Create Your Own Valuation *

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Abstract

I find noticeable bunching in venture capital (VC)-backed company valuations at $1 billion, the minimum threshold to be so-called unicorn companies. Exploiting the practice that reported valuations include authorized but unissued shares, VC-backed companies strategically authorize more shares for future employee compensation (e.g., stock options) to achieve unicorn status. Various stakeholders of VC-backed companies, especially employees who face uncertainties and information asymmetry, interpret unicorn status as a positive signal. Contrary to employees' interpretation, however, inflating valuations to achieve unicorn status lowers the expected value of their stock options. Providing simple stock option payoff diagrams to employees can reduce information frictions.

Keywords: Valuation, Startup, Venture Capital, Stock Option, Human Capital
JEL Classification: G24, G32, L26

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High-growth young firms disproportionately create new jobs, innovate, and lead productivity growth (Haltiwanger, Jarmin, Kulick and Miranda (2017), Gornall and Strebulaev (2021a)). These firms are primarily private and venture capital (VC) backed, and VC financing involves a complex structure of securities (Kaplan and Stromberg (2003)). Their valuations are calculated based on a set of unique practices (Metrick and Yasuda (2021)), even making sophisticated institutional investors, such as mutual funds, report different valuations for the same VC-backed company (Imbierowicz and Rauch (2021), Agarwal, Barber, Cheng, Hameed and Yasuda (2022)).

The valuation matters not only for investors but also for other stakeholders such as customers, suppliers, and employees. Given the increased importance of intangible assets over time ((Stulz (2020)), labor is one of the most critical inputs for young VC-backed companies, which are typically human capital-intensive organizations (Zingales (2000)). As an anonymous startup employee review of their employer suggests, '*... comp(ensation) is a little on the lower side given how hot the job market is at the moment but the stock options mostly make up for it...,*' startup employees often receive wages lower than the market rate but also receive stock options, viewed as "lottery tickets" by employees.[1]

In this paper, I find that VC-backed companies use valuations as a signal to employees, one of the most important stakeholders. I show that VC-backed companies systematically stretch their valuations to achieve certain targets, and these inflated valuations make employees more favorably assess the startups they work for. Contrary to employees' interpretation that a high valuation means higher compensation, however, inflating valuations lowers the expected value of employee stock options. Information frictions surrounding VC-backed company valuations can result in employees making sub-optimal career choices, potentially distorting the labor market outcomes.

To start with, I show two distinctive but related bunching patterns in reported startup valuations. First, startups systematically avoid down rounds – raising new capital at a lower share price than they did in the previous financing round. Instead, they disproportionately conduct flat rounds – raising new capital at the same share price as the previous financing round (Figure 1). Second, I document a noticeable bunching at exactly $1 billion, the minimum threshold to be called a unicorn – a private VC-backed company with a valuation of $1 billion or higher. For example, startups are

[1]The anonymous employee review is from Glassdoor, written in March 2021 for 6Sense, a San Francisco-based technology company. The phrase "Stock options as lottery tickets" is from the *Financial Times* article titled "Reality bites for the stock-based pay lottery" written in May 2022 (`https://on.ft.com/3dXqxgV` – Retrieved as of September 2022). Throughout the paper, I use the terms "startups" and "high-growth young firms" interchangeably, referring to private (non-exchange listed) companies that have received external funding from professional investors, such as venture capitalists.

more likely to have a reported valuation of exactly $1 billion than between $850 million and $999 million (Figure 2). I ask *how* startups achieve certain valuations they want, and *why* they do so.

To answer *how* startups stretch their headline valuations, I start from the fact that a company's valuation is the product of price per share and number of shares.[2] While prior studies, such as Gornall and Strebulaev (2020), document that startup valuations can be overstated by applying a single price per share to all shares when different share classes have different rights, I focus on the number of shares side. Using a novel dataset based on California's state security registration exemption filings governing equity-based employee compensation, I find that authorized but unissued shares for future employee compensation (e.g., stock options in employee option pools) account for 11% of the headline valuations. In other words, an average startup with an exact $1 billion valuation would be valued at $890 million if it did not include these unissued shares in the valuation calculation. This calculation is based on the standard practice in venture capital that uses fully diluted shares to derive headline valuations – fully diluted shares not only include outstanding (basic) shares but also all possible conversions, such as convertible preferred stock that venture capital investors hold, employee stock options outstanding, and even authorized but unissued shares in employee option pools (Metrick and Yasuda (2021)).

From the perspective of startups that issue stock options, the value of options is realized over time as employees provide labor to earn those options. Given the uncertainty about whether all of the authorized stock options will be granted, vested, and exercised, treating newly authorized but not yet granted options as having the same value as already outstanding shares is hard to justify. Exacerbating the problem, startups can achieve desirable valuations merely by authorizing more shares. Indeed, I find that technology startups strategically authorize 65% more shares for future employee compensation per dollar raised for financing rounds that lead them to achieve unicorn status, compared to all other financing rounds with a reported valuation of $500 million or higher.

If a startup can easily create its own valuation, why aren't all startups unicorns? My simple back-of-the-envelope calculation shows that authorizing more shares to achieve a higher valuation can be costly – when raising the same amount of capital, existing shareholders may have to dilute their ownership more with a larger option pool. Having more shares in option pools potentially

[2] For private companies, headline valuations are also known as reported valuations and post-money valuations. I use these three terms interchangeably. They are created after each financing round and are defined as *Post-Money Valuation = Pre-Money Valuation + Capital Raised = The Number of Fully Diluted Shares × The Share Price from the Most Recent Financing Round*. I discuss the definition more in detail in Section 4 along with how reported valuations can be overstated.

leads new investors to demand more shares to protect themselves from potential dilutions, all else equal, resulting in diluting the existing shareholders instead. This analysis resembles the discussion of Gornall and Strebulaev (2020, 2021b) about how providing preferential rights, such as liquidation preferences, to new investors can dilute existing shareholders when those rights are exercised.

What types of startups find that the benefits of being a unicorn outweigh the costs of stretching their valuations? To test this, I examine startup financing rounds with reported valuations between $800 million and $1 billion because startups with a $800 million valuation could have achieved $1 billion by authorizing more shares in employee option pools. I find that when top-tier venture capital firms invest, the probability of startups having a valuation of precisely $1 billion increases from 43% to 57%.[3] This probability increases to 84% when technology startups receive funding from top VCs.

To answer *why* certain startups stretch their valuations, I focus on the second bunching pattern: the tendency to achieve unicorn status. I explore the potential benefits of being a unicorn, as Davydova, Fahlenbrach, Sanz and Stulz (2022) do, but exclude the possibility that unicorn status itself attracts sophisticated VCs, given that the bunching at the $1 billion threshold happens more when top VCs invest. Next, I consider startups' operational side, their customers and suppliers, and focus on a particular service provider: human capital. This focus is not only because human capital is one of the most important inputs for startups (Zingales (2000) and Stulz (2020)) but also because the way I identify to inflate reported valuations and achieve unicorn status, authorizing more shares in employee option pools, directly affects employees and the expected payoffs of their stock options.

I hypothesize and find that achieving unicorn status makes employees more favorably assess the startups they work for. This finding is based on within-startup and within-year comparisons using Glassdoor employee review data. In the Internet Appendix, I employ a regression discontinuity design (RDD), using reported valuations as a running variable and $1 billion as a sharp cutoff. This identification strategy exploits the institutional feature that the term "unicorn" was first introduced in 2013.[4] I find a four to seven times larger improvement in employee ratings compared to the correlational (within-startup and within-year) findings.

What are the reasons behind these improved employee assessments? To answer this question, I conduct textual analyses on free-text responses written with numeric review scores. I apply Latent

[3] I define top-tier venture capital firms as the seven firms Metrick and Yasuda (2021) list in Chapter 5: Accel, Benchmark, Khosla Ventures, Kleiner Perkins, New Enterprise Associates (NEA), Sequoia Capital, and Union Square Ventures (USV).

[4] Indeed, bunching at $1 billion began after the term "unicorn' was introduced in the market. Before then, $1 billion was just one of the many round numbers.

Dirichlet Allocation (LDA) models to extract topics discussed in the reviews. I find that employees complain less about compensation, but more about leadership and culture after their employers achieve unicorn status. They also write more positive reviews of employee benefits, including stock options. Overall, employees' satisfaction with their compensation and benefits is the main reason behind the improved assessments, offsetting their complaints about leadership and cultural changes.

Finally, even though employees are more satisfied on account of unicorn status, two findings raise concerns about the value of their stock options. First, authorizing more shares to stretch valuations potentially dilutes existing options and lowers the expected payoffs. Second, I find that startups that bunch at the $1 billion threshold tend to go public less often compared to startups that do not bunch (e.g., $950 million). On top of the illiquidity problem that private companies' shareholders face, private startups typically install various restrictions regarding employee share sales. Thus, even if employees earn and exercise stock options, they will find it harder to monetize them freely. To mitigate this problem, I suggest a simple policy requiring startups to provide a payoff diagram of their stock options based on future exit types and exit valuations.

My study contributes to the literature in three ways. First, I extend the literature on unique and complex features of startup valuations. Prior studies have examined startup financing contracts and valuations, including Kaplan and Stromberg (2004), Korteweg and Sorensen (2010), and Fu, Jenkinson and Rauch (2022). In particular, Gornall and Strebulaev (2020, 2021b, 2022) study how venture capital financing affects existing shareholders differently, focusing on the price-per-share side of the valuation. I examine the number-of-shares side, documenting the magnitude of reported valuations attributable to unissued shares in employee option pools.

Second, I contribute to the literature examining how finance-related signals affect decision-making under uncertainty (Megginson and Weiss (1991) and Bernstein, Mehta, Townsend and Xu (2022), among others). Like Hsu (2004), who finds that entrepreneurs are willing to pay for a reputable VC affiliation, I ask what types of startups are willing to pay for unicorn status.

Third, I contribute to the literature examining equity-based compensation. For example, Hellmann and Puri (2002), Kahl, Liu and Longstaff (2003), Oyer and Schaefer (2005), Bergman and Jenter (2007), Babenko, Du and Tserlukevich (2021) study issues surrounding equity-based compensation for non-executive employees. Importantly, as Aran and Murciano-Goroff (2021) find, employees might form expectations on stock options based on irrelevant signals. This problem can be exacerbated, given that startups can strategically inflate their valuations, which determine stock option values. My simple policy suggestion to disclose a stock options payoff schedule, in effect treating startup employees as pseudo-angel investors, would help employees form accurate expectations and make more informed career and investment choices.

1. Conceptual Framework

Startups need capital to finance their growth. The pecking order theory of capital structure predicts startups would first seek debt financing (Myers and Majluf (1984)). However, their businesses frequently rely on intangible assets, such as human and organizational capital, making them unsuitable to collateralize to secure debt financing. These intangible assets are hard to value for the majority of public market investors (Stulz (2020)). Thus, startups typically receive funding from specialized investors, primarily venture capitalists.

The startup's venture capital financing environment can be characterized by two major economic frictions – uncertainty and information asymmetry. In response to the high level of uncertainty, startup financing usually takes the form of stage financing. For example, if a startup's planned investment project requires a total \$100 million investment, the startup does not raise \$100 million at once. Instead, it would secure, say, \$10 million to conduct an initial development and test the waters. If the outcome turns out to be promising, the startup will raise further capital. On the other hand, if the initial development suggests that the planned investment is not a positive net present value (NPV) project, both the startup and the investor (venture capitalist) can exercise an abandonment option. The real option is a key feature of startup financing, which entails high uncertainty (Gompers (1995), among others).

Even though venture capitalists are sophisticated and specialized investors, they typically have less information about the uncertain future of the startup's businesses than the founders. In response to this information asymmetry and the potential agency problem, venture capital financing mainly involves issuing convertible preferred stock, which is senior to common stock in the capital structure but can be converted into common stock. Moreover, the convertible preferred stock almost always comes with various liquidation preference clues (Metrick and Yasuda (2021)), allowing venture capitalists to protect themselves against downside risks while keeping the upside potential.

1.1. Supply and Demand for the Unicorn Status

Uncertainty and information asymmetry, two major economic frictions in the startup financing environment, incentivize startups to both send out and interpret various signals ((Gompers, Kovner, Lerner and Scharfstein (2008, 2010), Bernstein, Korteweg and Laws (2017)). Valuations, in particular unicorn status, can serve as an important signal in this environment.

Following the seminal work of Spence (1973), let's assume that there are two types of startup, A and B, whose fair valuations are both \$900 million. They both have an option to stretch their valuations to \$1 billion, achieving unicorn status, by taking advantage of how startup valuations are determined, which I discuss in Section 4. Unicorn signaling has one key difference compared to the original model of Spence (1973) – the costs of sending a signal (inflating valuations) are the same between firms A and B while the benefits are different.

On the cost side, stretching valuations from \$900 million to \$1 billion is not free. The key intuition is that the existing shareholders, including founders, have to dilute their ownership to inflate reported valuations, as I later discuss in Section 5.1 and Table 5. The dilution cost is a function of how much startups inflate their valuations, making the costs equal between firms A and B if they are both valued at \$900 million.

Instead, I hypothesize and show in Section 6 that the benefits of unicorn status differ across startups. Startups have various stakeholders, such as existing investors, potential new investors, employees, customers, and suppliers. For example, assume that firm A is a consumer-targeting space tourism company, and firm B is a biotechnology company working on developing a type 2 diabetes drug. While both A and B face uncertainties, firm A's outsiders, such as potential rank-and-file employees, will find it especially hard to evaluate the success probability of the business, not to mention that it is hard to assess what the market size will be even if firm A succeeds. On the other hand, the overall market size of type 2 diabetes patients is already known, and the success probability of the new drug development can be reasonably estimated by the U.S. Food and Drug Administration (FDA) approval process.

In a nutshell, the cost of stretching valuations to become unicorns is the function of the true valuation (i.e., \$900 million for both firm A and B in the above example), same across different firms, $C_A = C_B$. On the other hand, the benefit of being a unicorn differs (x) between Firm A, $U_A x$, and Firm B, $U_B x$. Then there is a certain valuation threshold that firms similar to firm B do not find it optimal to inflate valuations to become unicorn, while firms similar to firm A still do, resulting in a situation similar to a separating equilibrium ($U_A x > C_A$ and $C_B > U_B x$).

Lastly, while public companies' valuations (measured as the market capitalization of equity) change constantly reflecting the market's evaluation, startups' valuations determined from previous funding rounds remain the same until they raise new capital (Metrick and Yasuda (2021)).[5] The average time between two financing rounds in my sample is 14 months. This long-lasting nature of startup valuations makes them even more important.

2. Data and Sample Construction

I use four main data sources. I identify private startups' financing events from Pitchbook. Pitchbook data have both startup- and financing round-level information, such as the age and industry of startups, deal sizes (capital raised), share prices, and post-money valuations. I use Certificates of Incorporation filings, which include various contractual terms for each financing round, to augment Pitchbook data. I collect data on the stock-based employee compensation from the California state government's security registration requirement exemption filings – Corporations Code Section 25102(o) Employee Plan Exemption Notice (EPEN). Finally, I collect employees' review data from Glassdoor, a website where employees anonymously rate and review their employers. In Appendix A1, I provide more information about the data sources and related institutional details.

My sample consists of startup financing rounds with a post-money valuation of $500 million or higher between January 2002 and December 2021. Pitchbook reports 3,996 financing rounds by 2,421 unique startups satisfying these conditions. I restrict the sample to U.S. headquartered companies, having 2,372 financing rounds by 1,397 unique startups. For some analyses, I further restrict the sample to California headquartered companies: 1,388 financing rounds by 770 unique startups. Panel A of Table 1 shows key deal-level summary statistics for all startups. Panel B shows the same statistics for California headquartered startups.[6]

[5]Unlike public companies, there is no liquid and systematic secondary market for private startups' shares. Secondary transaction platforms for private startup shares have been growing recently. However, transactions on these platforms are considerably more expensive and less liquid than public markets. Moreover, even if secondary transactions occur, startups' headline valuations from previous rounds are still quoted as their valuations until they conduct a new financing round.

[6]In Table 1, I provide statistics for U.S.-headquartered VC-backed companies with a post-money valuation of $500

— PLACE TABLE 1 ABOUT HERE —

I collect a total of 24,782 California Employee Plan Exemption Notice (EPEN) filings filed between January 2014 and December 2021 from the California Department of Financial Protection and Innovation website.[7] Figure A1 shows an example of the notice filed by 23andMe Inc. in 2015. Panel C of Table 1 shows that, on average, startups authorize 4.79 million shares for future stock-based employee compensation (full data).[8] For the filings that are matched to startup financing rounds with a reported valuation of $500 million or higher, the average is 10.32 million shares (matched sample). Based on the industry practice that startups add new shares to employee option pools each time they raise new capital, this number implies that each financing round comes with authorizing 4.79 million shares (or 10.32 million shares for the matched sample) for future employee compensation.

