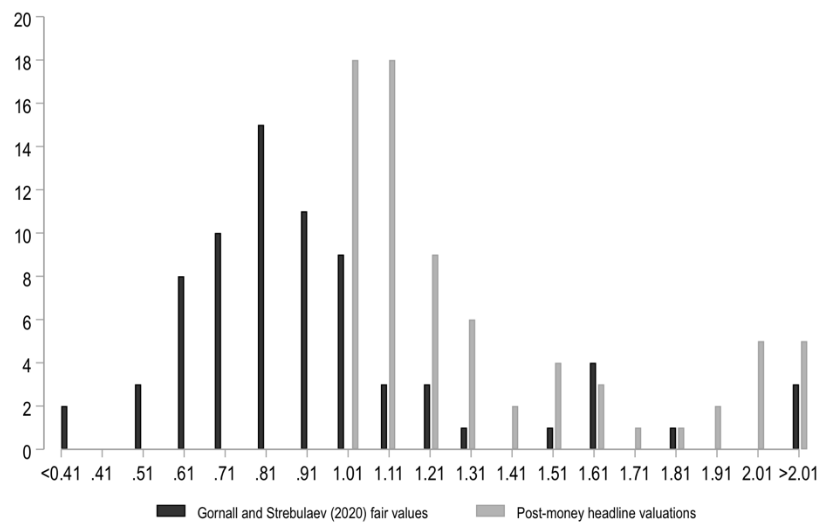


Figure 4. U.S. unicorns' headline valuations vs. fair values

The figure shows the distribution of post-money headline valuations and fair values of unicorn financing rounds using the valuation model of Gornall and Strebulaev (2020). Unicorns are private companies with a post-money headline valuation of at least $1 billion. The sample period is from Q3 2005 to Q3 2021. Panel A compares the distribution of fair values according to the valuation model of Gornall and Strebulaev (2020) (black bars) to the distribution of post-money headline valuations (gray bars). Panel B shows the value of the benefits in dollars (black bars) and the value of the benefits as a fraction of fair value (gray bars) given to the unicorn round investors across fair value bins (in billions of dollars).

Panel A: Unicorn round post-money headline valuations vs. Gornall and Strebulaev (2020) fair valuations



Panel B: Value of benefits given to unicorn round investors based on Gornall and Strebulaev (2020) fair valuations

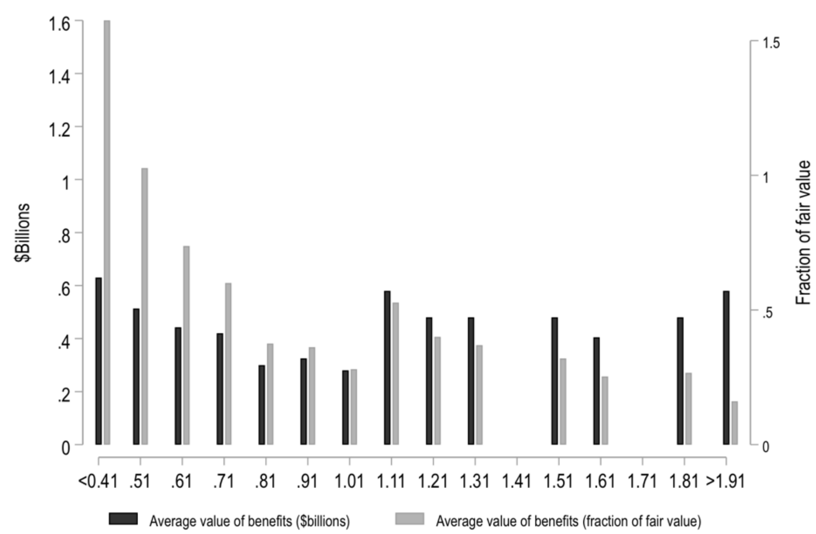


Figure 5. Patent activity of unicorn IPOs vs non-unicorn matched IPOs

The figure shows the median of the ratio of the total number of patents per dollar of total funding (in millions), for the six quarters before and after the IPO. The sample consists of 98 unicorn IPOs between Q1 2010 and Q3 2021 and, for each unicorn IPO, the nearest neighbor VC-backed IPO based on firm pre-unicorn round year, headline valuation, funds raised, and age using the Mahalanobis metric. Data are from CB Insights. The solid black line shows the median ratio for unicorns, and the gray dashed line shows the ratio for the matched startups. The vertical black dashed line represents the IPO quarter.

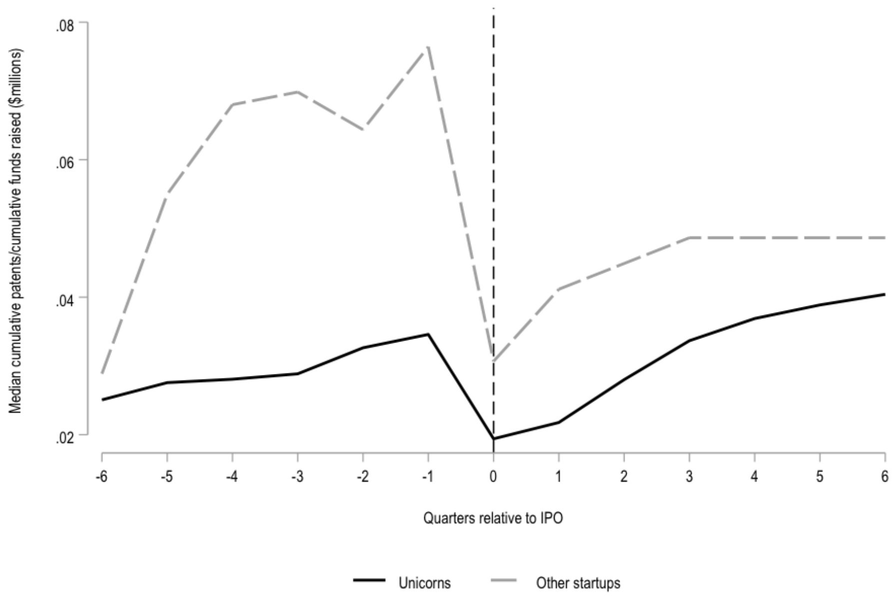


Table 1. Summary statistics on unicorns

The table shows summary statistics on the financing, post-money headline valuations, and status of 639 U.S. unicorns, defined as private companies that reach a post-money headline valuation of at least $1 billion. The sample period is Q2 1995 (the earliest funding round for firms that eventually become unicorns) to Q3 2021. Panel A shows summary statistics for the entire sample of unicorns, and Panel B shows summary statistics for the 212 unicorns that had an exit. Unicorns exit the sample because of a down round, a failure (outright failure or acquisition at less than 25% of unicorn post-money headline valuation), a public listing through an IPO, a de-SPAC transaction, and a direct listing, or an acquisition. Data are from CB Insights, S&P's Capital IQ, Gornall and Strebulaev (2020), and Crunchbase. Appendix B contains detailed variable definitions.

Panel A: All unicorns

	Obs	Mean	25th Pct.	Median	75th Pct.
	(1)	(2)	(3)	(4)	(5)
Years between founding and unicorn status	639	6.91	4.15	6.28	8.70
Equity rounds between founding and unicorn status	639	5.27	4.00	5.00	7.00
PMV unicorn round ($ billions)	639	1.64	1.00	1.20	1.70
Market value after last round ($ billions)	554	4.07	1.17	2.00	3.90
Total funding until unicorn status ($ millions)	630	328.34	181.50	252.96	381.00
Total funding after unicorn status ($ millions)	639	376.65	0.00	1.28	280.00
Total funding while private ($ millions)	633	707.96	235.75	383.40	666.00
Total equity funding while private ($ millions)	633	623.90	225.00	351.64	602.82
Equity fraction, funds raised	633	0.95	0.99	1.00	1.00
Exit (=1)	639	33.18			
Years between unicorn status and exit	212	3.08	1.52	2.63	4.21

Panel B: Exited unicorns

	Down (10 obs.)		Failed (21 obs.)		IPO (110 obs.)		SPAC (18 obs.)		Direct listings (9 obs.)		M&A (44 obs.)	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Years between unicorn status and exit	2.83	2.54	4.42	4.59	2.79	2.35	3.55	3.48	3.99	3.43	2.84	2.49
Equity rounds btw. unicorn status and exit	2.80	1.00	1.90	2.00	2.34	1.00	2.44	1.50	3.22	2.00	1.07	1.00
PMV unicorn round ($ billions)	1.25	1.19	1.99	1.25	1.52	1.20	1.79	1.10	1.62	1.50	1.60	1.02
PMV at exit			0.06	0.00	7.61	3.49	5.00	3.35	17.57	6.08	4.26	2.23
Total funding while private ($ millions)	2255.81	506.52	651.03	509.30	1022.99	482.50	914.29	632.57	789.02	538.67	703.34	402.00
PMV at exit/PMV unicorn round			0.04	0.00	4.78	2.57	4.19	2.89	10.58	5.07	3.15	1.57
PMV at exit/total equity funding			0.17	0.00	10.67	7.92	9.45	8.21	27.29	15.37	15.93	5.92
PMV at exit < total fundraising (=1)			0.90	1.00	0.02	0.00	0.06	0.00	0.00	0.00	0.07	0.00

Table 2. Startup exits around the Alice Corp v. CLS Bank International, 573 U.S. 208 (2014) Supreme Court decision

The table reports results from difference-in-differences regressions of IPO startup exits around the Alice Corp v. CLS Bank International, 573 U.S. 208 (2014) Supreme Court decision using a linear probability model. The sample is a panel of 3,641 VC-backed startups that obtained at least $50m in cumulative financing between Q2 2009 and Q1 2019. *IPO exit (=1)* equals one in the quarter when a VC-backed startup has an IPO and is zero otherwise. *Treatment* equals one for VC-backed startups in the CB Insights Software sector, or in a CB Insights Software subsector. Accounting variables are calculated as the average of all young public firms in an industry. Young firms are firms in the lowest quartile of firm age each year. *Post* equals one from quarter Q2 2014 to Q1 2019. *P*-values based on standard errors clustered at the firm level are shown in parentheses below the coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, and *, respectively. Appendix B contains detailed variable definitions.

	IPO exit (=1)			
	No controls		Industry controls fixed in Q1 2014	
	(1)	(2)	(3)	(4)
Treatment	-0.001	-0.001	<0.001	<0.001
	(0.405)	(0.235)	(0.861)	(0.852)
Post	0.003***		-0.003**	
	(0.000)		(0.049)	
Treatment x Post	-0.003**	-0.003**	-0.003**	-0.003**
	(0.011)	(0.027)	(0.017)	(0.011)
Ln(Industry funding flow)			0.006***	0.006***
			(0.000)	(0.000)
Tobin's q			0.003	0.003
			(0.140)	(0.127)
Ln(Assets)			0.003**	0.003**
			(0.015)	(0.010)
Fixed assets/total assets			0.016*	0.015*
			(0.070)	(0.071)
CAPX/total assets			-0.129	-0.126
			(0.116)	(0.114)
Cash/total assets			-0.031*	-0.031*
			(0.088)	(0.081)
COGS/total sales			-0.015	-0.014
			(0.142)	(0.147)
R&D/total assets			0.228**	0.225**
			(0.047)	(0.044)
SG&A/total assets			0.038	0.036
			(0.203)	(0.216)
Loss firm			-0.004	-0.004
			(0.512)	(0.529)
Ln(Age)			<-0.001	-0.000
			(0.941)	(0.994)
Scale			0.001	0.001
			(0.219)	(0.239)
Near San Francisco			0.001	0.001*
			(0.106)	(0.084)
IPO volume$_{t-1}$			<0.001	
			(0.903)	
EW IPO first day returns$_{t-1}$			-0.004	
			(0.466)	
Real GDP growth$_{t-1}$			-0.017	
			(0.881)	
EW market returns$_{t-3 \text{ to } t-1}$			-0.007*	
			(0.059)	
Aggregate MB$_{t-1}$			0.007***	
			(0.001)	
			-0.001	

Credit spread$_{t-1}$				
			(0.573)	
Federal funds rate$_{t-1}$			<-0.001	
			(0.876)	
Fixed effects				
Quarter	No	Yes	No	Yes
Observations	54,427	54,427	52,061	54,219
Adj./Pseudo R2	0.01	0.01	0.01	0.01

Table 3. Unicorn round investors

The table reports summary statistics on the participation of unicorn round investors in pre-unicorn rounds and the rounds of matched startups. The sample consists of 1,152 unicorn round investors and 1,130 pre-unicorn round investors of 546 unicorns with a matched VC-backed startup on pre-unicorn round year, headline valuation, funds raised, and age using the Mahalanobis metric.