I map Pitchbook with EPEN, and it produces a total of 515 financing rounds. (Appendix A1 explains the mapping procedure.) The reduction from Pitchbook's total of 1,388 deals to 515 deals is based on several reasons. First, while Pitchbook's sample period is between January 2002 and December 2021, California EPEN filing's sample period is between January 2014 and December 2021. Second, financing rounds in 2021 from Pitchbook are mostly not yet ready to be mapped to EPEN filings, because most startups file EPEN notices well after funding rounds based on the filing requirements I discuss in Appendix A1. The venture capital market boomed in 2021, having more deals in 2021 than any other year. Out of 515 mapped rounds, 165 are unicorn rounds in which startups achieved valuations of $1 billion or higher for the first time.

For Glassdoor rating and review data, I start from 770 California headquartered startups identified by Pitchbook. I search Glassdoor for reviews written about these startups between January 2014 and September 2021. Out of 770 companies, I find 504 companies, with a total of 76,794 reviews (i.e., 152 reviews per company on average).[9] Panel D of Table 1 shows that the average rating score is 3.9, with 1 being the lowest and 5 the highest.

million or higher. Davydova et al. (2022) provide more comprehensive statistics of U.S.-based unicorn companies.

[7] https://docqnet.dfpi.ca.gov/search retrieved as of September 2022

[8] I winsorize outliers by converting fewer than 1,000 shares to 1,000 shares and converting more than 1 billion shares to 1 billion shares. My results are robust to different cutoffs.

[9] I do not impose company-level conditions, such as each company should have at least a certain number of reviews. This is because the focus of my study is the group of startups with certain valuation ranges, not each specific startup.

3. Startup Financing and Valuation Bunching

In this section, I document startups' valuation bunching behaviors in two unique settings.[10] The first bunching, documented by Figure 1, is consistent with the startups' tendency to avoid down rounds. Down rounds are defined as startups raising capital in a given round with a share price lower than their previous round's share price. In practice, since startups' share prices are only updated when they raise new equity capital, down rounds can also be defined as startups raising equity capital based on a pre-money valuation lower than their previous round's post-money valuation. In most cases, conducting a down round triggers downside protection clauses that recent investors with convertible preferred shares hold, further diluting earlier shareholders, especially founders and employees who hold common shares. (For a more detailed discussion of downside protections, see Metrick and Yasuda (2021) and Gornall and Strebulaev (2021b)) Thus startups face strong incentives to avoid down rounds, as documented in Figure 1.

— Place Figure 1 About Here —

To provide a benchmark, I calculate the change in valuations from one financing round to the next. Panel A of Figure 1 compares the pre-money valuation of a startup's given round (Pre-Money_t) to the post-money valuation of its previous round (Post-Money_{t-1}).

- Down rounds are when: $\text{Post-Money}_{t-1} > \text{Pre-Money}_t$ (or, $\text{Share Price}_{t-1} > \text{Share Price}_t$)
- Flat rounds are when: $\text{Post-Money}_{t-1} = \text{Pre-Money}_t$ (or, $\text{Share Price}_{t-1} = \text{Share Price}_t$)
- Up rounds are when: $\text{Post-Money}_{t-1} < \text{Pre-Money}_t$ (or, $\text{Share Price}_{t-1} < \text{Share Price}_t$)

Panel A of Figure 1 shows that there is a sharp spike at flat rounds. On the other hand, Panel B of Figure 1 compares the post-money valuation of a startup's given round (Post-Money_t) to the post-money valuation of its previous round (Post-Money_{t-1}) – a reasonable benchmark, but it is *not* used to define down rounds in practice. The purpose of this comparison is to illustrate that there is a sharp bunching pattern in Panel A, the benchmark that defines down rounds, but not in Panel B, a reasonable alternative that does not define down rounds.

The second bunching pattern that I document in Figure 2 is more nuanced and requires some background to understand. Ewens and Farre-Mensa (2022) discuss the growth of private capital

[10] Studies have found bunching patterns in other settings, such as Burgstahler and Dichev (1997) in reported earnings, Saez (2010) in income taxes, and Ewens, Xiao and Xu (2022b) in public float.

markets, especially the exponential growth of late-stage venture capital-backed companies. They find that, starting in 2019, the U.S. headquartered private startups raised more capital from their late-stage VC financing rounds compared to what the U.S.-listed public companies raised by combining initial public offerings and follow-on offerings (seasoned equity offerings).[11] In a similar vein, Kwon, Lowry and Qian (2020), Chernenko, Lerner and Zeng (2021), and Agarwal et al. (2022) document that mutual funds, once thought to be exclusively investing in public companies, started to invest in late-stage VC financing rounds along with hedge funds.

The growth of private capital markets is not just a recent phenomenon. The gradual influx of capital into private markets over time allowed a growing number of startup companies to stay private longer while becoming larger. In November 2013, observing this trend, venture capitalist Aileen Lee posted an article on Tech Crunch titled "Welcome to The Unicorn Club: Learning from Billion-Dollar Startups."[12] Her posting was the first to label unlisted VC-backed startups with a valuation of $1 billion or higher as "unicorns." Silicon Valley thus started to consider being a unicorn as a milestone achievement for VC-backed startups.

Figure A2 shows that in 2013 and earlier years, startups with a valuation of $1 billion were still rare enough to be called unicorns. Based on Pitchbook data, only 33 VC-backed startups reached a $1 billion valuation prior to 2014, while there were 337 in 2021 alone. The number of unicorn startups started to grow exponentially, coinciding with the decline in the number of U.S. public companies documented by Gao, Ritter and Zhu (2013) and Doidge, Karolyi and Stulz (2017).

Reflecting the importance of this particular valuation threshold, Panel A of Figure 2 shows a noticeable pattern that startups are bunching at the $1 billion valuation threshold, achieving unicorn status. This finding comports with the findings of Brown and Wiles (2015, 2020) and Davydova et al. (2022) that about 27−30% of unicorns have a post-money valuation of exactly $1 billion.

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There can be two potential concerns or alternative explanations regarding this stark bunching pattern at the unicorn threshold. The first concern with my findings in Figure 1 and Figure 2 is that both figures are based on Pitchbook data, and every data provider is prone to errors. This concern is not severe for Figure 1, as I find the bunching pattern only when I compare Pre-Money$_t$

[11] Ewens and Farre-Mensa (2022) define late-stage as series C or later. See their Figure 1 for more details.

[12] https://techcrunch.com/2013/11/02/welcome-to-the-unicorn-club retrieved as of September 2022

to Post-Money$_{t-1}$ (definition of down rounds), not when I compare Post-Money$_t$ to Post-Money$_{t-1}$ (*not* a definition of down rounds). However, the bunching pattern I document in Figure 2 can raise concerns that Pitchbook might round up valuations to the nearest round numbers (e.g., $1,000 million instead of $998 million). Even worse, Pitchbook may make reporting errors.

I examine these concerns in Appendix A1 with Table A1. I randomly select ten deals with the exact $1 billion post-money valuation reported by Pitchbook and compare it to independent sources, such as press releases and news articles. I verify that 8 out of 10 deals have independent sources stating that these deals had exactly $1 billion valuations. For the remaining 2 out of 10 deals, one deal had a newspaper article referring to Pitchbook as a data source. I cannot find third-party sources for only one deal. Combined with the fact from both Figure 1 and that this bunching pattern was salient in 2015 or later only, Table A1 assures the reliability of Pitchbook data and my analysis.

Second, $1 billion is a well-rounded number, and it is widely shown in various settings that round numbers are preferred to non-round numbers. For example, Panel A of Figure 2 shows that $800 million valuation is preferred to $750 million. However, Panel A reports deals completed between January 2015 and December 2021 only. Panel B of Figure 2 documents the same distribution of deals completed between January 2002 and December 2014 – the bunching pattern in Panel B is noticeably weaker than in Panel A.

This structural break can be explained by the fact I discussed earlier that the term "unicorn" was first introduced in November 2013. Figure A2 shows that there were no *Wall Street Journal* or *Financial Times* articles including the two words "venture" and "unicorns" together before 2014. Articles mentioning the two words together started to appear in late 2014 – about three-fourths of the 2014 articles were published in the last quarter. Therefore, in 2014 or earlier, $1 billion was just another round number, such as $700 million.

This difference suggests that the well-round number preference can explain the weaker bunching pattern in Panel B of Figure 2 – the magnitude at $1 billion in Panel A of Figure 2 is too stark to be explained without the term unicorn. Overall, the outcomes from Figures 1 and 2 are consistent with the possibility that startups *create* their own valuations to achieve unicorn status.

4. How to Create Your Own Valuation

In this section, I explore *how* startups achieve desirable valuations, as I find in Figures 1 and 2. The textbook definition of an all-equity company's valuation is

$$\text{Valuation} = \sum_{t=1}^{T} \frac{FCF_t}{(1+R_t)} = \text{Price per Share} \times \text{Number of Shares Outstanding}$$

where FCF_t refers to a company's free cash flow at time t and R_t refers to an appropriate discount rate for time t, assuming that the company liquidates at time T with the liquidation value of FCF_T. In other words, valuation equals the present value of future free cash flows. A company's stock price in public markets should be equal to the valuation divided by the number of shares outstanding.

Valuations should be calculated the same for companies regardless of their public or private status. Compared to public companies, however, private startups typically have a more complex capital structure (i.e., have different classes of shares), and they follow a set of unique practices. Reported valuations, also known as headline valuations and post-money valuations, are created after each financing round and are defined as *Reported Valuations = Pre-Money Valuation + Capital Raised = The Share Price from the Most Recent Financing Round × The Number of Fully Diluted Shares*. Both *The Share Price from the Most Recent Financing Round* and *The Number of Fully Diluted Shares* allow a startup to create its own valuation.

For the price per share side, Gornall and Strebulaev (2020) document the industry practice of applying *The Share Price from the Most Recent Financing Round* to all securities, including common shares, results in reported valuations overstated by 48% on average. This is because new security issued in the most recent financing round typically includes preferential rights that other securities do not have, as pointed out by Metrick and Yasuda (2021) as well. For example, Gornall and Strebulaev (2020) show that Square Inc. raised $150 million in October 2014 in its series E financing round with a share price of $15.46. Series E investors had downside protection clues, including liquidation preferences and IPO ratchets. Based on their valuation model, Gornall and Strebulaev (2020) estimate that common shares, which did not have any downside protection clues, were only worth $5.62 per share. Thus, multiplying the series E share price of $15.46 by common shares that are worth only $5.62 per share results in overvaluing common shares by 175% ($= \frac{\$15.46-\$5.62}{\$5.62}$), and eventually overstating its reported valuation.

In this study, I focus on how *The Number of Fully Diluted Shares* can inflate headline valuations, a possibility that has not been empirically examined in the literature. For example, Gornall and Strebulaev (2020) made certain assumptions regarding *The Number of Fully Diluted Shares* to estimate the difference between reported valuations and fair valuations.

In the following sections, I discuss an industry practice that when calculating headline valuations, *The Number of Fully Diluted Shares* includes not only outstanding shares (basic shares) but also all possible conversions, such as convertible preferred stock that venture capital investors typically hold, stock options outstanding, and even authorized but unissued shares in employee option pools (Metrick and Yasuda (2021)). I discuss how startups can stretch their reported valuations, which are calculated on a fully diluted basis, by authorizing more shares in employee option pools. Finally, I estimate the magnitude of reported startup valuations that can be explained by including authorized but not yet issued shares in employee option pools.

4.1. Basic Valuation v.s. Fully Diluted Valuation v.s. Headline Valuation

The distinction between basic valuation and fully diluted valuation is how to define the number of shares outstanding. Basic valuation considers only outstanding shares (i.e., basic shares). On the other hand, fully diluted valuation considers the maximum number of shares based on a scenario in which all the outstanding warrants, options, and convertible securities will be converted to common shares (i.e., fully diluted shares). For the conversion of options, fully diluted valuation implicitly assumes that options have a zero exercise price, in which case their value is the same as a common share, assuming no dividend payments prior to exercise. Thus, a company's "true" valuation lies somewhere between the basic valuation and the fully diluted valuation.

Using Facebook Inc. (currently Meta Platform Inc.)'s IPO, I explain the difference between basic valuation and fully diluted valuation in Table 2. I introduce two different versions of fully diluted valuation. Facebook went public in 2012 with an offer price of $38 per share.[13] It had 2,138 million shares outstanding after the public offering. It had 603 million stock options that had been granted but not yet exercised. It also had 77 million shares reserved (authorized but not yet issued) for future issuances.[14] Based on these three numbers (2,138 million, 603

[13]See https://www.sec.gov/Archives/edgar/data/0001326801/000119312512235588/d287954ds1a.htm

[14]The exact phrase for these 77 million shares in Facebook's S-1 filing: *77,466,293 shares of our common stock reserved for future issuance under our equity compensation plans, consisting of 25,000,000 shares of Class A common stock reserved for issuance*

million, and 77 million), I define three versions of Facebook's valuation: 1) basic valuation method, 2) fully diluted valuation method widely used by public companies, 3) fully diluted headline valuation method widely used by private startups.

— PLACE TABLE 2 ABOUT HERE —

The difference between the basic and fully diluted (public) valuation is 28% (= $\frac{603M}{2{,}138M}$ = $\frac{\$104B-\$81B}{\$81B}$). The difference between the basic and fully diluted (private: headline) valuation is 32% (= $\frac{603M+77M}{2{,}138M}$ = $\frac{\$107B-\$81B}{\$81B}$). The 28% (or 32%) difference is substantial – this difference is usually wider for VC-backed or formerly VC-backed companies that heavily rely on stock-based compensation. However, these companies rely less on stock-based compensation as they mature and create stable operating cash flows. Facebook's (Meta Platform's) 10-Q quarterly financial statements as of June 2022 report that it has 2,688 million shares outstanding with 158 million shares of outstanding stock options and RSUs – resulting in a 6% difference (= $\frac{158M}{2{,}688M}$), a substantial decrease from 28%.

In the startup world, it is customary to report valuations based on a single "fully diluted (private: headline)" method that led to $107 billion valuation for Facebook's IPO (Metrick and Yasuda (2021)). The number of shares outstanding for reported startup valuation calculations includes 1) granted and fully vested stock options (and RSUs), regardless of moneyness; 2) granted but not yet vested stock options (and RSUs); and 3) authorized but not yet granted stock options (and RSUs), also known as the option pool.[15]

4.2. Startup Option Pools: Authorized but Unissued Shares

Studies point out the growing usage of stock options by companies (Hall and Murphy (2003), Fama and French (2005), and Babenko, Lemmon and Tserlukevich (2011), among others). Receiving labor now and but, in effect, paying employees later by issuing stock options would be valuable for the firms that need to invest in intangible assets to grow but do not have enough cash to pay the employees higher salaries now (Sun and Xiaolan (2019)). Thus almost all high-growth startups utilize stock-based compensation. To do so, they establish employee

under our 2012 Equity Incentive Plan, and 52,466,293 shares of Class B common stock reserved as of March 31, 2012.

[15]In addition to the inclusion of authorized but unissued shares, the headline valuation method also applies the price of the securities issued in the most recent round to all equity securities, including common shares with no preferential rights. Gornall and Strebulaev (2020) discuss this practice in depth.

option pools – a pool of authorized but unissued shares held for future employee compensation. Each financing round usually involves startups authorizing and reserving extra shares in their option pools (Gornall and Strebulaev (2022)). Because of the practice's dilutive nature, granting stock options typically requires approval from the company's board of directors or shareholders. Establishing a pre-approved option pool gives startup management more flexibility. Also, a sizeable option pool can help attract employees.

In Section 4.1, I provide an example of public company valuations based on the Facebook (currently Meta Platform) IPO in Table 2. I include an additional example in Table 2 illustrating how employee option pools affect reported startup valuations based on a consumer-based healthcare technology company 23andMe Inc. On July 2, 2015, 23andMe Inc. announced that it agreed to raise $115 million in its series E round. According to Pitchbook, the deal was closed on October 14, 2015, and the reported post-money valuation was $1.05 billion. It was the first time that 23andMe Inc. had a valuation exceeding the $1 billion threshold. On August 20, 2015, between the announcement (July 2, 2015) and the closing (October 14, 2015) of this unicorn round, 23andMe Inc. filed a notice to the California state government under the California Corporations Code Section 25102(o).[16] The filing states that the company renewed its 2006 Equity Incentive Plan (an option pool) by authorizing an additional 11,392,717 shares (See Figure A1 for the actual filing document).

To raise $115 million, 23andMe Inc. issued 10,621,329 new shares with a price per share of $10.83, according to Pitchbook. The company's reported post-money valuation was $1.05 billion, with 96,952,908 total shares. That total includes 11,392,717 newly authorized shares added to the option pool (2006 Equity Incentive Plan). Based on the industry practice of applying the most recent round's share price, $10.83, to all share classes (Gornall and Strebulaev (2020)), the value of the 11,392,717 additional shares in the option pool was $123 million (= $10.83 $\times$ 11,392,717). That value slightly surpasses the amount of capital raised ($115 million), and represents 11.7% of the reported post-money valuation (= $\frac{\$115M}{\$1{,}050M}$).[17]

From a strictly economic point of view, these new shares reserved in the option pool should not be included in the valuation because the corresponding labor to earn them has not yet occurred (Gornall and Strebulaev (2020)). In other words, authorizing shares itself does not add value to the

[16] Section 2 explains the California Corporations Code Section 25102(o) in detail.

[17] A caveat of the California Corporations Code Section 25102(o) data is that I cannot distinguish between authorized but not granted shares and granted shares, leaving the fully diluted (public) row blank in Table 2.

company. The value is created when stock options are vested – that is, when employees provide labor to earn these options. Even if we assume that valuations are forward-looking and the newly authorized shares represent the present value of labor in the future, treating unissued shares the same as already outstanding shares is hard to justify.

However, Metrick and Yasuda (2021) and Gornall and Strebulaev (2020) point out the common practice in the startup and venture capital industry that even unissued shares reserved for future grants are included in the post-money headline valuation calculation. This practice is consistent with the optimism in the startup world (Camerer and Lovallo (1999), Puri and Robinson (2013), and Astebro, Herz, Nanda and Weber (2014), among others). These unissued shares will become outstanding if startups prosper – if they were to hire more people and grant all of the stock options reserved in the pool, and if all the stock options were to be vested and exercised.

4.3. Excluding Option Pools – Losing Unicorn Status

In this section, I estimate how many authorized but unissued shares are included in startup employee option pools. Specifically, in Table 3, I show the percentage of post-money valuations that unissued shares in option pools account for. The sample consists of California-based private startups' unicorn rounds, financing rounds reaching reported post-money valuations of $1 billion or higher for the first time. Panel A of Table 3 reports the number of newly authorized shares divided by the deal size (i.e., capital raised) of the associated financing round. In this way, Panel A measures how many new shares for future employee compensation are authorized per $1 million raised. Panel B reports the value of increased option pools (calculated as *the number of newly authorized shares* × *price per share of the most recent financing round*) as a fraction of the deal size and the post-money valuation.[18]

— PLACE TABLE 3 ABOUT HERE —

Table 3 shows that, on average, 11% of reported startup valuations of unicorn rounds can be explained by newly authorized shares reserved for future employee compensation.[19] This result

[18]The correct value of reserved shares in employee option pools should be calculated using common share prices, not based on prices of convertible preferred shares issued to new investors in that financing round (Gornall and Strebulaev (2020)). In practice, however, reported valuations are calculated by multiplying the price of shares issued in the most recent financing round by the number of fully diluted shares (Metrick and Yasuda (2021)). Accordingly, I use the price of the most recently issued convertible preferred shares, not common shares, to have an apples-to-apples comparison.

[19]This average is close to 23andMe Inc.'s 11.7%.

extends Gornall and Strebulaev (2020)'s work that unicorn startups' reported valuations are on average 48% above their fair values. Gornall and Strebulaev (2020)'s calculation assumes that authorized but not granted stock options account for 5% of the reported post-money valuation, leaving out the exact magnitude for future research. Although my sample period differs from theirs, if I apply 11% to their model, the magnitude of unicorn startups' overvaluation becomes even greater than 55% (See Table 8 of Gornall and Strebulaev (2020)).

In panel A of Figure 4, using the subsample of California startups with matched EPEN filings, I find a similar valuation bunching pattern, which I show in Panel A of Figure 2 and which is based on all U.S. headquartered startups. I find that this bunching can be achieved by authorizing more shares in employee option pools and including them in the fully diluted number of shares. In panel B of Figure 4, when I calculate post-money valuations excluding unissued shares in employee option pools from the number of shares calculation, I find no bunching. Based on this sharp contrast between Panels A and B, I conclude that, following a simple economic rationale, not-yet issued shares should not have the same value as outstanding shares, which would remove the unusual bunching pattern – startups at exactly a $1 billion valuation would lose their unicorn status.

— PLACE FIGURE 4 ABOUT HERE —

4.4. Authorizing More Shares for Unicorn Rounds

Do startups disproportionately authorize more shares in financing rounds that led them to achieve unicorn status? To answer this question, I examine the size of new shares in option pools (*the number of newly authorized shares* $\times$ *price per share of the most recent financing round*) as a fraction of the deal size (i.e., capital raised)). I divide my sample into three different groups based on post-money valuations: 1) pre-unicorn rounds (i.e., financing rounds with a valuation of $500 million or higher but lower than $ 1 billion), 2) unicorn rounds (i.e., financing rounds that achieve a valuation of at least $1 billion for the first time), and 3) post-unicorn rounds (i.e., financing rounds that have a valuation of at least $1 billion for the second time or later).[20] Based on this classification, I run the following regression:

$$\frac{Option\ Pool(\$)_i}{Deal\ Size(\$)_i} = \beta_1 Unicorn\ Rounds_i + \beta_2 Tech\ Startups_i + \beta_3 Unicorn_i \times Tech_i + X_i + \lambda_t + e_i \quad (1)$$

where $Option\ Pool(\$)$ is the number of newly authorized but unissued shares in the option pool × the price per share. $Option\ Pool(\$)$ is same as *Value of Shares ($M)* in Panel B of Table 3. $Deal\ Size(\$)$ is the amount of capital raised for that financing round. $Deal\ Size(\$)$ is same as *Deal Size ($M)* in Panel B of Table 3. $Unicorn\ Rounds$ is a dummy variable that equals 1 if startups achieve unicorn status for the first time from this financing round. $Tech\ Startups$ is a dummy variable that equals 1 if the financing round is conducted by startups in the technology industry based on Pitchbook's classification. $Unicorn \times Tech$ is an interaction term between $Unicorn\ Rounds$ and $Tech\ Startups$. X is a vector of control variables, including a dummy variable for top VCs investing, a dummy variable representing each financing round sequence (e.g., series A as 1, series B as 2...), the natural logarithm of the startup age (year of the financing round − startup founding year), the natural logarithm of days between the date of the current financing round and the date of the previous financing round (if previous financing round information is unavailable, I subtract 250 days). I include year-fixed effects based on the year of the financing round (λ_t).

Column (1) of Table 4 shows that, compared to pre- and post-unicorn financing rounds of California startups that eventually achieve unicorn status, unicorn rounds do not authorize more shares in employee option pools. On the other hand, column (2) shows that technology startups tend to authorize more than other startups, such as biotechnology and energy firms. When I interact unicorn rounds with technology startups, column (3) shows that technology startups tend to authorize particularly more shares in employee option pools in financing rounds that lead them to achieve unicorn status. The magnitude, 65.2%, is both economically and statistically significant. The null hypothesis is that the size of option pools, relative to the deal size, should be the same across rounds for any startups, including technology startups. This is because the growth of option pools represents future employment growth, and the future employment growth should be reflected in the deal size. Not surprisingly, startups tend to raise substantially more capital in later rounds as they need more employees.

[20] Down rounds making unicorn startups non-unicorns happen in my larger sample. However, my sample for this particular analysis does not include any down rounds removing unicorn status.

— PLACE TABLE 4 ABOUT HERE —

Results from Table 4 are consistent with the view that technology startups strategically authorize relatively larger option pools in unicorn rounds, allowing them to achieve unicorn status. The follow-up question is if you can create your own valuations, why don't all startups do it? In Section 5, I examine whether any costs are associated with authorizing more shares in employee option pools to stretch valuations.

5. Determinants of Valuation Bunching and its Costs

Figures 2 and 4 show that not all startups stretch their valuations to achieve unicorn status. Based on my findings from Table 3, startups with a post-money valuation of, say, $950 million presumably could have achieved a $1 billion valuation. Also, Table 4 shows that technology startups authorize more shares in employee options pools, particularly in financing rounds where they achieve unicorn status. In this section, I examine why certain startups stretch their valuations to achieve unicorn status while others do not. I first explore potential costs associated with stretching valuations by authorizing more shares in employee option pools.

5.1. Costs of Bunching: Extra Dilution

If startups can easily create their own valuations, why aren't all startups unicorns? In this section, I show that inflating reported valuations is not free. As a company's valuation is the product of price per share and number of shares, there are two ways to inflate reported valuations – the price per share side and the number of shares side.

For the price per share side, Gornall and Strebulaev (2021b) show that granting preferential rights to the new investors to increase the price per share can make existing shareholders worse off. By focusing on the number of share side, I find a similar conclusion. In Table 5, I conduct a back-of-the-envelope calculation showing that achieving a higher valuation by authorizing more shares is not free – existing shareholders, including founders and employees, may dilute their ownership more to raise the same amount of capital.

— PLACE TABLE 5 ABOUT HERE —

Assume that a startup with a present value of all future free cash flows (or pre-money valuation) of \$600 million wants to raise \$200 million. Then the post-money valuation will be \$800 million, and existing shareholders will own 75% and new investors will own 25% of the startup. However, if the startup wants to include an employee option pool worth 25% of the pre-money valuation, then new investors will demand 25% more shares compared to the case without an option pool. The reported valuation numbers for three groups will be: \$600 million for existing shareholders, \$150 million (\$600 million $\times$ 25%) for employees that receive the options, and \$250 million (\$200 million $\times$ 125%) for new investors, making the headline valuation to be \$1,000 million.

Why would new investors demand extra shares when none of the shares in employee option pools have been granted to employees yet? This is because although new shareholders may participate in the board and provide guidance on hiring and compensation decisions, they have limited control over future dilution. Instead, existing shareholders, including founders and management, typically decide how many stock options to grant, employees decide how many shares will be vested, and the future startup stock price will decide how many will eventually be converted to common shares.

Thus new investors find it rational to demand more shares upfront – up to 25% in this case – when startups authorize more shares in employee option pools, potentially diluting new shareholders' ownership. This is to have the same ownership (25%) of the post-money valuation for the same capital invested (\$200 million), regardless of the ownership structure of existing shareholders. In practice, how many extra shares will be issued to new investors depends on different factors, such as the expectation of the magnitude of potential dilution and the bargaining dynamics between new and existing investors.

Assuming that new shareholders receive the maximum protection (i.e., receiving 25% more shares for the option pool, which is equivalent to 25% of the pre-money valuation), what would be the eventual wealth and ownership distributions among the three parties? I show two examples based on both ends of the spectrum – when all of the shares in the employee option pool will be converted to common shares (full conversion), and when none of the shares in the employee option pool will be converted to common shares (no conversion).

For the full conversion case, existing shareholders will own 60% of the startup (\$480 million), employees that receive the options will own 15% (\$120 million), and new investors will

	No Option Pool		Option Pool				
			Headline	Full Conversion		No Conversion	
	Wealth	% Own	Valuation	Wealth	% Own	Wealth	% Own
Existing Investors	$600M	75%	$600M	$480M	60%	$565M	71%
Option Pool	$0	0%	$150M	$120M	15%	$0	0%
New Investors	$200M	25%	$250M	$200M	25%	$235M	29%
Total (Post-money)	$800M	100%	$1,000M	$800M	100%	$800M	100%

own 25% ($200 million). Compared to the no option pool case, the total value of the startup ($800 million) and the new investors' ownership percentage (25%) do not change.[21] For the no conversion case, existing shareholders will own 71% ($\$800\text{M}\times\frac{\$480\text{M}}{\$480\text{M}+\$200\text{M}}$) of the startup ($565 million rather than $600 million), and new investors will own 29% ($\$800\text{M}\times\frac{\$200\text{M}}{\$480\text{M}+\$200\text{M}}$) of the startup ($235 million rather than $200 million).

The fact that existing shareholders, including founders, have to dilute their ownership, regardless of whether newly authorized shares in employee option pools are converted or not, explains why some startups stay with the reported valuation of $900 million, instead of stretching to exactly $1 billion. Furthermore, the headline valuation number is calculated following a widely used convention. Although the "fake it till you make it" mantra is popular in Silicon Valley, if a firm stretches its valuation too far, it may lose its credibility.[22]

5.2. Who are the Bunchers?

To answer which startups stretch their valuations to achieve unicorn status and which do not, I focus on financing rounds by U.S. headquartered startups with post-money valuations of between $800 million and $1 billion from January 2015 to December 2021.[23] There is a total of 560 financing rounds meeting these conditions, 247 (44%) with exactly a $1 billion valuation and 313 (56%) with valuations between $800 million and $999 million. This focus on a narrow valuation band is based on Table 3's conclusion that it is reasonable to assume that startups can and do stretch valuations up to

[21]This calculation is based on the assumption that the option pool does not add any value to the company. On the other hand, if employees provide the same labor but receive cash compensation lower than the market rate by receiving the options, the total value of the startup would be greater than $800 million but the relative percentage ownership structure among the three parties would stay the same.

[22]For example, see *Bloomberg* article "Fake It Till You Make It Will Live On After Theranos" at https://www.bloomberg.com/opinion/articles/2022-01-04/elizabeth-holmes-theranos-verdict-won-t-end-faking-it-in-silicon-valley retrieved as of September 2022

[23]My sample extends to January 2002, but I focus on the period after the term unicorn is widely recognized in the market based on Figure A2. The results are qualitatively the same if I start from January 2002.

25%.[24] I collect observable startup and deal characteristics and run the following probit regression:

$$Bunching\ at\ \$1B_i = \beta_1 Top\ VC_i + \beta_2 Tech_i + \beta_3 Top\ VC_i * Tech_i + \beta_4 Ln(Deal\ Size)_i + \beta_5 Ln(Age)_i + \lambda_t + \alpha_i + e_i \tag{2}$$

where *Bunching at $1B* is a dummy variable equals 1 if the given financing round has exactly a $1 billion reported valuation. *Top VC* has two different specifications. *Top VC (Exist)* is a dummy variable that equals 1 if the financing round includes any of the top seven VC firms defined by Metrick and Yasuda (2021) as existing investors. [25] *Top VC (Invest)* is a dummy variable that equals 1 if the funding round includes top VC firms as new investors. *Tech* is a dummy variable that equals 1 if the startup's primary industry sector is in technology based on Pitchbook's classification. *Ln(Deal Size)* is the natural logarithm of the capital raised from the financing round. *Ln(Age)* is the natural logarithm of the year of the financing round minus the startup's founding year. I include year fixed effects (λ_t) and industry fixed effects (α_i) in certain specifications.

Table 6 reports the results. The negative coefficients, although insignificant, on *Top VC (Exist)* are consistent with my finding in Section 5.1 that authorizing more shares in employee options pools is costly to the existing investors. Top VCs presumably have a greater bargaining power than other VCs, influencing founders not to dilute existing shareholders. On the contrary, *Top VC (Invest)* has a larger and more statistically significant positive correlation with the bunching. Again, as Section 5.1 shows that dilution costs of authorizing more shares are born by existing shareholders, I interpret this as suggesting that top VCs demand unicorn status at the expense of existing shareholders. Note that it is possible to have both *Top VC (Exist)* and *Top VC (Invest)* equal to 1 or 0.

— PLACE TABLE 6 ABOUT HERE —

When *Top VC (Exist)* and *Top VC (Invest)* dummies are interacted with *Top VC (Exist)*, the coefficients become more statistically significant and larger in economic magnitude. For *Top VC (Exist) * Top VC (Exist)*, the sign of the coefficient changes from negative to positive – it is consistent with the interpretation that existing top VCs are more willing to bear dilution costs when the startup they invested in is a technology company. *Top VC (Invest) * Top VC (Exist)* shows that the probability of technology startups bunching to exactly a $1 billion valuation

[24] In untabulated results, I examine different valuation ranges, and the results I find in Table 3 hold.

[25] Studies emphasize the importance of venture capital reputation (Hsu (2004) and Bernstein et al. (2022), among others).

almost doubles when top VCs invest. Given that the unconditional probability of having exactly a \$1 billion valuation is 44%, this increase is substantial.

Capital raised from the financing round (*deal size*) is positively associated with the probability of bunching at \$1 billion threshold. This is consistent with the intuition that startups raise more capital, which will mechanically lead to higher valuations. In other words, because startups' reported valuations last on average 14 months (i.e., the time between two consecutive financing rounds for an average startup is 14 months), they have incentives to raise more capital at once to achieve unicorn status now, instead of raising less capital twice. The startup's age at the time of the deal is negatively associated with the probability of bunching at the \$1 billion threshold. This is consistent with the interpretation that younger startups value unicorn status more because they have less time to build a reputation than their more mature counterparts and thus rely more on the signaling effects of unicorn status. While my analysis focuses on startups with valuations of between \$800 million and \$1,000 million, Davydova et al. (2022) examine which private companies tend to achieve unicorn status in general, looking at characteristics such as investor types, more granular industry classifications, and various accounting variables.

Motivated by the pronounced tendency to achieve unicorn status by technology startups, I examine differences in the preference for unicorn status among different types of startups in Section 6. I discuss *why* certain types of startups might benefit more from valuation-based signals compared to other types of startups.

6. Why Create Your Own Valuation: Rationalizing Bunching

In this section, I address *why* certain startups stretch their valuations to achieve unicorn status, even doing so is costly as I discuss in Section 5.1. In Section 6.1, I explore different possibilities for why startups might benefit from unicorn status, as Davydova et al. (2022) do. While Davydova et al. (2022) explore potential benefits of staying private compared to going public, such as building organizational capital with less expropriation risk as a private company, I focus on a specific input to startups: human capital. In Section 6.2, I document that having unicorn status positively affects employees' view of the startups using Glassdoor review data. In Section 6.3, I conduct textual analyses to examine specific reasons behind this positive relationship. In Appendix A2.1, I provide causal evidence that achieving unicorn status explains my finding in Section 6.2.