	N	(%)
	(1)	(2)
Unicorn round investors not in any pre-unicorn round	310	27%
Pre-unicorn round investors not in any prior round	123	11%
Unicorn round investors	1,152	
Pre-unicorn round investors	1,130	

Table 4. Unicorn investors

Panel A of the table lists the top 20 investors in B rounds of firms that eventually become unicorns. Panel B shows the top 20 investors in unicorn rounds. Panel C lists the top 20 investors in unicorn rounds that are not in B rounds. The sample consists of 639 U.S. unicorns, defined as private companies with a post-money headline valuation of at least $1 billion. The sample period is Q2 1995 (the earliest funding round for firms that eventually become unicorns) to Q3 2021. Data are from CB Insights and Gornall and Strebulaev (2020).

Panel A: Top 20 Series B investors

Rank	Investor	Deals
1	Andreessen Horowitz	42
2	Accel	41
3	Sequoia Capital	39
4	Kleiner Perkins	33
5	Google Ventures	32
6	Lightspeed Venture Partners	32
7	Khosla Ventures	25
8	Founders Fund	24
9	New Enterprise Associates	23
10	Greylock Partners	23
11	Index Ventures	21
12	Benchmark	20
13	General Catalyst	20
14	Thrive Capital	19
15	Insight Partners	19
16	Institutional Venture Partners	18
17	Redpoint Ventures	18
18	Bessemer Venture Partners	17
19	Y Combinator	17
20	Battery Ventures	16

Panel B: Top 20 unicorn round investors

Rank	Investor	Deals
1	Tiger Global Management	70
2	Sequoia Capital	56
3	Andreessen Horowitz	54
4	Accel	45
5	Insight Partners	43
6	SoftBank Group	38
7	Sapphire Ventures	37
8	Institutional Venture Partners	37
9	Lightspeed Venture Partners	35
10	Kleiner Perkins	35
11	Google Ventures	35
12	T. Rowe Price	35
13	Fidelity Investments	33
14	New Enterprise Associates	32
15	ICONIQ Capital	32
16	Coatue Management	31
17	Meritech Capital Partners	30
18	Bessemer Venture Partners	30
19	Index Ventures	30
20	General Catalyst	28

Panel C: Top 20 unicorn round investors not in Series B rounds

Rank	Investor	Deals
1	Tiger Global Management	70
2	SoftBank Group	38
3	Sapphire Ventures	37
4	T. Rowe Price	35
5	Fidelity Investments	33
6	ICONIQ Capital	32
7	Coatue Management	31
8	Meritech Capital Partners	30
9	Wellington Management	22
10	Spark Capital	22
11	Salesforce Ventures	21
12	Goldman Sachs	21
13	capitalG	20
14	General Atlantic	19
15	Dragoneer Investment Group	19
16	BlackRock	17
17	Norwest Venture Partners	17
18	DST Global	17
19	GGV Capital	16
20	Silver Lake	16

Table 5. The composition and distance of unicorn investors

The table reports results from panel regressions of changes in the composition and distance of investors when startups that eventually become unicorns achieve unicorn status. The sample is a unicorn-funding round-investor (Panels A and C) or a unicorn-funding round (Panels B and D) panel of 639 U.S. unicorns, defined as private companies that reach a post-money headline valuation of at least $1 billion. The sample period is Q2 1995 (the earliest funding round for startups that eventually become unicorns) to Q3 2021. In Panels A and B, the dependent variables are indicator variables that equal one if an investor of a given type (*Angel, Venture, Asset management, Corporate,* or *Growth*) participates in a funding round and zero otherwise, and the share of investors of a given type that participate in a given round, respectively. In Panel C, the dependent variables are *Ln(Investor distance from unicorn)* and *Ln(Investor distance from San Francisco)*, defined as the distance of an investor in a funding round from the unicorn headquarters and San Francisco, respectively. In Panel D, the dependent variables are *Ln(Average investor distance from unicorn)* and *Ln(Average investor distance from San Francisco)*, defined as the average distance of the investors in a funding round from the unicorn headquarters and San Francisco, respectively. *Pre-unicorn round* is an indicator variable that equals one for funding rounds before the unicorn round and zero otherwise. *Post-unicorn round* is an indicator variable that equals one for funding rounds after the unicorn round and zero otherwise. *Unicorn round* is an indicator variable that equals one for the unicorn round and zero otherwise. *Near San Francisco* is an indicator variable that equals one if a unicorn is headquartered within 200 miles of central San Francisco. *P*-values based on standard errors clustered at the firm level are shown in parentheses below the coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, *, respectively. Appendix B contains detailed variable definitions.

Panel A: Investor composition

	Investor type				
	Angel	Venture	Asset management	Corporate	Growth
	(1)	(2)	(3)	(4)	(5)
Pre-unicorn round	-0.005	0.113***	-0.071***	-0.004	-0.031***
	(0.652)	(0.000)	(0.000)	(0.672)	(0.000)
Post-unicorn round	-0.022**	-0.040**	0.070***	-0.007	-0.002
	(0.018)	(0.016)	(0.000)	(0.538)	(0.860)
Near San Francisco	0.031***	0.037**	-0.020**	-0.005	-0.042***
	(0.006)	(0.012)	(0.012)	(0.599)	(0.000)
Fixed effects					
Industry	Yes	Yes	Yes	Yes	Yes
Funding round date	Yes	Yes	Yes	Yes	Yes
Observations	16,221	16,221	16,221	16,221	16,221
Adj. R2	0.16	0.07	0.09	0.06	0.06

Panel B: Investor composition shares					
	Investor type				
	Angel share	Venture share	Asset management share	Corporate share	Growth share
	(1)	(2)	(3)	(4)	(5)
Unicorn round	-0.015***	-0.071***	0.050***	0.001	0.037***
	(0.008)	(0.000)	(0.000)	(0.901)	(0.000)
Fixed effects					
Unicorn	Yes	Yes	Yes	Yes	Yes
Funding round	Yes	Yes	Yes	Yes	Yes
Observations	3,924	3,924	3,924	3,924	3,924
Adj. R2	0.16	0.23	0.19	0.20	0.30

Panel C: Investor distance		
	Ln(Investor distance from unicorn)	Ln(Investor distance from San Francisco)
	(1)	(2)
Pre-unicorn round	-0.554***	-0.374***
	(0.000)	(0.000)
Post-unicorn round	0.200**	0.175*
	(0.015)	(0.062)
Near San Francisco	-1.434***	-1.103***
	(0.000)	(0.000)
Fixed effects		
Industry	Yes	Yes
Funding round date	Yes	Yes
Observations	15,044	15,044
Adj. R2	0.10	0.08

Panel D: Average investor distance		
	Ln(Average investor distance from unicorn)	Ln(Average investor distance from San Francisco)
	(1)	(2)
Unicorn round	0.538***	0.478***
	(0.000)	(0.000)
Fixed effects		
Unicorn	Yes	Yes
Funding round	Yes	Yes
Observations	4,182	4,182
Adj. R2	0.26	0.23

Table 6. Industry sector comparisons of public firms, IPOs, unicorns, and other large VC-backed startups

The table reports firm counts by CB Insights industry sectors. Columns (1) and (2) show the number and (%) of unicorns, columns (3) and (4) show the number and (%) of VC-backed startups that obtained at least $50m in cumulative financing between Q1 2010 and Q3 2021, columns (5) and (6) show the total number and (%) of public firms, and columns (7) and (8) show the number and (%) of IPOs. Appendix B contains detailed variable definitions.

	Unicorns	Unicorns (%)	VC-backed startups	VC-backed startups (%)	Public	Public (%)	IPOs	IPO (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Metals & Mining	0	0	6	0.1	58	0.8	12	0.3
Risk & Security	33	5.2	178	3.5	7	0.1	7	0.2
Retail	0	0.0	32	0.6	199	2.8	97	2.7
Media	16	2.5	97	1.9	256	3.5	167	4.6
Environment	4	0.6	9	0.2	38	0.5	5	0.1
Leisure	18	2.8	71	1.4	156	2.2	39	1.1
Agriculture	2	0.3	37	0.7	12	0.2	7	0.2
Transportation	6	0.9	64	1.3	213	2.9	75	2.1
Computer	20	3.1	194	3.8	781	10.8	401	11.0
Energy & Utilities	9	1.4	205	4.0	276	3.8	86	2.4
Financial	86	13.5	502	9.9	1,098	15.2	283	7.8
Food & Beverages	3	0.5	65	1.3	188	2.6	42	1.2
Business	168	26.3	449	8.9	394	5.5	505	13.9
Electronics	2	0.3	140	2.8	846	11.7	410	11.3
Industrial	27	4.2	240	4.7	710	9.8	485	13.3
Consumer	17	2.7	146	2.9	216	3.0	90	2.5
Software	16	2.5	186	3.7	421	5.8	275	7.6
Mobile	28	4.4	255	5.0	169	2.3	30	0.8
Healthcare	73	11.4	1,427	28.1	907	12.6	586	16.1
Internet	111	17.4	767	15.1	279	3.9	37	1.0
Total	639	100	5,070	100	7,224	100	3,639	100

Table 7. Determinants of unicorn status

The table reports results from cross-sectional regressions of the determinants of unicorn status. The sample consists of 5,690 startups in the CB Insights Database that cumulatively obtained at least $50 million in financing between Q1 2010 and Q3 2021. The dependent variable is *Unicorn status*, an indicator variable that equals one if the firm reached a post-money headline valuation of at least $1 billion at any time during the sample period and zero otherwise. Industry assignments are from CB Insights. The CB Insights industry assignment process is described in Section 4 of the paper. *Birth cohort* is the first year a company reaches $50m in cumulative funding. *Near San Francisco* is an indicator variable that equals one if a company is headquartered within 200 miles of central San Francisco. *P*-values based on heteroskedasticity-robust standard errors are shown in parentheses below coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, *, respectively. Appendix B contains detailed variable definitions.

	Unicorn status		
	(1)	(2)	(3)
Metals & Mining	-0.078***		-0.050**
	(0.000)		(0.046)
Risk & Security	0.041		0.033
	(0.184)		(0.279)
Retail	-0.074***		-0.077***
	(0.000)		(0.000)
Media	0.048		0.041
	(0.214)		(0.289)
Environment	0.023		0.036
	(0.698)		(0.551)
Leisure	0.095**		0.096**
	(0.028)		(0.028)
Agriculture	-0.031		-0.028
	(0.439)		(0.481)
Transportation	-0.004		-0.013
	(0.906)		(0.733)
Computer	-0.017		-0.025
	(0.519)		(0.348)
Energy & Utilities	-0.044**		-0.043*
	(0.048)		(0.050)
Financial	0.043*		0.040*
	(0.050)		(0.069)
Food & Beverages	-0.041		-0.048
	(0.174)		(0.113)
Business	0.081***		0.075***
	(0.000)		(0.001)
Electronics	-0.099***		-0.097***
	(0.000)		(0.000)
Consumer	0.018		0.009
	(0.534)		(0.767)
Software	0.034		0.030
	(0.363)		(0.411)
Mobile	0.024		0.022
	(0.425)		(0.448)
Healthcare	-0.045**		-0.046**
	(0.016)		(0.013)
Internet	0.059**		0.059***
	(0.010)		(0.010)
Birth cohort 2011		0.057**	0.052**
		(0.016)	(0.028)

Birth cohort 2012		0.024	0.011
		(0.227)	(0.584)
Birth cohort 2013		0.086***	0.066***
		(0.001)	(0.007)
Birth cohort 2014		0.090***	0.071***
		(0.000)	(0.001)
Birth cohort 2015		0.083***	0.064***
		(0.000)	(0.001)
Birth cohort 2016		0.086***	0.067***
		(0.000)	(0.001)
Birth cohort 2017		0.111***	0.093***
		(0.000)	(0.000)
Birth cohort 2018		0.085***	0.065***
		(0.000)	(0.000)
Birth cohort 2019		0.066***	0.048***
		(0.000)	(0.003)
Birth cohort 2020		0.069***	0.056***
		(0.000)	(0.001)
Birth cohort 2021		-0.016	-0.036***
		(0.159)	(0.002)
Scale	0.035***	0.054***	0.034***
	(0.000)	(0.000)	(0.000)
Near San Francisco	0.073***	0.079***	0.072***
	(0.000)	(0.000)	(0.000)
Fixed effects			
Industry	Yes	No	Yes
Birth cohort	No	Yes	Yes
Observations	5,690	5,690	5,690
Adj. R2	0.04	0.04	0.06