6.1. The Supply and Demand for Unicorn Status

Studies have examined what investors should focus on predicting the success of a startup (Kaplan, Sensoy and Stromberg (2009)) and how they make actual investment decisions (Gompers, Gornall, Kaplan and Strebulaev (2020, 2021)). Others have studied whether receiving venture capital funding influences companies' success (Puri and Zarutskie (2012)). However, the future of high-growth young firms remains notoriously hard to predict.

Given this uncertainty and the information asymmetry between startup insiders (i.e., founders, existing investors) and outsiders (i.e., new investors, customers, and suppliers), startups both interpret and send out various signals ((Gompers et al. (2008, 2010), Bernstein et al. (2017)). In particular, when a startup's quality is harder to evaluate, I posit that unicorn status serves as an important signal.

To whom are startups sending the unicorn signal? One possibility is new investors. However, Table 6 shows that investments by reputable VCs are associated with a higher probability of bunching. This result implies that investors not only understand how reported valuations work but also demand or indirectly engage in stretching valuations to achieve desirable targets.[26] Thus, if there is a positive correlation between startups having unicorn status and future VC investments, this is because there are other benefits of being a unicorn that VCs value.

For example, startups may find that potential customers are more willing to purchase goods or services from unicorns because they interpret unicorn status as a quality signal. Similarly, suppliers might be willing to extend more credit if they view unicorn status as a sign of financial stability.

Among these mutually non-exclusive potential benefits of being a unicorn, I opt to focus on a particular service provider to startups, employees, for two reasons. First, Stulz (2020) and Davydova et al. (2022) discuss the increased importance of intangible assets over time, especially for young and innovative firms. Young and innovative firms are human capital intensive, making labor one of their most important inputs (Zingales (2000)). Hellmann and Puri (2002) point out that human capital is especially critical for the technology sector, which

[26] Similarly, based on the author's conversations with practitioners, it seems unlikely that sophisticated venture capitalists would make investment decisions based on reported valuations.

utilizes employee stock options extensively (Table 4).

Second, the very way to stretch reported valuations I document in Section 4 is based on authorizing more shares in employee option pools. Since it is almost truism that high-growth young firms disproportionately use stock options and their employees receive part of their compensation based on these options, it is natural to study the implication of reported valuations on startup employees via stock options. Importantly, startups' unicorn status might influence employees' expectations of the value of their options, which would in turn affect their career choices.

For these two reasons, I focus on the impact of unicorn status on startup employees. By doing so, I aim to answer *why* startups stretch their reported valuations to achieve unicorn status, even when doing so is costly. In a similar vein, I suggest a simple policy improvement that can help employees correctly assess the expected value of their stock options in Section 7.

6.2. Unicorn Status and Employee Satisfaction: Correlation

What is the overall relationship between startups achieving unicorn status and the employees' assessment of their companies? To answer this question, I examine California-based startups with a post-money valuation of $500 million or higher that had nonmissing Glassdoor employee review data between January 2014 and December 2021.

For this analysis, I restrict the sample in two ways. First, the sample only includes California-based startups' financing rounds that have a post-money valuation of $500 million or higher between January 2014 and December 2021. Second, for the pre-unicorn financing rounds (i.e., financing rounds with a valuation of at least $500 million or higher but lower than $ 1 billion), I only include startups that eventually achieve unicorn status in my sample period. For example, a financing round by a California-based startup with a post-money valuation of $700 million in 2019 will only be included in the sample if it achieves unicorn status, say, in 2021. By doing this, I ensure that startups with pre-unicorn rounds eventually become unicorns. It mitigates a potential concern that I am comparing not-so-successful startups to successful ones. Based on this sample, I run the below regression:

$$Overall\ Rating_{ij} = \beta_1 Announced_j + \beta_2 Completed_j + \lambda_t + \alpha_j + e_{ij}, \tag{3}$$

where *Overall Rating* is the score that a review writer gives to her company, with a scale of 1 to 5, with 5 being the highest. *Announced* is a dummy variable that equals 1 if the review is written between the unicorn round announcement date and the completion date. If the announcement date is not available from Pitchbook, I assume that the deal was announced six months ahead (-183 days) of the completion date. *Completed* is a dummy variable that equals 1 if the review is written within six months (183 days) of the deal completion date. The unit of observation is a review *(i)*, which is written for a specific startup *(j)* and in a specific year or a year-quarter *(t)*. I include year or year-quarter fixed effects (λ_t) and startup fixed effects (α_j).

Table 7 report the outcomes. When the unicorn round is announced, employees give higher ratings to their companies, but the magnitude is not statistically significant. This is partly because many of the financing rounds do not have announcement dates. Even with the available announcement dates, it potentially shows that deal negotiations between startups and investors are not always communicated to rank-and-file employees who write Glassdoor reviews. Alternatively, it may reflect the uncertain nature of startup financing – not all announced deals are completed.

— Place Table 7 About Here —

However, once the unicorn financing round is completed, I find statistically significant positive increases in overall ratings. This result shows that achieving unicorn status is positively associated with employees' more favorable assessments of the startups they work for. The regression specification in equation (3) includes both startup and financing year fixed effects, estimating within-startup variations in employee assessments while controlling overall sentiments of the labor market.

The effects I find in Table 7 may stem not just from unicorn status but from the financing round itself. Raising capital, even without achieving unicorn status, might make employees more satisfied. However, this concern is muted, given that the average time between the two financing rounds in Table 7 is 14 months, and my measurement period is 12 months (6 months of announcement period and 6 months of completion period). That is, most of my control period is either the announcement period or completion period of other non-unicorn financing rounds, ruling out the impact of capital raising itself. Moreover, in untabulated results, I repeat the analysis based on Poisson models and multinomial logit models because the dependent variable is integers from 1 to 5. The results are robust and qualitatively do not change.

6.3. Textual Analysis: Specific Channels

The results from Tables 7 and A2 show that achieving unicorn status makes employees more favorably assess the startups they work for. Although the numerical rating from Glassdoor shows employees' overall satisfaction, it does not reveal specific channels behind this improvement. In this section, I examine why achieving unicorn status makes employees more satisfied.

To answer this question, I analyze Glassdoor's written reviews – Glassdoor requests new users provide both numerical ratings (multiple choices on a scale of 1 to 5) and written reviews (free responses) when they first access the platform to browse other reviews. (More about Glassdoor data and examples can be found in Section 2 and Appendix A1.) Glassdoor collects written reviews in four different categories: Title of the Review, Pros about the Company, Cons about the Company, and Advice to the Management. Since Titles are usually short and do not consist of full sentences, I exclude them from my analysis. Advice to management is often missing because it is not consistently collected over time. Thus I exclude this category as well, and focus on the reviews written in Pros and Cons categories for the analysis.

I conduct a topic modeling analysis based on latent Dirichlet allocation (LDA) model (Blei, Ng and Jordan (2003)) in three steps. First, I identify that five is the appropriate number of topics to classify the reviews (for Pros and Cons separately) into different groups (Figure A5). Second, I identify the most frequent words for each of the five topics. I also measure how each review is similar to each of these five topics (Table A3). Finally, focusing on the startups that achieve unicorn status in my sample period, I calculate the changes in the composition of topics between reviews written before achieving unicorn status and reviews written afterward (Table A4). I provide details regarding these three steps in Appendix A4.

After achieving unicorn status, employees write less about compensation in the Cons section (i.e., complain less), more about leadership and culture in the Cons section, and more about employee benefits in the Pros section. This finding suggests that the increased satisfaction with compensation and benefits is the main reason behind the improvement in overall satisfaction, outweighing any disappointment with changes in leadership and culture.

7. Employee Stock Options and Policy Implications

In Section 6, I show that achieving unicorn status makes employees more favorably assess the startups they work for. Improved employee sentiment can benefit startups – it can help motivate existing employees and attract new ones.

In this section, I ask whether employees do indeed benefit from unicorn status. Although workers may derive utilities from nonpecuniary aspects of their jobs, I focus on a specific pecuniary aspect – the value of employee stock options. Specifically, I discuss the potential impacts of startup valuation bunching on employee stock option payoffs. Because startup employees may trade off cash compensation for stock-based compensation, understanding how unicorn status influences employees' expectations of their stock option payoffs is critical. This expectation may affect employees' important labor market choice – job selection.

Startup employees face three layers of uncertainty regarding their stock options. First, it is uncertain whether they will be able to earn stock options (i.e., meeting the vesting requirements). Second, conditional on vesting, it is uncertain how much their stock options will be worth (i.e., whether stock options would be in the money). Third, conditional on exercising, it is uncertain whether employees can monetize their shares by freely trading them. The first two uncertainties exist for any company, but the third only applies to private (unlisted) startups.

How does valuation bunching affect these uncertainties? For the first uncertainty, I do not have direct evidence of the average tenure of startup employees. In other words, I cannot directly test whether unicorn startups induce employees to stay longer, making more stock options vested. That said, I posit a positive relationship between the two, given my findings in Section 6 that achieving unicorn status makes employees more satisfied, potentially incentivizing them to stay longer.[27]

For the second uncertainty, I provide a simple back-of-the-envelope analysis of the impact of bunching on the expected value of employee stock options. Consider the simple case that a startup needs a $350 million investment to conduct a project with a net present value (NPV) of $250 million. Assume that $50 million of the NPV comes from paying its employees less than the market wage, making up the difference with stock options.[28] If the startup can raise $350

[27] Oyer and Schaefer (2005) argue that the purpose of granting stock options to rank-and-file employees is not necessarily to align incentives but rather lock them in with "golden handcuffs" – companies discourage their employees from moving to other companies with vesting requirements, especially when the job market is prosperous.

[28] Kim (2018) and Sorenson, Dahl, Canales and Burton (2021) document that the wage difference between young and

million by issuing common shares, as most public companies do, then the post-issuance valuation would be \$600 million, in which existing investors would own 41.7% (=$\frac{\$250M}{\$600M}$) of the startup. Employees would own 8.33% (=$\frac{\$50M}{\$600M}$) of the startup.

However, if the startup raises \$350 million from venture capital, it will most likely issue convertible preferred shares. Because convertible preferred shares are senior to the common shares existing investors hold, the price should be higher than that of common shares. If I follow Metrick and Yasuda (2021) and Gornall and Strebulaev (2020, 2021b), the reported post-issuance valuation would be \$705 million, because of the practice that reported valuations are derived by multiplying the share price of the most recent round (convertible preferred shares) to even different share classes (common shares). Suppose the startup offers extra preferential rights to the venture capital investor and authorizes extra shares in employee option pools. In that case, it can have a reported post-issuance valuation of \$ 1 billion. In this case, because of the extra dilution costs from option pools, employees would own 6.17% of the startup, not 8.33%.[29] I summarize these three cases in Figure 5.

— Place Figure 5 About Here —

The horizontal axis represents exit valuation, and the vertical axis represents the value of stock options. There are two noticeable results. First, while stock options have value under any positive exit values for common share financing (i.e., public company financing), their value is zero if the exit valuation is lower than \$350 million for convertible preferred share financing (i.e., venture capital financing). This is because convertible preferred shares are senior to the common shares on which stock options are based. Second, while the common share financing and plain venture capital financing cases have a slope of 0.0833 (8.33%), the unicorn financing case has a slope of 0.0617 (6.17%), because of the extra dilution.

I suggest regulators require startups to provide the simple diagram I outline in Figure 5 to employees who are granted stock options. This diagram is nothing new to sophisticated investors – it is also called a waterfall chart. When startups raise capital from investors, they create capitalization tables detailing what each share class is entitled to. However, there is no clear standard regarding what is shared with rank-and-file employees. As Aran and Murciano-Goroff (2021) find

mature firms is more nuanced.

[29] This back-of-the-envelope calculation is based on a simplified case – see Metrick and Yasuda (2021) and Gornall and Strebulaev (2020, 2021b) for actual cases with various exercises.

from their field experiments that college graduates with STEM (science, technology, engineering, and mathematics) majors do not fully distinguish relevant and irrelevant information, providing this diagram is likely to substantially help startup employees form more accurate expectations.

Now I discuss the third uncertainty that employees might not be able to monetize their shares. Unlike public companies, virtually all private companies require employees to secure the company's approval to sell their shares. Many startups employ a right of first refusal (ROFR) – before employees can sell shares to outsiders, they must first offer the company the opportunity to buy the shares. Also, private startups often include restrictions on the transfer of employee shares to outsiders. Even if employees can sell their shares, secondary platforms are illiquid and charge hefty transaction fees.

If staying private restricts employee shares, what about exit events based on acquisitions? Based on mergers and acquisitions (M&A) when the U.S. listed companies are the target, Babenko et al. (2021) study what happens to employee stock options.[30] They document that, in 80% of M&A deals, at least some of the stock options are canceled, and the value of canceled options accounts for 38% of the total stock option value. Thus, even though Babenko et al. (2021) or I do not have direct evidence on private targets because of data limitations, assuming that the magnitude is similar, an acquisition would not be an ideal outcome either.[31]

Therefore IPO exits are the most favorable outcome for employees, who can freely sell their shares except for the first six months of the lock-up period, which may not include rank-and-file employees.[32] Using the same sample of a reported valuation window between \$800 million and \$1 billion that I use in Section 5.2 and Table 6, I test whether the bunching is associated with the probability of being public in the future. I run the following probit regression:

$$Public_i = \beta_1 Buncher_i + \beta_2 Tech_i + \beta_3 Buncher_i * Tech_i + \beta_4 Top\ VC_i + \beta_5 Ln(Deal\ Size)_i + \beta_6 Ln(Age)_i + \lambda_t + \alpha_i + e_i \tag{4}$$

where *Public* is a dummy variable that equals 1 if the startup is publicly listed on the NYSE or NASDAQ as of March 2022. *Buncher* is a dummy variable that equals 1 if the given financing

[30]The paper collects the value of stock options from Compustat, limiting the sample to publicly listed companies.

[31]Based on the author's conversation with investment bankers, vested but out-of-the-money shares and not-yet-vested options are usually canceled. Sometimes, even vested and in-the-money shares are subject to new restrictions, making them harder to sell.

[32]IPO exits can be expensive for startups, but I do not discuss this point here. For comparing costs of different going public methods, see Gahng, Ritter and Zhang (2022).

round has exactly \$1 billion of reported valuation. *Tech* is a dummy variable that equals 1 if the startup's primary sector is in technology based on Pitchbook's classification. *Top VC* has two different specifications. *Top VC (Exist)* is a dummy variable that equals 1 if the financing round includes any of the top seven VC firms defined by Metrick and Yasuda (2021) as existing investors. *Top VC (Invest)* is a dummy variable that equals 1 if the funding round includes top VC firms as new investors. *Ln(Deal Size)* is the natural logarithm of the capital raised from the financing round. *Ln(Age)* is the natural logarithm of the year of the financing round minus the startup's founding year. I include year fixed effects (λ_t) and industry fixed effects (α_i) in certain specifications.

Table 8 reports the outcome. Column (1) shows that unconditionally, startups that conducted financing rounds with a valuation of exactly \$1 billion are 28.4% less likely to be public, compared to startups with reported valuations of between \$800 million and \$999 million. If we include control variables, column (2) shows that the coefficient becomes insignificant. However, when I interact the *Buncher* dummy with the *Tech* dummy, the result shows that tech startups that achieved unicorn status based on the reported valuation of exactly \$1 billion tend to be 64.7% less likely to be public. This finding is economically significant.

— PLACE TABLE 8 ABOUT HERE —

Therefore, based on Figure 5 and Table 8, I find that startups stretching their valuations to achieve unicorn status create less favorable conditions for their employee stock options. Achieving unicorn status is costly, making the payoff schedule for stock options worse (Figure 5). Furthermore, tech startups that bunch more than others tend to be public with a much lower probability (Table 8), making it hard for employees to sell their illiquid shares or even subjecting them to share cancellation if the startups they work for are acquired. Although it is unrealistic to predict outcomes for startups, startups should, at minimum, provide the stock options payoff schedule similar to Figure 5 to employees to help them make more informed career choices about these possibilities.

8. Conclusions

Human capital is one of the most important inputs for startups, which play a critical role in the economy. In this paper, I connect startup valuations and employee compensation as startup employees are partly compensated based on stock options, and the expected value of stock options depends on valuations. However, correctly understanding startup valuation is challenging, considering the lack of information regarding startups and the complexity of financing contracts.

I start my analysis by finding unusual bunching in the distribution of startup valuations, suggesting that startups systematically stretch their valuations to avoid down rounds and achieve unicorn status. I ask *how* they do it and *why*.

Startups' reported valuations are calculated as *The Share Price from the Most Recent Financing Round* $\times$ *The Number of Fully Diluted Shares*. Thus both the price per share and the number of shares allow a startup to create its own valuation. I focus on the number of shares side, which has not been empirically examined in the literature. When calculating headline valuations, the number of shares includes all possible conversions, even authorized but unissued shares in employee option pools (e.g., stock options). Using a novel dataset based on California's state security registration exemption filings governing equity-based employee compensation, I find that authorized, but unissued shares in employee option pools account for 11% of the reported valuations.