Table 8. Panel regressions of fraction of startups that are unicorns by industry

The table reports results from panel regressions of the determinants of the fraction of unicorns by industry. The sample is an industry-quarter panel of 5,141 startups (863 industry-quarter observations) in the CB Insights database that cumulatively obtained at least $50m in VC financing between Q1 2010 and Q3 2021. The dependent variable is *Unicorn (%)*, the fraction of startups in a given industry in that quarter that have a post-money headline valuation of at least $1 billion. Accounting variables are calculated as the average of all young public firms in an industry. Young firms are firms in the lowest quartile of firm age each year. Model (1) shows results for the entire sample, and Model (2) shows results omitting the year 2021. *P*-values based on robust standard errors are shown in parentheses below the coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, and *, respectively. Appendix B contains detailed variable definitions.

	Unicorn (%)	
	2010Q1-2021Q3	2010Q1-2020Q4
	(1)	(2)
Tobin's q_{t-1}	0.031***	0.030***
	(0.000)	(0.000)
$Ln(Assets)_{t-1}$	0.003	0.006
	(0.624)	(0.445)
Fixed assets/total $assets_{t-1}$	-0.118***	-0.078**
	(0.000)	(0.010)
CAPX/total $assets_{t-1}$	-0.024	-0.190
	(0.893)	(0.333)
Cash/total $assets_{t-1}$	-0.288***	-0.280***
	(0.000)	(0.000)
COGS/total $assets_{t-1}$	-0.300***	-0.322***
	(0.000)	(0.000)
R&D/total $assets_{t-1}$	-0.369	-0.247
	(0.122)	(0.320)
SG&A/total $assets_{t-1}$	0.291**	0.411***
	(0.029)	(0.002)
Loss $firm_{t-1}$	0.013	0.003
	(0.510)	(0.879)
$Ln(Age)_{t-1}$	0.028	0.010
	(0.369)	(0.770)
Fixed effects		
Industry	No	No
Quarter	Yes	Yes
Observations	863	803
Adj. R2	0.27	0.24

Table 9. Panel regressions of unicorn status

The table reports results from panel regressions of the determinants of unicorn status. The sample is a firm-quarter panel of 5,141 startups (77,054 firm-quarter observations) in the CB Insights database that cumulatively obtained at least \$50m in VC financing between Q1 2010 and Q3 2021. The dependent variable is *Unicorn status*, an indicator variable that equals one from the quarter a firm reached a post-money headline valuation of at least \$1 billion until the end of the sample and zero otherwise. Accounting variables are calculated as the average of all young public firms in an industry. Young firms are firms in the lowest quartile of firm age each year. Column (1) shows OLS results, and columns (2) and (3) present the first- and second-stage of instrumental variables regressions, where we instrument *Ln(Industry funding flow)* with *Ex ante target SoftBank industry* and *Ln(flows into buyout funds)*. *Ex ante Softbank industry* is an indicator variable that equals one after Q2 2017 for industries targeted by SoftBank when it created its first Vision Fund. *Ln(flows into buyout funds)* are the new funds raised by buyout funds over the four prior quarters. *P*-values based on standard errors clustered at the firm level are shown in parentheses below the coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, and *, respectively. Appendix B contains detailed variable definitions.

	OLS	First stage	Second stage
	Unicorn status	Ln(Industry funding flow)	Unicorn status
	(1)	(2)	(3)
Ln(Industry funding flow)$_{t-1}$	0.020***		
	(0.002)		
Ex ante target SoftBank industry		0.552***	
		(0.000)	
Ln(Flows into buyout funds)$_{[t-4,t-1]}$		0.061***	
		(0.000)	
Instrumented Ln(Industry funding flow)$_{t-1}$			0.052***
			(0.001)
Tobin's q$_{t-1}$	0.011**	-0.162***	0.017***
	(0.042)	(0.000)	(0.009)
Ln(Assets)$_{t-1}$	-0.003	-0.094***	0.000
	(0.647)	(0.000)	(0.993)
Fixed assets/total assets$_{t-1}$	-0.093***	-0.237***	-0.076***
	(0.001)	(0.000)	(0.008)
CAPX/total assets$_{t-1}$	0.070	1.855***	0.009
	(0.416)	(0.000)	(0.918)
Cash/total assets$_{t-1}$	-0.213***	3.615***	-0.352***
	(0.000)	(0.000)	(0.000)
COGS/total assets$_{t-1}$	-0.091	1.434***	-0.142*
	(0.221)	(0.000)	(0.062)
R&D/total assets$_{t-1}$	-0.340*	-5.780***	-0.122
	(0.097)	(0.000)	(0.583)
SG&A/total assets$_{t-1}$	0.443**	-7.216***	0.685***
	(0.017)	(0.000)	(0.001)
Loss firm$_{t-1}$	0.023	-0.114***	0.032
	(0.272)	(0.000)	(0.136)
Ln(Age)$_{t-1}$	0.014	-0.461***	0.019
	(0.499)	(0.000)	(0.351)

Scale	0.022***	0.019**	0.021**
	(0.009)	(0.034)	(0.013)
Near San Francisco	0.045***	-0.013	0.046***
	(0.000)	(0.151)	(0.000)
IPO volume$_{t-1}$	0.002	0.201***	-0.001
	(0.566)	(0.000)	(0.788)
EW IPO first day returns$_{t-1}$	0.026*	-0.779***	0.028*
	(0.088)	(0.000)	(0.073)
Real GDP growth$_{t-1}$	0.004	-0.012	0.022
	(0.847)	(0.792)	(0.311)
EW market returns$_{t-3 \text{ to } t-1}$	0.024***	0.158***	0.022***
	(0.002)	(0.000)	(0.005)
Aggregate MB$_{t-1}$	0.026***	0.354***	0.007
	(0.001)	(0.000)	(0.541)
Credit spread$_{t-1}$	0.021***	0.320***	0.011**
	(0.000)	(0.000)	(0.032)
Federal funds rate$_{t-1}$	0.003	0.158***	-0.007
	(0.386)	(0.000)	(0.147)
Fixed effects			
Industry	No	No	No
Quarter	No	No	No
Year	Yes	Yes	Yes
Observations	77,054	77,054	77,054
Adj. R2	0.05	0.69	0.02