Why aren't all startups unicorns if a startup can easily create its own valuation? My simple back-of-the-envelope calculation shows that authorizing more shares in employee option pools to achieve a higher valuation can be costly. When raising the same capital, existing shareholders may dilute their ownership more with a larger option pool. Then *why* do certain startups stretch their valuations when doing so can be costly?

I find that achieving unicorn status positively impacts employees, based on within-startup and within-year comparisons using Glassdoor employee review data. I establish causality for this finding by employing a regression discontinuity design (RDD) using reported valuations as a running variable and $1 billion as a sharp cutoff. The positive impact of unicorn status on employee satisfaction based on the RDD setting is four to seven times larger than the correlational (within-startup and within-year) findings. Textual analysis suggests that increased satisfaction with compensation and benefits is the main reason behind this improvement.

Even though employees have increased satisfaction based on unicorn status, authorizing more shares to stretch valuation dilutes existing employee stock options and lowers their expected payoffs. To make matters worse, startups that stretch their valuations tend to go public less than startups that do not, making employee shares illiquid.

I thus suggest a simple policy that requires startups to provide employees with a payoff schedule of their stock options based on future exit types and exit valuations. This requirement, treating startup employees as pseudo-angel investors, would help them form accurate expectations and make better-informed career and investment choices by reducing information frictions.

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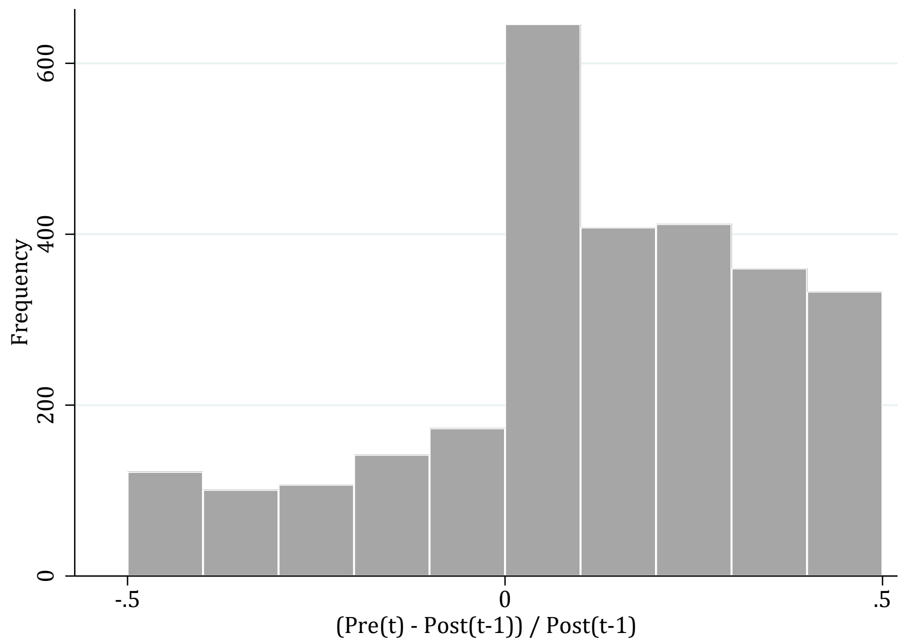
Figure 1. Valuation Bunching to Avoid Down Rounds

Figure 1 reports the distribution of valuation differences between a given company's two consecutive financing rounds. The sample consists of all U.S. headquartered private startups' financing rounds with a minimum deal size of \$5 million between January 2002 and December 2018. **Panel A** compares a given financing round's pre-money valuation to the previous round's post-money valuation. **Panel B** compares a given financing round's post-money valuation to the previous round's post-money valuation. For example, 23andMe Inc. raised \$250 million in a series F financing round in 2017 with a pre-money valuation of \$1,700 million and a post-money valuation of \$1,950 million. It previously conducted a series E financing round in 2015 with a post-money valuation of \$1,050 million. In this case, I report 0.62 ($= \frac{\$1{,}700M - \$1{,}050M}{\$1{,}050M}$) for **Panel A** and 0.86 ($= \frac{\$1{,}950M - \$1{,}050M}{\$1{,}050M}$) for **Panel B**. Having **Panel A** value < 0 is known as a down round. Each bar represents 10%. For example, the first bar includes the valuation change of [-50%, -40%).

Panel A. Pre-Money$_t$ v.s. Post-Money$_{t-1}$ (a **benchmark** to determine down rounds)



Panel B. Post-Money$_t$ v.s. Post-Money$_{t-1}$ (**not** a benchmark to determine down rounds)

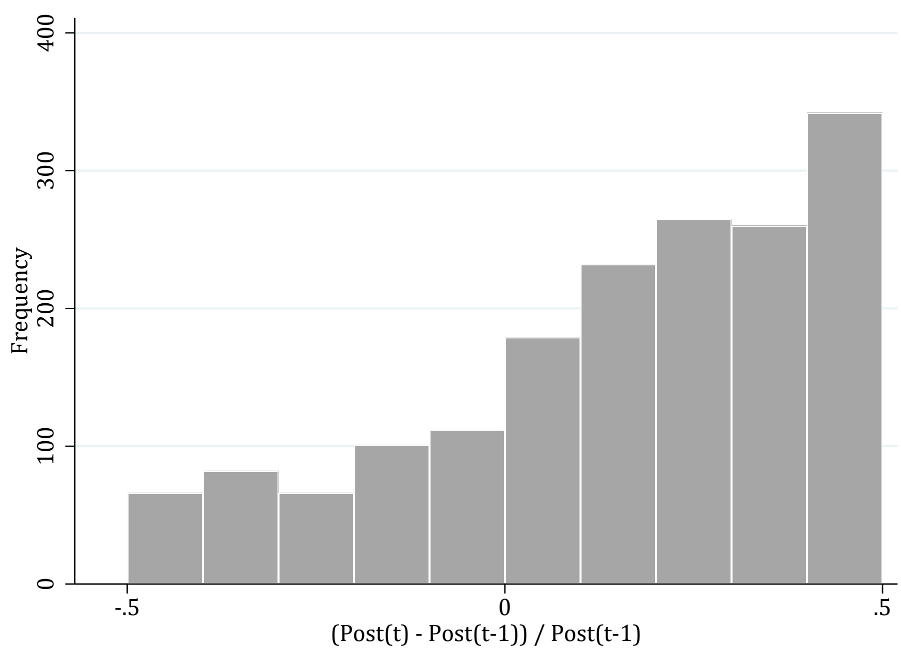
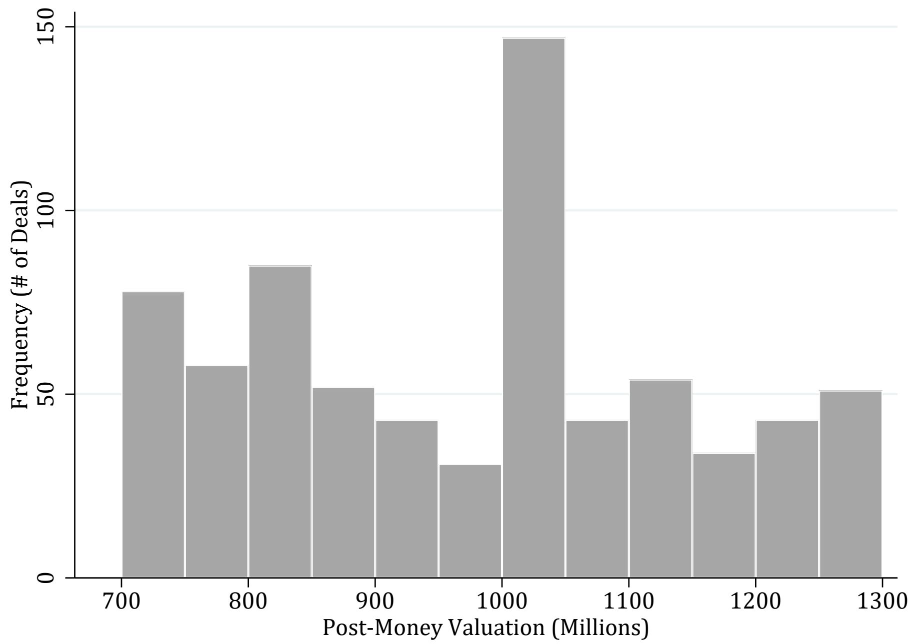


Figure 2. Valuation Bunching to Achieve Unicorn Status

Figure 2 reports the distribution of all U.S. headquartered private startup financing rounds' post-money valuations when the post-money valuations are between $700 million and $1,300 million. **Panel A** is based on financing rounds completed between January 2015 and December 2021. **Panel B** is based on financing rounds completed between January 2002 and December 2014. The December 2014 cutoff is based on findings from Figure A2 that the market started to use the term 'unicorn' in the last quarter of 2014, and it usually takes about 3-6 months to negotiate and finalize startup financing rounds. Each bar represents $50 million. For example, the first bar includes post-money valuations of [$700 million, $750 million).

Panel A. January 2015 to December 2021 (**with** the term 'unicorn')



Panel B. January 2002 to December 2014 (**without** the term 'unicorn')

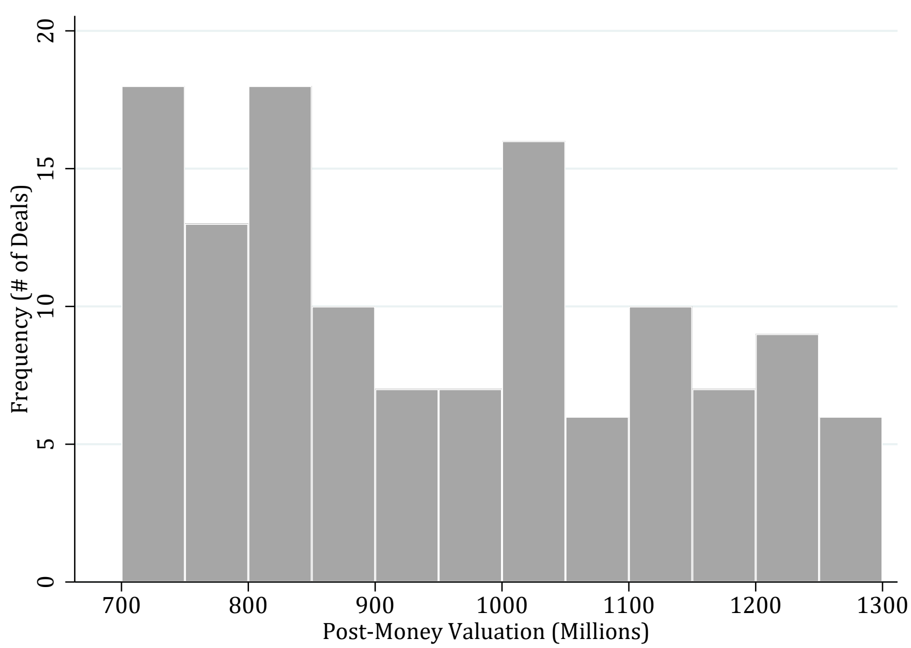
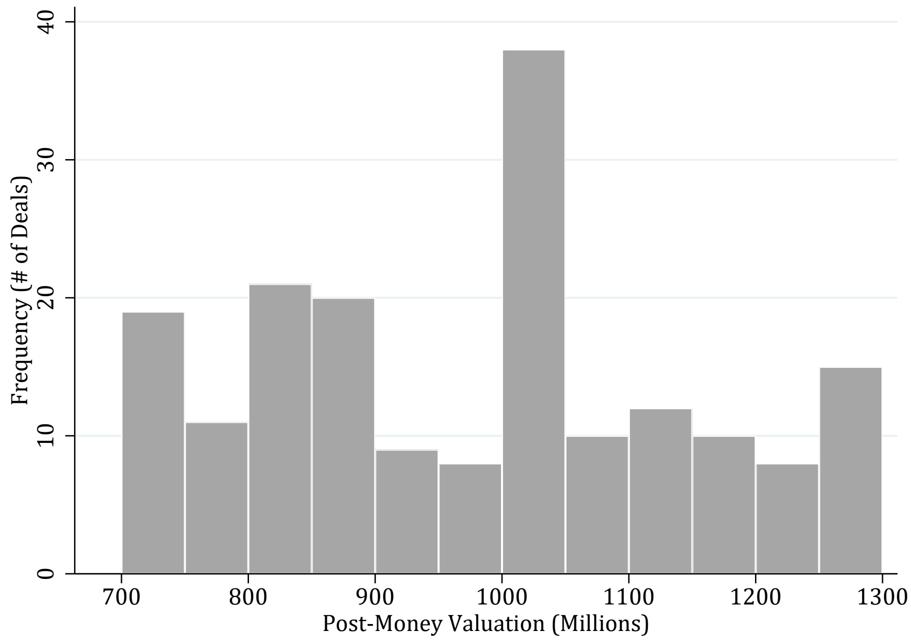


Figure 3. Unicorn Bunching – With and Without Option Pools

Figure 3 reports the distribution of private startups' post-money valuations when the post-money valuations are between $700 million and $1.3 billion. I restrict the sample to startups that file California Code 25102(o) Exemption Filings, referred to as 'California-based Startups.' The sample period is between January 2015 and December 2021. **Panel A** reports the distribution of post-money valuations including the value of employee option pools calculated in Table 3. **Panel B** reports the distribution of post-money valuations excluding the value of employee option pools calculated in Table 3. Each bar represents $50 million. For example, the first bar includes post-money valuations of [$700 million, $750 million).

Panel A. Distribution of California-based Startups' Valuations **Including** Option Pools



Panel B. Distribution of California-based Startups' Valuations **Excluding** Option Pools

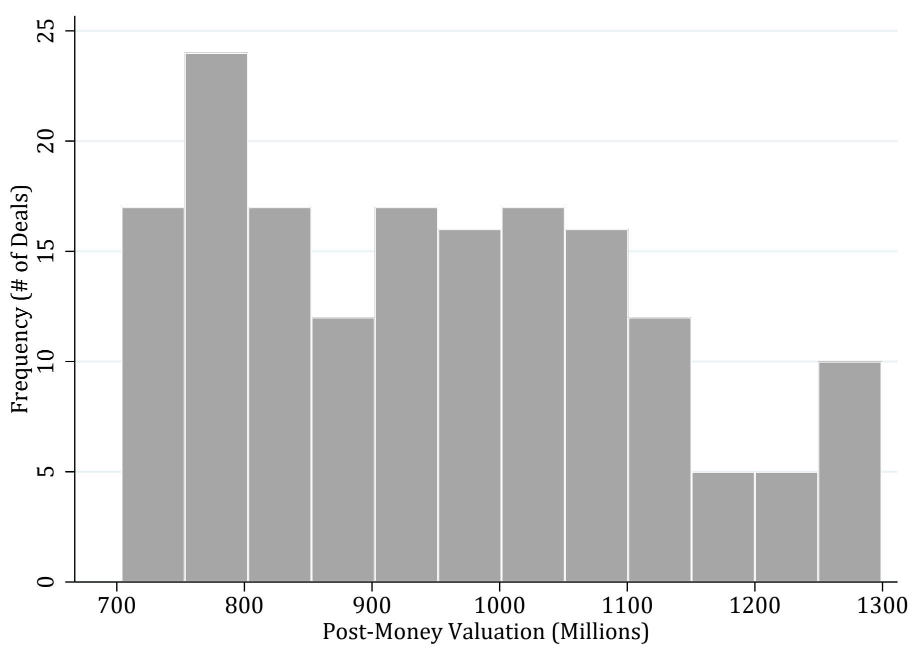
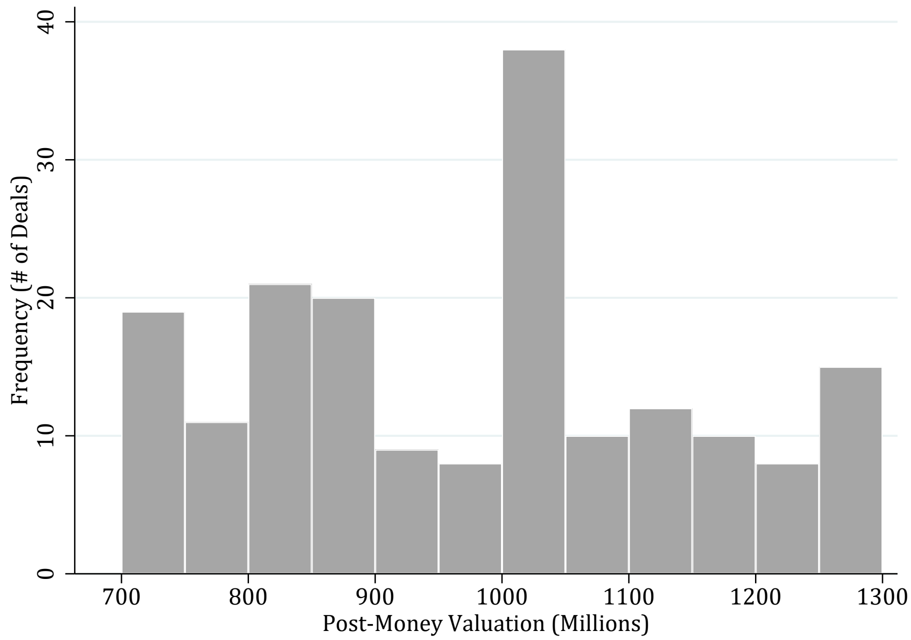


Figure 4. Unicorn Bunching – With and Without Option Pools

Figure 4 reports the distribution of private startups' post-money valuations when the post-money valuations are between $700 million and $1.3 billion. I restrict the sample to startups that file California Code 25102(o) Exemption Filings, referred to as 'California-based Startups.' The sample period is between January 2015 and December 2021. **Panel A** reports the distribution of post-money valuations including the value of employee option pools calculated in Table 3. **Panel B** reports the distribution of post-money valuations excluding the value of employee option pools calculated in Table 3. Each bar represents $50 million. For example, the first bar includes post-money valuations of [$700 million, $750 million).

Panel A. Distribution of California-based Startups' Valuations **Including** Option Pools



Panel B. Distribution of California-based Startups' Valuations **Excluding** Option Pools

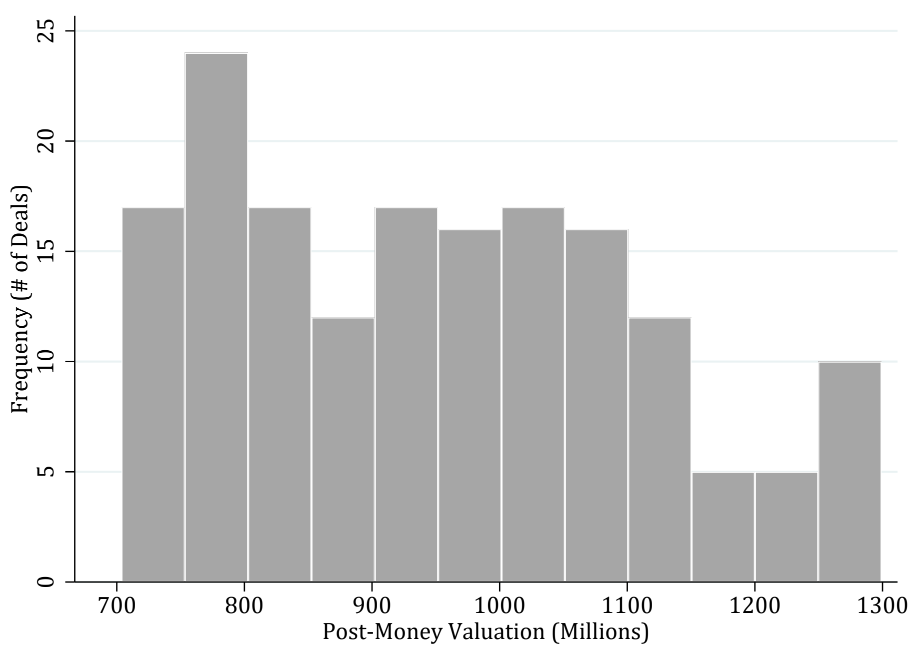


Figure 5. Employee Stock Option Payment Diagram

Figure 5 shows an example of an exit diagram (or, payoff waterfall chart) for employee stock options. A startup raises $350 million from investors based on three possible scenarios. The first is issuing common stock, the second is issuing standard convertible preferred stock, and the third is issuing convertible preferred stock with extra shares in option pools and various preferential rights for investors. The below chart summarizes three cases.

	(1) Common Stock	(2) VC: Vanilla	(3) VC: Unicorn
Pre-Money Valuation	$250M	$250M	$250M
Invested Capital	$350M	$350M	$350M
Liquidation Preference	-	Yes	Yes
Participating Preferred	-	-	Yes
Cumulative Dividends	-	-	Yes
Extra Option Pools	-	-	Yes
Reported Valuation	$600M	$705M	$1,000M
Employee Ownership	**8.33%**	**8.33%**	**6.17%**

Three lines in the figure correspond to each of the three cases. The horizontal axis, exit valuation, represents the value of startups when employees exercise stock options. The vertical axis, the value of stock options, represents the value of stock options based on that corresponding exit valuation. For example, at $300 million exit valuation, stock options in case (1) would earn $25 million ($300 million $\times$ 8.33%), and stock options in cases (2) and (3) would earn $0.

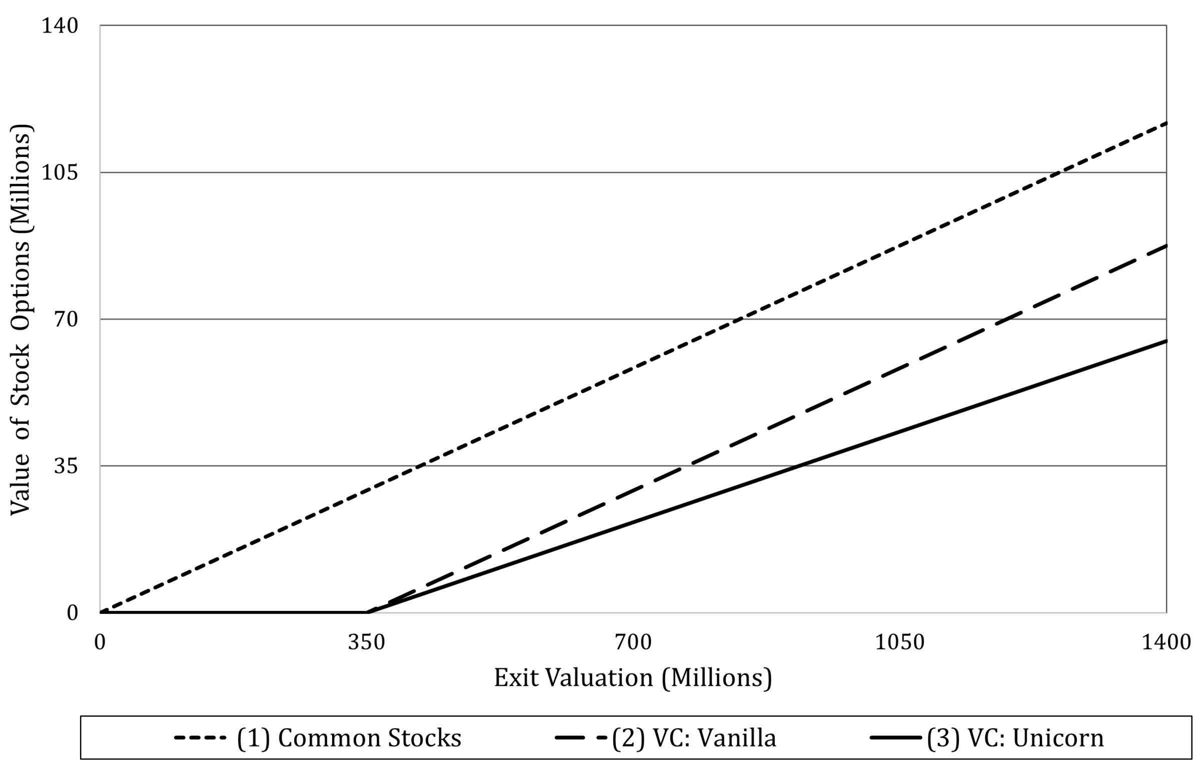


Table 1. Summary Statistics

Table 1 tabulates summary statistics for the main variables in the study based on three data sources. Panels A and B are based on Pitchbook's startup financing rounds between January 2002 and December 2021 with a post-money valuation of $500 million or higher. *Top VC Exist* equals 1 if any of the top seven venture capital firms defined in Metrick and Yasuda (2021) invested in prior rounds. *Top VC Invest* equals 1 if any of the top seven venture capital firms defined in Metrick and Yasuda (2021) invest in the financing round.

Panel A. Pitchbook Startup Financing Deal Statistics: All Startups

	No.	Mean	Std.	25%	50%	75%
Deal Size ($M)	3,906	221.0	475.6	70.0	118.0	220.0
Raised to Date ($M)	3,976	504.4	1,122.7	146.3	248.3	460.7
Pre-Money Valuation ($M)	3,886	2,393.7	8,471.4	600.0	924.7	1,800.0
Post-Money Valuation ($M)	3,996	2,669.3	8,749.4	700.0	1,035.0	2,000.0
Price per Share ($) – U.S. only	2,042	62.1	876.7	6.5	12.9	25.6
No. of Investors	3,871	7.4	5.9	3	6	10
No. of New Investors	3,680	4.9	4.8	2	3	6
No. of Follow-on Investors	2,863	3.6	2.4	2	3	5
Deal Year − Year Founded	3,916	6.9	4.9	4	6	9
Top VC Exist	3,996	38.5%	48.7%	0	0	1
Top VC Invest	3,996	21.4%	41.0%	0	0	1

Panel B. Pitchbook Startup Financing Deal Statistics: California-headquartered Startups

	No.	Mean	Std.	25%	50%	75%
Deal Size ($M)	1,377	188.3	434.9	65.0	108.0	200.0
Raised to Date ($M)	1,387	483.3	1219.1	153.7	240.7	422.0
Pre-Money Valuation ($M)	1,375	2,668.6	6,913.5	592.0	950.0	1,911.4
Post-Money Valuation ($M)	1,388	2,928.4	7,273.1	675.0	1,067.5	2,067.5
Price per Share ($)	1,212	38.2	370.1	6.0	11.7	23.0
No. of Investors	1,355	8.8	6.6	4	7	12
No. of New Investors	1,305	5.8	5.4	2	4	8
No. of Follow-on Investors	1,070	4.0	2.6	2	4	5
Deal Year - Year Founded	1,368	7.1	3.9	4	7	9
Top VC Exist	1,387	49.7%	50.0%	0	0	1
Top VC Invest	1,387	28.0%	44.9%	0	0	1

Panel C. California EPEN Stats: Authorized but Unissued Shares for Employee Compensation

	No.	Mean	Std.	25%	50%	75%
No. Shares (full data)	24,782	4,790,619	26,349,251	555,500	1,337,675	3,000,000
No. Shares (matched sample)	2,075	10,321,615	37,837,877	1,236,034	3,000,000	9,200,000

Panel D. Glassdoor Employee Review Statistics

	No.	Mean	Std.	25%	50%	75%
Overall Ratings (1 to 5)	76,794	3.9	1.4	3	5	5
No. of Reviews per Startup	76,794	152.4	218.6	24	77	185

Table 2. Basic Valuations vs Fully Diluted Valuations

Table 2 provides two valuation examples discussed in Section 4.1 and Section 4.2. **Facebook** represents the valuation practice of publicly traded companies, based on the initial public offering of Facebook Inc. (currently Meta Platform Inc.) in 2012 with an offer price of $38 per share. **603 million** shares are stock options that had been granted but not yet exercised and RSUs that had been granted but not yet converted. **77 million** shares are authorized but unissued shares in employee option pools for future employee compensation. **23andMe** represents the valuation practice of non-listed private companies, based on 23andMe's series E financing round in 2015 when it raised $115 million based on $10.83 per share. **11 million** shares are authorized but unissued shares in employee option pools for future employee compensation.

	Facebook ($38 per share)		23andMe ($10.83 per share)	
Valuation Method	No. of Shares	Valuation	No. of Shares	Valuation
Basic	2,138M	$81B	86M	$927M
Fully Diluted (Public)	2,138M + **603M**	$104B	N/A	N/A
Fully Diluted (Private: Headline)	2,138M + 603M + **77M**	$107B	86M + **11M**	$1,050M

Table 3. Size of Newly Authorized but Unissued Shares in Employee Option Pools

Table 3 documents the size of employee option pools created in unicorn financing rounds in which the startups achieve post-money valuations of $1B or higher for the first time. The sample consists of financing rounds mapped to California 25102(o) exemption filings between January 2014 and December 2021. **Panel A** reports the total number of newly authorized but unissued shares in employee option pools from unicorn financing rounds. It also reports the number of shares per $1 million capital raised. **Panel B** compares the value of newly authorized but unissued shares in option pools (in $ value) to the deal sizes and post-money valuations. The value of newly authorized but unissued shares in option pools refers to the number of new shares multiplied by the per-share price of the associated financing round. Deal size (in million dollars) and post-money valuation (in million dollars) data are from Pitchbook. The number of observations reduces because Pitchbook does not report share prices for certain financing rounds. For example, if the value of new shares in the option pool is $180 million, the deal size is $200 million, and the post-money valuation is $1 billion, I report 90% ($= \frac{\$180M}{\$200M}$) for 'Compared to Deal Size (Capital Raised),' and 18% ($= \frac{\$180M}{\$1{,}000M}$) for 'Compared to Post-money Valuation.'

Panel A: Number of Newly Authorized but Unissued Shares in Unicorn Financing Rounds

	No.	Mean	25%	Median	75%
# of Shares	165	15,599,846	2,365,608	7,143,556	16,201,457
# of Shares per $1M Raised	164	115,084	16,411	54,387	130,601

Panel B: Value of Authorized but Unissued Shares as a Fraction of Post-Money Valuations

	No.	Mean	25%	Median	75%
Deal Size (Capital Raised, $M)	164	185	100	133	200
Post-money Valuation ($M)	165	1,645	1,050	1,265	1,700
Value of New Shares in Option Pools ($M)	145	180	49	95	206
Compared to Deal Size (Capital Raised)		97%	49%	71%	103%
Compared to Post-money Valuation		11%	5%	7%	12%

Table 4. Strategic Use of Option Pools to Achieve Unicorn Status

Table 4 regresses the incremental size of option pools per dollar raised on different stages of startup financing rounds. Specifically, it reports results from regressions defined in equation (1), given by

$$\frac{Option\ Pool(\$)_i}{Deal\ Size(\$)_i} = \beta_1 Unicorn\ Rounds_i + \beta_2 Tech\ Startups_i + \beta_3 Unicorn_i \times Tech_i + X_i + \lambda_t + e_i$$

where $Option\ Pool(\$)$ is the number of newly authorized but unissued shares in the option pool $\times$ the price per share. $Option\ Pool(\$)$ is the same as *Value of Shares ($M)* in Panel B of Table 3. $Deal\ Size(\$)$ is the amount of capital raised for that financing round, defined as price per share multiplied by the number of new shares issued to investors. $Deal\ Size(\$)$ is the same as *Deal Size ($M)* in Panel B of Table 3. $Unicorn\ Rounds$ is a dummy variable that equals 1 if startups achieve unicorn status for the first time from this financing round. $Tech\ Startups$ is a dummy variable that equals 1 if the financing round is conducted by startups in the technology industry based on Pitchbook's classification. $Unicorn \times Tech$ is an interaction term between $Unicorn\ Rounds$ and $Tech\ Startups$. X is a vector of control variables, including a dummy variable for top VCs investing, a dummy variable representing each financing round sequence (e.g., series A as 1, series B as 2...), a natural logarithm of the startup age (year of the financing round $-$ startup founding year), a natural logarithm of days between the date of the current financing round and the date of the previous financing round (if previous financing round information is not available, I subtract 250 days). I limit the sample to financing rounds with a post-money valuation of $500 million or higher. I include year-fixed effects based on the year of the financing round (λ_t). t-statistics are reported in parentheses. Statistical significance levels: *** p-value$<$0.01, ** p-value$<$0.05, * p-value$<$0.10.

	Option Pool ($) / Deal Size ($)		
	(1)	(2)	(3)
Unicorn Rounds	0.014	0.001	-0.293
	(0.06)	(0.00)	(-1.06)
Tech Startups		0.682*	0.584
		(1.91)	(1.46)
Unicorn X Tech			0.652**
			(2.11)
Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
N. Obsevations	429	429	429
R-sq	0.046	0.049	0.050

Table 5. Costs of Achieving Unicorn Status

Table 5 shows an example of how a given VC-backed company's ownership structure (percentage ownership) can change based on whether the company's valuation includes an option pool or not. Since the purpose of this example is to show how does increasing an option pool dilute existing investors, it assumes granting employee options does not increase firm value (i.e., employees are more motivated and work harder). For the case when the company has an option pool, it assumes the option pool accounts for 15% of the fully diluted shares. Full conversion assumes all of the shares in the employee option pool will be converted to common shares. No conversion assumes none of the shares in the employee option pool will be converted to common shares.