Table 10. Summary statistics for the matched sample

The table reports summary statistics on startup characteristics. The sample consists of 546 unicorns and 546 matched VC-backed startups on pre-unicorn round year, headline valuation, funds raised, and age using the Mahalanobis metric. Columns (1) to (3) report summary statistics for unicorns, and columns (4) to (6) report summary statistics for matched VC-backed startups. Column (7) reports differences in means between unicorns and matched VC-backed startups. Column (8) reports differences in medians between unicorns and matched VC-backed startups. The stars correspond to *t*-tests (Wilcoxon tests) of differences in means (medians). Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, and *, respectively.

	Unicorns			Matched non-unicorn startups			Differences	
	Obs	Mean	Median	Obs	Mean	Median	Means	Medians
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Matched pre-unicorn round valuation ($ billions)	546	0.43	0.42	413	0.42	0.40	0.02	0.02
Matched pre-unicorn cumulative funds raised ($ millions)	546	127.63	103.24	413	126.19	100.00	1.44	3.24
Matched age	546	6.18	6.00	413	6.18	6.00	0.00	0.00
Matched pre-unicorn round year	546	2017	2018	413	2017	2018	-0.11	0.00
Year founded	546	2011	2012	413	2012	2012	-0.10	0.00
Market value after last round ($ billions)	477	4.17	2.00	265	0.58	0.50	3.59***	1.50***
Total funding while private ($ millions)	544	691.41	379.10	411	209.97	160.25	481.44***	218.85***
Total equity funding while private ($ millions)	544	612.93	351.09	411	184.95	146.02	427.97***	205.07***
Equity fraction, funds raised	544	0.95	1.00	411	0.92	1.00	0.03***	0.00
Exit (=1)	546	0.31	0.00	413	0.46	0.00	-0.16***	0.00
Failed (=1)	546	0.03	0.00	411	0.03	0.00	-0.00	0.00
Scale (=1)	546	0.48	0.00	413	0.39	0.00	0.09***	0.00
Near San Francisco (=1)	546	0.51	1.00	413	0.43	0.00	0.08**	1.00**

Table 11. Startup exits

The table reports results from Cox proportional hazard regressions of startup exit and multinomial logit regressions of exits through listings and M&As. The sample consists of 546 unicorns between Q1 2010 and Q3 2021 and, for each unicorn, the nearest neighbor VC-backed startup matched on pre-unicorn round year, headline valuation, funds raised, and age using the Mahalanobis metric. This corresponds to a firm-quarter panel of 1,092 startups (14,664 firm-quarter observations). In column (1), the time variable is the number of quarters until a firm exits the sample. In columns (2) and (3), a firm can exit through a *Listing*, including an IPO, SPAC, and direct listing, or through an *M&A*. The baseline case includes firms that remain alive during the sample period and firms that failed. In column (1), *unicorn status* is an indicator variable that equals one from the quarter a startup reached a post-money headline valuation of at least $1 billion until the end of the sample and zero otherwise. In columns (2) and (3), *unicorn status* is an indicator variable that equals one if a startup reached a post-money headline valuation of at least $1 billion between Q1 2010 and Q3 2021 and zero otherwise. Accounting variables are calculated as the average of all young public firms in the startup's industry. Young firms are firms in the lowest quartile of firm age each year. *P*-values based on standard errors clustered at the firm level are shown in parentheses below exponentiated log-odds ratios. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, and *, respectively. Appendix B contains detailed variable definitions.

	Cox Proportional Hazard	Multinomial logit	
	Time to exit	Listing	M&A
	(1)	(2)	(3)
Unicorn status	0.531***	1.353**	0.264***
	(0.000)	(0.047)	(0.000)
Ln(Industry funding flow)$_{t-1}$	0.965	1.606***	1.061
	(0.460)	(0.005)	(0.790)
Tobin's q$_{t-1}$	0.961	1.129	0.823
	(0.336)	(0.400)	(0.332)
Ln(Assets)$_{t-1}$	0.882*	1.490	3.362***
	(0.096)	(0.269)	(0.002)
Fixed assets/total assets$_{t-1}$	0.289***	1.038***	1.001
	(0.000)	(0.002)	(0.922)
CAPX/total assets$_{t-1}$	4.057*	0.905	1.029
	(0.072)	(0.200)	(0.705)
Cash/total assets$_{t-1}$	0.835	1.030	1.042
	(0.679)	(0.231)	(0.168)
COGS/total assets$_{t-1}$	0.661	0.992	1.044**
	(0.454)	(0.685)	(0.034)
R&D/total assets$_{t-1}$	0.002***	1.078	1.109
	(0.000)	(0.550)	(0.410)
SG&A/total assets$_{t-1}$	0.356	1.001	1.160**
	(0.533)	(0.993)	(0.029)
Loss firm$_{t-1}$	1.489***	0.352	1.995
	(0.001)	(0.276)	(0.314)
Foreign income$_{t-1}$	1.137	2.044	0.190**
	(0.512)	(0.420)	(0.014)
Scale	0.976	1.208	1.151
	(0.710)	(0.201)	(0.419)
Near San Francisco	1.000	1.010	0.996
	(0.997)	(0.944)	(0.985)

IPO volume$_{t-1}$	1.245***	1.408	1.438
	(0.000)	(0.280)	(0.337)
EW IPO first day returns$_{t-1}$	0.992***	1.008	1.007
	(0.000)	(0.500)	(0.603)
Real GDP growth$_{t-1}$	1.390**	0.017	3.665
	(0.025)	(0.187)	(0.735)
EW market returns$_{t-3 \text{ to } t-1}$	1.601***	1.114	0.596
	(0.000)	(0.867)	(0.524)
Aggregate MB$_{t-1}$	0.464***	1.384	1.201
	(0.000)	(0.519)	(0.756)
Credit spread$_{t-1}$	0.838***	1.256	1.206
	(0.000)	(0.534)	(0.645)
Federal funds rate$_{t-1}$	0.882***	0.955	1.030
	(0.000)	(0.813)	(0.891)
Observations	14,664	14,664	14,664
Pseudo R2	0.01	0.06	0.06