	No Option Pool		Option Pool				
			Headline	Full Conversion		No Conversion	
	Wealth	% Own	Valuation	Wealth	% Own	Wealth	% Own
Existing Investors	$600M	75%	$600M	$480M	60%	$565M	71%
Option Pool	$0	0%	$150M	$120M	15%	$0	0%
New Investors	$200M	25%	$250M	$200M	25%	$235M	29%
Total (Post-money)	$800M	100%	$1,000M	$800M	100%	$800M	100%

Table 6. Determinants of Valuation Bunching at $1B

Table 6 analyzes how observable characteristics of startups and their financing rounds can predict the likelihood of achieving the exact $1 billion valuation. The sample consists of startups' venture capital financing rounds between January 2015 and December 2021 with reported post-money valuations of between $800 million and $1,000 million. Specifically, it reports results from Probit models defined in equation (2), given by

$$\textit{Bunching at \$1B}_i = \beta_1 \textit{Top VC}_i + \beta_2 \textit{Tech}_i + \beta_3 \textit{Top VC}_i * \textit{Tech}_i + \beta_4 \textit{Ln(Deal Size)}_i + \beta_5 \textit{Ln(Age)}_i + \lambda_t + \alpha_i + e_i$$

where *Bunching at $1B* is a dummy variable equals 1 if the given financing round has an exact $1 billion reported valuation. *Top VC* has two different specifications. *Top VC (Exist)* is a dummy variable equals 1 if the financing round includes any of top seven VC firms by Metrick and Yasuda (2021) as existing investors. The seven VC firms Metrick and Yasuda (2021) list in their Chapter 5 are Accel, Benchmark, Khosla Ventures, Kleiner Perkins, New Enterprise Associates (NEA), Sequoia Capital, Union Square Ventures (USV). *Top VC (Invest)* is a dummy variable that equals 1 if the funding round includes top VC firms as new investors. *Tech* is a dummy variable that equals 1 if the startup's primary industry sector is in technology based on Pitchbook's classification. *Ln(Deal Size)* is a natural logarithm of the capital raised from the financing round. *Ln(Age)* is a natural logarithm of the year of the financing round minus the startup's founding year. I include year fixed effects (λ_t) and industry fixed effects (α_i) in certain specifications. *t-statistics* are reported in parentheses. Statistical significance levels: *** p-value<0.01, ** p-value<0.05, * p-value<0.10.

	Bunching at $1B Valuation = 1			
	(1)	(2)	(3)	(4)
Top VC (Exist)	0.004	-0.072	0.026	-0.066
	(0.03)	(-0.43)	(0.07)	(-0.40)
Top VC (Exist) X Tech			0.635***	
			(2.89)	
Top VC (Invest)	0.145	0.223	0.201	0.296
	(0.77)	(1.17)	(1.05)	(0.80)
Top VC (Invest) X Tech				0.896***
				(3.54)
Ln(Deal Size)	0.445***	0.453***	0.451***	0.451***
	(5.39)	(5.24)	(5.24)	(5.24)
Ln(Age)	-0.316***	-0.320***	-0.314***	-0.313***
	(-3.55)	(-3.50)	(-3.44)	(-3.43)
Year FE	No	Yes	Yes	Yes
Industry FE	No	Yes	No	No
N. Obsevations	528	528	528	528
Pseudo R-sq	0.075	0.113	0.108	0.108

Table 7. Employees' Responses to Unicorn Status: Correlation (Full Sample)

Table 7 analyzes the impact of achieving unicorn status (post-money valuation of $1 billion or higher) on the employees' overall ratings of the startups they work for. The sample consists of California startups with a post-money valuation of $500 million or higher and had non-missing Glassdoor employee review data between January 2014 and December 2021. Based on this sample, it reports results from the two-way fixed effects regression model defined in equation (3), given by

$$\textit{Overall Rating}_{ij} = \beta_1 \textit{Announced}_{ij} + \beta_2 \textit{Completed}_{ij} + \lambda_t + \alpha_j + e_{ij},$$

where *Overall Rating* is the score that a review writer gives to her company, based on a scale of 1 to 5, with 5 being the highest. *Announced* is a dummy variable that equals 1 if the review is written between the unicorn round announcement date and the deal completion date. If the announcement date is not available from Pitchbook, I assume that the deal was announced six months ahead (-183 days) of the completion date. *Completed* is a dummy variable that equals 1 if the review is written within six months (183 days) of the deal completion date. The unit of observation is a review *(i)*, which is written for a specific startup *(j)* and in a specific year or a year-quarter *(t)*. I include year or year-quarter fixed effects (λ_t) and startup fixed effects (α_j). Standard errors are clustered at a firm level and reported in parentheses. Statistical significance levels: *** p-value<0.01, ** p-value<0.05, * p-value<0.10.

	Overall Rating	
	(1)	(2)
Announced	0.081	0.058
	(0.071)	(0.071)
Completed	0.111**	0.107**
	(0.045)	(0.045)
Constant	3.854***	3.855***
	(0.005)	(0.005)
Time FE	Year	Year-Quarter
Firm FE	Yes	Yes
N. Obsevations	76,777	76,777
Adj. R-sq	0.124	0.126

Table 8. Unicorn Bunching and the Probability of Going Public

Table 8 analyzes how observable characteristics of startups and their bunching behaviors can predict the startups' going public decisions. Specifically, it reports results from Probit models defined in equation (4), given by

$$Public_i = \beta_1 Buncher_i + \beta_2 Tech_i + \beta_3 Buncher_i * Tech_i + \beta_4 Top\ VC_i + \beta_5 Ln(Deal\ Size)_i + \beta_6 Ln(Age)_i + \lambda_t + \alpha_i + e_i$$

The sample consists of startups' financing rounds between January 2015 and December 2021 with reported post-money valuations of between \$800 million and \$1,000 million. *Public* is a dummy variable that equals 1 if the company is listed in NYSE or NASDAQ as of March 2022. *Buncher* is a dummy variable that equals 1 if the company's valuation is exactly \$1B. *Tech* is a dummy variable that equals 1 if the startup primarily operates in the technology sector based on Pitchbook's classification. *Top VC* has two different specifications. *Top VC (Exist)* is a dummy variable that equals 1 if the funding round includes VC firms identified as top VC firms by Metrick and Yasuda (2021) as existing investors. *Top VC (Invest)* is a dummy variable that equals 1 if the funding round includes VC firms identified as top VC firms by Metrick and Yasuda (2021) as new investors. *Ln(Deal Size)* is a natural logarithm of the capital raised from the financing round. *Ln(Age)* is a natural logarithm of the year of the funding minus the startup's founding year. λ_t denotes year fixed effects (the year of the financing round). α_i denotes industry fixed effects. *t-statistics* are reported in parentheses. Statistical significance levels: *** p-value<0.01, ** p-value<0.05, * p-value<0.10.

	Publicly Listed as of March 2022 = 1		
	(1)	(2)	(3)
Buncher	-0.284**	-0.180	-0.476
	(-2.05)	(-1.15)	(-1.26)
Buncher X Tech			-0.647***
			(-3.06)
Top VC (Exist)		0.238	0.236
		(1.23)	(1.22)
Top VC (Invest)		-0.337	-0.334
		(-1.43)	(-1.42)
Ln(Deal Size)		-0.037	-0.044
		(-0.44)	(-0.51)
Ln(Age)		0.139	0.130
		(1.22)	(1.14)
Year FE	Yes	Yes	Yes
Industry FE	No	Yes	No
N	560	528	528
Pseudo R-sq	0.151	0.174	0.173

Internet Appendix

A1. Institutional Details and Data

In this section, I expand Section 2 by providing institutional backgrounds and detailed descriptions of the four data sources that I use in this paper: Pitchbook, Certificate of Incorporation Filings, California Employee Plan Exemption Notice (EPEN) Filings, and Glassdoor.

Pitchbook

Startups' venture capital financing data come from Pitchbook. I collect financing rounds of startup companies between January 2002 and December 2021 with a reported post-money valuation of $500 million or higher. Pitchbook reports a total of 3,996 financing rounds satisfying these conditions by 2,421 unique companies. Given the data availability, I restrict the sample to U.S.-headquartered or California-headquartered startups in my later analyses. I also use international (non-U.S. headquartered) startups when I tabulate additional statistics in the appendix.

Pitchbook has several advantages over other commercially available data providers, such as VentureEconomics. According to Ewens, Gorbenko and Korteweg (2022a), Pitchbook data is based on venture capital contract terms beyond the simple ownership share sold to investors, with reasonable coverage dating to 2002. Pitchbook collects venture capital contract data from certificates of incorporation filings from Delaware and California and estimates the total number of issued shares based on its proprietary model. (See Appendix B of Ewens et al. (2022a) for more details and Lerner and Kaplan (2017) for comparing VC data sources in general.) Therefore I believe that my sample represents the most accurate and comprehensive picture of startup financing events.

As I discuss in Section 3, the results in Figures 1 and 2 raise the concern that Pitchbook's post-money valuation data might be incorrect. Pitchbook has three options reporting their post-money valuations for each financing event for startup companies - actual valuations, estimated valuations, and no valuation data. My sample in this paper excludes financing deals with no valuation data but includes deals with estimated post-money valuation data. To check the accuracy of this estimated post-money valuation information, I randomly select 10 deals that Pitchbook estimates the post-money valuation as $1 billion, listed in Table A1.

— Place Table A1 About Here —

In order to verify the accuracy of the estimated post-money valuation, I search Factiva and other online sources. As Table A1 reports, for 9 out of 10 randomly selected financing rounds, I find articles mentioning the financing round. 8 out of 9 articles explicitly mention the post-money valuation as $1 billion. 1 of 8 articles cites Pitchbook as a source of post-money valuation information. Therefore, overall, 7 out of 10 estimated valuations of $1 billion cases are independently verified, alleviating the potential concern that the bunching outcome at $1 billion is due to Pitchbook's data recording error.

Certificate of Incorporation (COI)

I augment Pitchbook data with certificate of incorporation (COI) filings.[33] I access COI data from two sources – Harvard Business School's Private Capital Research Institute (PCRI) and the Stanford Graduate School of Business' Venture Capital Initiative (VCI).[34]

Startups with multiple financing rounds usually have multiple classes of shares because each round typically creates a new share class for new investors. Accordingly, a new COI is created in every financing round when a new share class is added to a startup. COI filings provide an overview of the capital structure of startups. They also show the different cash flow rights (Bengtsson and Sensoy (2015)) and governance rights (Chernenko et al. (2021) and Ewens and Malenko (2022)) that each share class holds. Based on the information contained in COI filings, I can construct payoff schedules of employee common shares based on startup exit valuations. Metrick and Yasuda (2021) call this payoff schedule an exit diagram; it is known as a waterfall chart among practitioners.

COI flings also include the total number of authorized shares for each financing round. Although a COI filing does not have the exact number of shares outstanding data, the authorized number of shares works as an upper-bound benchmark for my analysis.

California Employee Plan Exemption Notice (EPEN) Filing

The Securities Act of 1933 requires every offer or sale of securities to be registered with the U.S. Securities and Exchange Commission (SEC). This requirement applies to stock offered to employees as a form of compensation, such as stock options and restricted stock units (RSUs).[35]

[33]The certificate of incorporation can also be called the article of incorporation.

[34]I thank Will Gornall, Josh Lerner, and Iya Strebulaev for providing the data.

[35]RSUs are a type of stock-based compensation. Companies grant restricted stock to employees subject to certain performance benchmarks and/or vesting schedules. Compared to stock options, RSUs do not have exercise prices, and receiving employees pay ordinary income taxes. Stock options can be taxed as capital gains under certain conditions.

For the federal government level, SEC Rule 701 exempts private companies from the registration requirement when they issue stock or stock options for employee compensation purposes, unless the amount is greater than $10 million in 12 months. Within this limit, the grant of stock options and other compensatory employee benefits, such as RSUs, will not be deemed a sale of a security for purposes of the Securities Act by the SEC.

In California, however, the state government has a separate registration requirement on top of the federal rules. Equivalent to the Securities Act of 1933, California's Corporations Code Section 25110 states that any securities issued in California must either be exempted or qualified. Even if a company is not headquartered in California, the company is subject to this rule if it issues stock options to employees based in California. Similarly, equivalent to the SEC Rule 701, California's Corporations Code Section 25102(o) governs the exemption requirements for companies' employee compensation purpose stock issuances. There are two key requirements to receive a registration exemption under Corporations Code Section 25102(o) – the security offering should be exempted by SEC Rule 701 *and* the issuer must file a notice to the California state government no later than 30 days after the initial issuance of any security under the plan.

I exploit an important feature of this regulatory filing. Section 25102(o) requires companies to file the "plan", in lieu of filing every time they grant stock-based compensation to employees. In other words, companies file the number of shares that they will issue under a certain plan, within 30 days of the initial issuance of securities from that plan. This significantly reduces regulatory burden for companies, as they do not have to file a notice of transaction every time they grant stock to their employees. For example, assume that a California-based company's board of directors approves an option plan including 1 million shares of RSUs on May 10, 2015, and the first grant from this plan is 100,000 RSUs on November 5, 2015. Then the company must file for exemption of the whole 1 million shares of restricted stock units by December 4, 2015, although it can file as early as May 10, 2015. Figure A1 provides an actual filing document by 23andMe Inc., a consumer-based healthcare technology company, in 2015.

— Place Figure A1 About Here —

Importantly, a new 25102(o) notice is required not only when companies establish a new option plan but also when they increase the number of shares they can issue under an existing plan.

For example, consider a California-based company that previously filed for a plan with 1 million shares of RSUs on December 4, 2015, and then decided to increase the size of the plan to a total of 3 million shares of RSUs on March 20, 2017. The company must file for the exemption of the new 2 million shares of RSUs within 30 days of the first grant of securities out of the additional 2 million shares (not within 30 days from March 20, 2017).

Overall, California's Corporations Code Section 25110 allows me to identify increases in the size of California-based startups' option pools over time. However, the requirement that companies should file within 30 days of the *first grant* of shares of the newly authorized option pool, not within 30 days of the *authorization*, limits my observations. For example, assume that a California-based company authorized 2 million shares of stock options in March 2017 before its series-B financing rounding. However, the company did not grant any options out of these 2 million shares until its series-C financing rounding in December 2018. In this case, I cannot match the 2 million shares to the series-B, because the company has the option to file it after its series-C round.

I map Pitchbook deal-level data with EPEN filing data. The matching includes two steps. First, I require matching between Pitchbook's company names and EPEN's filer legal names. I start by cleaning company names, such as removing "Inc." and "corp." Then I conduct an automated mapping between the two. I manually inspect borderline cases to maximize the accuracy of the mapping. Second, conditional on the name-matched pairs, I require an additional matching between Pitchbook's deal date and EPEN's filing date. I map whether the EPEN is filed between Pitchbook's deal date minus 60 days (2 months) and the next deal date minus 60 days (2 months). This is based on the industry practice that startups decide the incremental size of the option pool before they finalize each financing round. Thus, if startups file EPEN notices as soon as they authorize new shares, notices will be filed prior to the financing round completion dates. However, as the California government requires companies to file within 30 days of the *first grant* of securities from the newly authorized option pool, not within 30 days of the *authorization*, startups usually file the notices after the financing rounds are completed. If a startup does not grant any shares out of the new option pool until after the next financing round, I cannot map this incremental option pool correctly. However, my conclusions are robust to different matching periods. If the next deal date is unavailable, I assume 250 days (8 months).[36] For example, assume that a startup raised a series B

[36]This is a conservative estimate, given that the average time between two financing rounds in my sample is about 14

financing on June 30, 2018, and a series C financing on March 17, 2020, without series D round data from Pitchbook. Assume that there are three EPEN filings for this startup – the first filing on June 20, 2018, the second on December 5, 2019, and the third on December 1, 2021. In that case, I map the first and second filings to series B and do not map the third filing to any of the deals.

Glassdoor

Glassdoor is a website where employees anonymously rate and review their companies. New users are asked to rate their companies and write reviews before they access certain features of the website (Green, Huang, Wen and Zhou (2019)). The rating asks employees to select how many stars they would like to give their companies, based on a scale of 1 (worst) to 5 (best). These overall ratings have been used by other studies, for example, measuring employees' satisfaction regarding maternity benefits (Liu, Makridis, Ouimet and Simintzi (2022)) and leveraged buyouts (Gornall, Gredil, Howell and Liu (2021) and Lambert, Moreno, Phalippou and Scivoletto (2021)). Written reviews ask employees to leave comments about their companies in three categories: pros, cons, and advice to the management.

Glassdoor launched in 2008, but it started to receive reviews in 2012 (Lambert et al. (2021)). I manually collect rating and review data from January 2014 to December 2021 for California-based startups that have had a post-money valuation of $500 million or higher at any point in this period based on Pitchbook. I focus on California-based startups because they have better coverage and more reviews, compared to non-California companies. This is especially true of the earlier period in my sample, which is critical for my analysis in Appendix A2.1. The better coverage for California-based companies is party because Glassdoor itself is a California-based company that received multiple rounds of funding from venture investors.

A2. Introduction of Unicorn in the Market

In Section 1, I explain that venture capitalist Aileen Lee first coined the term unicorn in November 2013, referring to private VC-backed startups with a valuation of $1 billion or higher. However, it does not mean that everybody started to use the term in November 2013. To understand when

months. My conclusions are robust to different assumptions.

the term unicorn has become salient, I search articles in the *Wall Street Journal* and *Financial Times* containing two key words “venture” and “unicorn” at the same time in Figure A2.