Table 12. Summary statistics for the matched IPO sample in the year before IPO

The table reports summary statistics on the offer characteristics of IPOs (Panel A), the financial characteristics of firms immediately before their IPO (Panel B), and on the governance and controls mechanisms of firms at their IPOs (Panel C). The sample consists of 101 unicorn IPOs between Q1 2010 and Q3 2021 and, for each unicorn IPO, the nearest neighbor VC-backed IPO based on firm pre-unicorn round year, headline valuation, funds raised, and age using the Mahalanobis metric. Columns (1) to (3) report summary statistics for unicorn IPOs, and columns (4) to (6) report summary statistics for the nearest neighbor non-unicorn IPOs. Column (7) reports differences in means between unicorn IPOs and the nearest neighbor non-unicorn IPOs. Column (8) reports differences in medians between unicorn IPOs and the nearest neighbor non-unicorn IPOs. The stars correspond to *t*-tests (Wilcoxon tests) of differences in means (medians). Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, and *, respectively.

Panel A: Offer characteristics

	Unicorns			Matched controls			Differences	
	Obs	Mean	Median	Obs	Mean	Median	Means	Medians
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IPO valuation ($millions)	101	7,701.23	3,310.14	101	1,646.64	1,007.77	6,054.59***	2,302.37***
Offer price	101	28.45	23.00	101	18.35	17.00	10.10***	6.00***
Underwriter spread (%)	101	5.86	6.34	99	6.82	7.00	-0.97***	-0.66***
Offer price below range	101	0.08	0.00	101	0.16	0.00	-0.08*	0
Offer price above range	101	0.65	1.00	101	0.50	0.00	0.15**	1.00**
Gross proceeds	101	886.37	413.75	100	203.50	144.23	682.87***	269.52***
Fraction of proceeds to company	101	0.93	1.00	99	0.95	1.00	-0.02	0
Fraction of proceeds to selling shareholders	101	0.07	0.00	99	0.05	0.00	0.02	0
First-day return	101	0.39	0.35	101	0.49	0.28	-0.1	0.07
Three-month return	101	0.37	0.25	101	0.70	0.51	-0.33***	-0.26***
Six-month return	101	0.21	0.07	101	0.48	0.33	-0.27**	-0.26***

Panel B: Accounting characteristics

	Unicorns			Matched controls			Differences	
	Obs	Mean	Median	Obs	Mean	Median	Means	Medians
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total assets	98	1,060.03	413.13	98	256.49	131.01	803.54***	282.12***
Sales	97	565.34	243.10	98	149.33	72.05	416.00***	171.05***
Cash and STI/total assets	97	0.47	0.50	98	0.54	0.55	-0.08**	-0.05**
Net PPE/total assets	98	0.12	0.08	98	0.15	0.09	-0.03	0.00
CAPX/total assets	96	0.05	0.03	98	0.06	0.03	-0.01	-0.01
R&D/total assets	98	0.15	0.13	98	0.28	0.20	-0.13***	-0.07***
SG&A/total assets	98	0.44	0.40	98	0.34	0.21	0.10**	0.19***
LT Debt/total assets	97	0.12	0.03	97	0.16	0.05	-0.04	-0.01
COGS/total assets	97	0.37	0.20	98	0.33	0.21	0.04	-0.01
Gross profit/total assets	97	0.39	0.40	98	0.25	0.20	0.14**	0.20**
Negative net income (=1)	98	0.88	1.00	98	0.88	1.00	0.00	0.00

Panel C: Governance and control

	Unicorns			Matched non-unicorn startups			Differences	
	Obs	Mean	Median	Obs	Mean	Median	Means	Medians
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dual class (=1)	101	0.52	1.00	101	0.24	0.00	0.29***	1.00***
Founder CEO (=1)	101	0.65	1.00	101	0.50	0.00	0.16**	1.00**
Founder Chairman (=1)	101	0.72	1.00	101	0.41	0.00	0.32***	1.00***
Founder Board Member (= 1)	101	0.86	1.00	101	0.68	1.00	0.18***	1.00***

Table 13. Unicorn status and firm characteristics at IPO for the matched IPO sample

The table reports results of cross-sectional regressions of unicorn status on firm characteristics. The sample consists of 98 unicorn IPOs between Q1 2010 and Q3 2021 and, for each unicorn IPO, the nearest neighbor VC-backed IPO based on firm pre-unicorn round year, headline valuation, funds raised, and age using the Mahalanobis metric. The dependent variable is *Unicorn status*, an indicator variable that equals one if the firm reached a post-money headline valuation of at least $1 billion as a private company at any time during the sample period and zero otherwise. *P*-values based on robust standard errors are shown in parentheses below the coefficient estimates. Statistical significance at the 1, 5, and 10 percent significance level is denoted by ***, **, and *, respectively. Appendix B contains detailed variable definitions.

	Unicorn status	
	(1)	(2)
Ln(Assets)	0.292***	0.210***
	(8.014)	(4.610)
Fixed assets/total assets	-0.345	-0.245
	(1.032)	(0.521)
CAPX/total assets	-0.294	-0.643
	(0.446)	(0.759)
Cash/total assets	-0.045	0.077
	(0.255)	(0.384)
COGS/total assets	0.248*	0.330**
	(1.888)	(2.491)
R&D/total assets	0.177	0.134
	(0.936)	(0.573)
SG&A/total assets	0.637***	0.443**
	(3.454)	(2.094)
Sales/total assets	-0.206	-0.260*
	(1.429)	(1.708)
Loss firm	0.294**	0.300**
	(2.308)	(2.180)
Scale	-0.041	-0.091
	(0.604)	(1.321)
Near San Francisco	0.138**	0.167**
	(2.117)	(2.325)
IPO volume$_{t-1}$	0.050	
	(0.921)	
EW IPO first day returns$_{t-1}$	0.852	
	(0.839)	
Real GDP growth$_{t-1}$	-0.106	
	(0.793)	
EW market returns$_{t-3\ to\ t-1}$	-0.027	
	(0.051)	
Aggregate MB$_{t-1}$	-0.271	
	(1.598)	
Credit spread$_{t-1}$	-0.269	
	(0.992)	
Federal funds rate$_{t-1}$	-0.081	
	(0.844)	
Fixed effects		
Industry	No	Yes
Year	No	Yes
Observations	189	189
Adj.R2	0.34	0.40

Appendix A. Details on the sample construction

We use historical snapshots of the CB Insights unicorn list as the starting point for our sample since the inception of the list in 2015. We obtain historical snapshots of the CB Insights unicorn list through the Internet Archive's Wayback Machine at https://archive.org/web/. Using historical snapshots enables us to obtain the names of unicorns that exit between 2015 and 2021Q3, the end of our sample period. From the CB Insights unicorn list, we obtain data on the date of the unicorn round as well as the name of the company and the headquarters address. For each of the unicorns on the CB Insights unicorn list, we download the full funding history with data on all available rounds from CB Insights and obtain data on the name of the round, type of investment (grant, equity round, debt round), names of the key investors, amount raised, post-money headline valuation, and date of the round. We obtain the founding year of the unicorn from Crunchbase. We verify the CB Insights data with funding round data from Crunchbase and Standard and Poor's CapitalIQ. When these databases yield diverging results, we obtain additional information through web-based searches. We exclude a small set of companies from the unicorn base sample when we cannot verify a post-money headline valuation of more than $1 billion or determine that instead of an announced funding round, the company was instead acquired.

Gornall and Strebulaev (2020) provide an online appendix with a list of their sample unicorns as well as all unicorn candidates they examined, compiled from different sources. Their online appendix is available for download free of charge at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2968003. Not all of those unicorn candidates make it to the final sample of Gornall and Strebulaev (2020), because they include additional exclusion filters (founding year before 1994, no VC round after 2004, or unavailability of a certificate of incorporation). We go through the list of all unicorn candidates in appendices B, C, and D of the online appendix to Gornall and Strebulaev (2020) and determine whether they are unicorns according to the CB Insights definition. Gornall and Strebulaev (2020) derive the unicorn status from amended certificates of incorporation that companies file after each additional funding round. As there is an overlap between the Gornall and Strebulaev (2020) sample and our CB Insights sample, we also compare the two data sources for a subset of unicorns. The comparison confirms the high quality of the CB Insights data.

Appendix B. Variable definitions

This appendix contains detailed definitions of dependent and independent variables used in the analysis. Compustat data mnemonics are in italics within parentheses.

Variable name	Description
Dependent variables	
Investor type	A set of indicator variables that identify investor types in a funding round. *Angel* is an indicator variable that equals one if an investor is classified as an angel investor and zero otherwise. *Venture* is an indicator variable that equals one if an investor is classified as a venture capital (VC) firm and zero otherwise. *Asset management* is an indicator variable that equals one if an investor is classified as a bank, mutual fund, sovereign wealth fund, or other asset management firm and zero otherwise. *Corporate* is an indicator variable that equals one if the investor is classified as a corporate venture and zero otherwise. *Growth* is an indicator variable that equals one if an investor is classified as a growth capital firm and zero otherwise.
Unicorn status	An indicator variable that equals one from the quarter a unicorn reached a post-money headline valuation of at least $1 billion until the end of the sample and zero otherwise.
Independent and other variables	
Aggregate MB	The equally weighted average of the market value of common equity (*ceqq*) divided by book value of equity (*cshoq*$\times$*prccq*) across all public firms in a quarter.
Cash/total assets	Cash (*chq*) divided by assets (*atq*).
CAPX/total assets	Capital expenditures (*capxy*) divided by assets (*atq*).
Credit spread	The spread between the yield of Baa-rated corporate bonds and 10-year treasuries at the end of a quarter.
Ex ante SoftBank target industry	An indicator variable that equals one after 2017Q2 for industries targeted by SoftBank when it created its first Vision Fund.
EW IPO first day returns	The difference between the first closing price and the offer price, divided by the offer price, averaged across all firms that went public in a quarter.
EW market returns	Compound monthly returns on the equally weighted index in a quarter.
COGS/total assets	Cost of goods sold (*cogsq*) divided by total assets (*atq*).
Federal funds rate	The effective federal funds rate at the end of a quarter.
Fixed assets/total assets	Fixed assets (*ppentq*) divided by assets (*atq*).
IPO volume	The total number of IPOs, excluding penny stocks, units, and closed-end funds, divided by the total number of listed firms in a quarter.
Ln(Age)	The natural log of age. Age is calculated as the number of years since the minimum of the first year a firm appears in CRSP and the first year a firm appears in Compustat.

Ln(Assets)	The natural log of assets (*atq*).
Ln(Industry funding flow)	The natural log of aggregate funding flows, calculated as the sum of the total amount of funding in an industry-quarter provided to VC-backed startups with more than $50 million in cumulative funding in the CB insights database.
Ln(Flows into buyout funds)	The natural log of new funds raised by buyout funds over the four prior quarters
Loss firm	The percentage of firms in an industry-quarter with negative net income.
Near San Francisco	An indicator variable that equals one if a company is headquartered within 200 miles of central San Francisco.
Real GDP growth	The quarterly growth rate of real GDP.
R&D/total assets	Research and development expenses (R&D, *xrdq*) divided by assets (*atq*). If R&D is missing, it is set equal to zero.
Scale	An indicator variable that equals one if the words "platform," "network," or "connect" appear in the textual description of a firm's business in CB Insights.
SG&A/total assets	Selling, general, and administrative expenses (SG&A, *xsgaq*) minus research and development expenses (R&D, *xrdq*) and in-process R&D (*rdipq*) divided by assets (*atq*). If SG&A, R&D, or in-process R&D are missing, they are set equal to zero. If R&D excess SG&A but is less than COGS, or if SG&A is missing, we do not subtract R&D and in-process R&D from SG&A.
Tobin's q	Book value of assets (*atq*) minus book value of equity (*ceqq*) plus the market value of common equity (*cshoq*×*prccq*) divided by total assets (*atq*).