— PLACE FIGURE A2 ABOUT HERE —

Figure A2 shows that *Wall Street Journal* or *Financial Times* articles containing two words “venture” and “unicorn” started to emerge in 2014. Most of the 2014 articles are from the last quarter of the year. The figure also reports that the number of newly minted unicorn startups has grown exponentially over time. According to Pitchbook data, only 33 VC-backed startups reached a $1 billion valuation prior to 2014, while there were 337 in 2021 alone.

A2.1. Unicorn Status and Employee Satisfaction: Causation

Table 3 suggests that startups can achieve desirable valuations by authorizing more stock options. Table 6 documents that certain startup and financing round characteristics predict the likelihood of bunching. Overall we cannot interpret the positive correlation between achieving unicorn status and the improved employee assessment from Table 7 as causal.

An ideal experiment that could overcome the endogenous nature of startup valuations would start in a world without the term "unicorn." In that world, there would exist two identical startups except that one would have a valuation of $950 million and the other with a valuation of $1,050 million. Then the term "unicorn" is unexpectedly introduced into the world. If we were to compare the changes in employee sentiment between the two startups after the introduction of the term, the difference would identify the causal impact of unicorn status on employee sentiment.

To mimic this ideal experiment, I exploit the introduction of the term "unicorn" in the startup world. As discussed in Section 3, venture capitalist Aileen Lee coined the term in November 2013. However, naming something does not force people to start using the name immediately. Indeed it took about a year for the market to adopt "unicorn" widely. Figure A2 shows that in 2013 or earlier years, there was no *Wall Street Journal* or *Financial Times* article containing the words "unicorn" and "venture" at the same time. Articles started to use them in 2014, but most of the articles in 2014 were published in the last quarter.

The magnitude of valuation bunching at $1 billion over time shows the same pattern. If we compare Panels A and B of Figure 2, we find a noticeable difference. Panel A shows that, in 2015 and later, startups clearly prefer a valuation of $1,050 million over a valuation of $950 million. On the other hand, Panel B shows that startups did not particularly prefer $1 billion. Although there were more startups with a valuation of $1 billion, compared to a valuation of $950 million, this was a part of a broader pattern that startups prefer round number valuations (e.g., $800 million instead of $750 million or $850 million).

Findings from Figure A2 and Figure 2 show that startups did not have a stronger incentive to have a $1 billion valuation than a $950 million valuation in 2014 or earlier. In other words, a $1 billion valuation was just one of many round numbers, such as $100 million and $2 billion, when the term "unicorn" did not exist or was not widely used. Therefore, if I select two startups that raised capital in 2014 with valuations of $950 million and $1 billion and compare employee sentiment between them in 2015 and later (i.e., when the term "unicorn" was widely used), I can replicate the ideal experiment I outlined above.

Based on these institutional features, I employ a regression discontinuity design (RDD). I have valuations as a running variable and $1 billion as a sharp cutoff, assigning startups into either the treated group ($1 billion or above: unicorns) or the control group (below $1 billion: non-unicorns). I restrict the sample to California-based non-publicly listed startups that received venture capital financing in 2014 with a post-money valuation of $500 million or higher. I compare the Glassdoor employee ratings between the treated and control groups based on reviews written from January 2015 to June 2016. This 18-month window ensures that I give enough time to measure the treatment effect but do not give so much time so that other events, such as new financing rounds, can influence employees' ratings.

This regression discontinuity design relies on two key identifying assumptions. First, startups cannot manipulate valuations (the running variable). Second, startups right below and above the cutoff ($1 billion) should be identical, except for the treatment assignment. Compared to cleaner settings, such as geographical (e.g., Chen, Ebenstein, Greenstone and Li (2013)) or government program cutoffs (e.g., Howell (2017)), however, my research design does not precisely satisfy these two conditions. For the first assumption, I show that startups can and do manipulate valuations in Section 4. For the second assumption, because of the lack of available firm-level data for private startups, I cannot conduct any meaningful balancing tests (i.e., comparing observable variables between groups right below and above the cutoff).

Valuation as a running variable does not satisfy the two assumptions precisely. However, I design my study to ensure that these assumptions are reasonably satisfied. For the first one, the comparison between Panels A and B of Figure 2 shows that startups could stretch their valuations anytime but did not have the incentive to do so in 2014. Given the costs of stretching that I discuss in Section 5.1, startups would not do it unless the benefits outweigh the costs.

For the second assumption, I ensure that companies below $1 billion resemble those above $1 billion without conducting balancing tests between the two groups. Specifically, for startups with a post-money valuation of between $500 million and $1 billion in 2014, I only include them if they achieve unicorn status in later years. For example, assume that both startups A and B raised capital with a valuation of $800 million in 2014. Startup A conducted an additional financing round in 2017 with a valuation of $1.5 billion, but startup B did not receive any further financing. In that case, I include only startup A in the sample. By ensuring that all of the non-unicorn companies in my sample eventually become unicorns, I minimize the potential concern that a startup with a post-money valuation of $950 million differs fundamentally from one with a post-money valuation of $1,050 million in 2014.

Therefore, although I cannot argue that the two assumptions are perfectly satisfied, my research design reasonably satisfies them. To ensure the local discontinuity, I provide a visual inspection of average employee ratings in Figure A3. The sample consists of California-based startups that conducted a financing round in 2014 with a post-money valuation of $500 million or higher. Each dot represents a $100 million range (e.g., the first dot = [$700M, $800M), the last dot = [$1,200M, $1,300M)). The horizontal axis reports the average employee ratings between January 2015 and June 2016.

— PLACE FIGURE A3 ABOUT HERE —

I conduct a sharp RDD test by running the following regression:

$$Overall\ Rating_i = \beta_1 Unicorn_j + \beta_2(Valuation_j - \$1B) + \beta_3(Valuation_j - \$1B)^2 +$$

$$\beta_4[Unicorn_j \times (Valuation_j - \$1B)] + \beta_5[Unicorn_j \times (Valuation_j - \$1B)]^2 + X_j + e_i, \quad (5)$$

where *Unicorn* is a dummy variable that equals 1 if the post-money valuation is $1 billion or higher, *Valuation* is the post-money valuations in millions, X is a vector of control variables.

Table A2 reports the outcomes. β_1 is the coefficient of interest, capturing the causal impact of being in the treatment group (unicorns), compared to being in the control group (non-unicorns). I include linear and quadratic valuation terms interacting with the treated status. The coefficients, β_2 to β_5, measure and control the relationship between the valuation (the running variable) and the overall ratings (the outcome variable), so that β_1 correctly captures the causal impact of unicorn status, not the high level of valuation itself, on employee ratings. I do not include time fixed effects because I focus on the narrow time window I defined above.

— Place Table A2 About Here —

Table A2 shows that achieving unicorn status increases employees' ratings substantially. β_1 coefficients on *Unicorn* are positive and significant across all specifications, even with the most stringent specification (column (6)) including control variables and both linear and quadratic terms for the interaction terms (*Unicorn* × *Valuation*). If I compare Table A2 to Table 7 focusing on the impact of achieving unicorn status, Table A2's causal impact (0.798) is about seven times larger than Table 7's correlational setting (0.111). Considering that the outcome variable, overall rating, is based on a scale of 1 (worst) to 5 (best), the magnitude is large.

A3. Bunching in Other Settings

In Section 1, I show unusual bunching patterns in startup valuations based on Figures 1 and 2. Is there any noticeable bunching pattern in other settings? In Figure A4, I report the same range of post-money valuations between $700 million and 1,300 million for the cases of IPOs. I define post-money valuations for IPOs as *price* × *the number of basic shares outstanding*. Unlike the definition of post-money valuation for private startups, *the number of basic shares outstanding* does not include potential conversions, such as stock options outstanding.

— PLACE FIGURE A4 ABOUT HERE —

Figure A4 shows that there is no bunching pattern for the $1 billion post-money valuation except for Panel A. Panel A of Figure A4 reports the post-money valuation of IPOs using the *low* price of the initial IPO offer price range. I interpret that some companies anchor on $1 billion to be the minimum valuation for their IPOs, although the frequency and magnitude are not comparable to the bunching I find in Figure 2. One noticeable fact is that private startups' valuation bunching pattern for $1 billion I find in Figure 2 is calculated based on the fully diluted basis, including even authorized but unissued shares in employee option pools to the share count. However, Figure A4 valuations are calculated based on the basic basis, only considering outstanding shares.

A4. Textual Analysis (Topic Modeling) in Detail

In Section 6, I document the positive impact of achieving unicorn status on employee sentiments. In this section, I aim to understand the underlying reasons behind the change in employee sentiments, expanding Section 6.3. I conduct a topic modeling based textual analysis on Glassdoor written reviews (free responses). The primary purpose of the topic modeling analysis is to group written reviews into different topics and to find changes in the relative frequency of each topic between before and after achieving unicorn status. Since this is comparing unicorn startups' within-firm variations, I restrict the sample to California-based startups that achieve unicorn status between 2014 and 2021 and use their reviews written during the same period.

For the specific method of my topic modeling analysis, I utilize latent Dirichlet allocation (LDA) model (Blei et al. (2003)), which is an extension of latent semantic analysis (LSA) and later probabilistic LSA (Hofmann (2001)). In contrast to LSA, LDA uses a Bayesian model that treats each document (each review for my case) as a mixture of latent topics (Loughran and Mcdonald (2016)). Thus, LDA suits my purpose to assign topics discussed in the Pros and Cons sections of each review. Lambert et al. (2021), which also conduct an LDA-based textual analysis on Glassdoor review data, point out that LDA is unsupervised by its design, not requiring assumptions about topics to be found in the document.

The analyses consist of three steps. First, I determine how many potential topics can be identified in reviews. I treat Pros and Cons independently thus analyzing them separately. This is because certain topics tend to show up more in Pros than in Cons and vice versa. To set the range of possible number of topics, I use three benchmarks, two contemporary papers that conduct similar topic modeling analyses on Glassdoor review data, and Glassdoor's guidelines. The first paper is Lambert et al. (2021) – the paper studies the impact of leveraged buyouts (LBOs) on employee satisfaction and categorizes reviews into 25 topics using LDA models. The second paper is Sockin (2022) – it examines the relationship between pay and job amenities and classifies reviews into 50 topics. Finally, Glassdoor suggests five broad topics – Work-Life Balance, Culture & Values, Career Opportunities, Compensation and Benefits, and Senior Management.[37] These five categories are visible to employees when they write reviews.

I follow Lambert et al. (2021), which follows Roder, Both and Hinneburg (2015), to identify the optimal number of topics in reviews. Specifically, I compute coherence scores of the topics based on the three benchmark numbers: 5 (Glassdoor), 25 (Lambert et al. (2021)), and 50 (Sockin (2022)) topics for both Pros and Cons categories. The coherence scores represent probabilities that words I identified in Table A3 exist in each review and are calculated based on two parameters, α and β. α controls the shape of Dirichlet distribution of reviews on topics and β controls the shape of Dirichlet distribution of topics on reviews (Roder et al. (2015) and Lambert et al. (2021)). Figure A5 shows coherence scores based on the three benchmark numbers. The first option, having 5 topics, reports the highest (i.e., least negative) score, meaning that topics are of greater quality when there are 5 topics compared to 25 and 50 topics.

— PLACE FIGURE A5 ABOUT HERE —

Based on Figure A5, I group Glassdoor reviews into five categories and assign topics to each of them. Before conducting the topic modeling analysis for both Pros and Cons sections, I perform a standard procedure in cleaning the texts. I remove stop words (e.g., 'a', 'the', 'is'), lemmatize words (e.g., 'caring' to 'care'), and remove certain categories words without meanings such as pronouns.

In Table A3, I report these topic assignments – Panel A reports five topics identified in the Pros review section and Panel B reports five topics identified in the Cons review section. For each topic, I include two rows. The first row reports the top 15 Unigrams (1–grams) – roots of the 15 most

[37] Glassdoor added the sixth category, Diversity & Inclusion, in 2020.

frequent words for each topic. In parenthesis, I report the total weight of these top 15 Unigrams as a percentage format, following Lambert et al. (2021). For example, in Panel A, the first topic 'Compensation' has 35%, while the second topic 'People and Culture' has 50%. It means that the top 15 Unigrams of the 'People and Culture' topic occur more frequently compared to the top 15 Unigrams of the 'Compensation' topic, on a relative basis. In the second row, I provide an actual review that is close to each topic to show representative examples.

— PLACE TABLE A3 ABOUT HERE —

Finally, I document the change in the composition of each of the five topics identified in both Pros and Cons sections. I follow two steps. First, I calculate each topic's document-topic density scores for the pre-unicorn period (up to six months) and the post-unicorn period (up to six months). For example, consider a startup that achieved unicorn status on March 17, 2020, based on Pitchbook's deal completion dates. Then the pre-unicorn period is between September 17, 2019, and March 16, 2020, and the post-unicorn period is between March 17, 2020, and September 16, 2020. Second I compare the percentage of reviews that have document-topic density scores higher than certain thresholds between the pre-unicorn period and the post-unicorn period. For example, assume that for the pre-unicorn period, 30% of the reviews had document-topic density scores higher than 50% for the Pros 1 Compensation topic. For the post-unicorn period, 27.93% of reviews had document-topic density scores higher than 50% for the Pros 1 Compensation topic. Then, I calculate -6.9% (= $\frac{27.93\%-30\%}{30\%}$) as the change in my second specification.

Table A4 reports these two specifications. The 'Mean' column is the first specification, change in the average document-topic density scores between the pre-unicorn period and the post-unicorn period. The 'Document-Topic Density' column is the second specification, change in the proportion of reviews that have document-topic density scores higher than certain thresholds. Three sub-specifications have different hurdle rates (thresholds), 50%, 70%, and 90%. In the 'Change' column, I have five options – no meaningful change (marked as '-'), weakly positive change, weakly negative change, strongly positive change, and strongly negative change. This is based on

— PLACE TABLE A4 ABOUT HERE —

Results in Table A4 show that after achieving unicorn status, startup employees write relatively more positive reviews about employee benefits, more negative reviews about leadership and culture, and fewer negative reviews about compensation. This shows that the main reason behind the increased assessments following unicorn status achievement is based on better satisfaction with employee benefits and compensation, even though increased dissatisfaction with leadership and culture change. I interpret that having relatively fewer reviews in the negative section means increased satisfaction with that topic.

Figure A1. California Section 25102(o) Exemption Filing Example – 23andMe Inc.

STATE OF CALIFORNIA – DEPARTMENT OF BUSINESS OVERSIGHT
NOTICE OF TRANSACTION PURSUANT TO SUBDIVISION (o) OF SECTION 25102 OF THE CORPORATIONS CODE
DBO – 25102(o) (Register 2002, No. 39) (Rev. 08-13)

N- 60158

(Department of Business Oversight Use Only)

Fee Paid $ ____________

Receipt No. ____________

DEPARTMENT OF CORPORATIONS
FILE No., if any: ____________
(Insert File numbers(s) of Previous Filings Before the Department, If Any)

FEE: **$2,500.00**

(See Corporations Code Section 25608(y) and Section 25608(e).
The fee is based on the current market value of the securities, or in the case of options, the underlying securities.)

1. Name of Issuer: **23andMe, Inc.**
2. State of Incorporation or Organization: **Delaware**
3. Address of Principal Place of Business:
   899 W. Evelyn Avenue, Mountain View, CA 94043
   Number and Street City State Zip Code
4. The security is issued pursuant to a: (Check One)

[ ] Purchase Plan or Agreement.
Name of Security: ____________
Number of Securities: ____________
Price per Security: $ ____________

[ ] Option Plan or Agreement.
Name and Number of Options: ____________
Name and Number of the Underlying Securities: ____________
Exercise Price Per Security: $ ____________

[X] "Flexible" Purchase/Option Plan or Agreement.
Name of Security/Option: **2006 Equity Incentive Plan**
Number of Securities/Options: **11,392,717**
Name and Number of the Underlying Securities: **11,392,717 shares of Common Stock**
Price Per Security: **$5.34**

5. Aggregate current market value of securities sought to be sold: **$ 60,837,108.78**
6. Date of Notice: **August ___, 2015**

(X) Check if Issuer has a consent to service of process on file with the Commissioner

23andMe, Inc.
Name of Issuer

____
Authorized Signature on behalf of Issuer

Andrew Page, President
Print Name and Title of Signatory

Name, Address and Phone Number of Contact Person:
Nicole Maroko (650) 614-7425
1000 Marsh Road
Menlo Park, CA 94025

Instructions: Each issuer (other than a California corporation) filing a notice under Section 25102(o) must file a consent to service of process (Form 260.165), unless it already has a consent to service on file with the Commissioner.

2015 AUG 20 PM 3:21

DEPT OF BUSINESS OVERSIGHT ACCOUNTING RECEIVED

OHSUSA 757887315.1
21537-1

2015 AUG 20 PM 3:

Figure A2. Number of Unicorns and Newspaper Articles

Blue dots report the number of new unicorn companies (including non-U.S. headquartered companies) per year (right axis). Red triangles report the number of new unicorn companies headquartered in the U.S. per year (right axis). Grey bars report the number of articles containing two words 'venture' and 'unicorn' at the same time by *Wall Street Journal* and *Financial Times* (left axis).

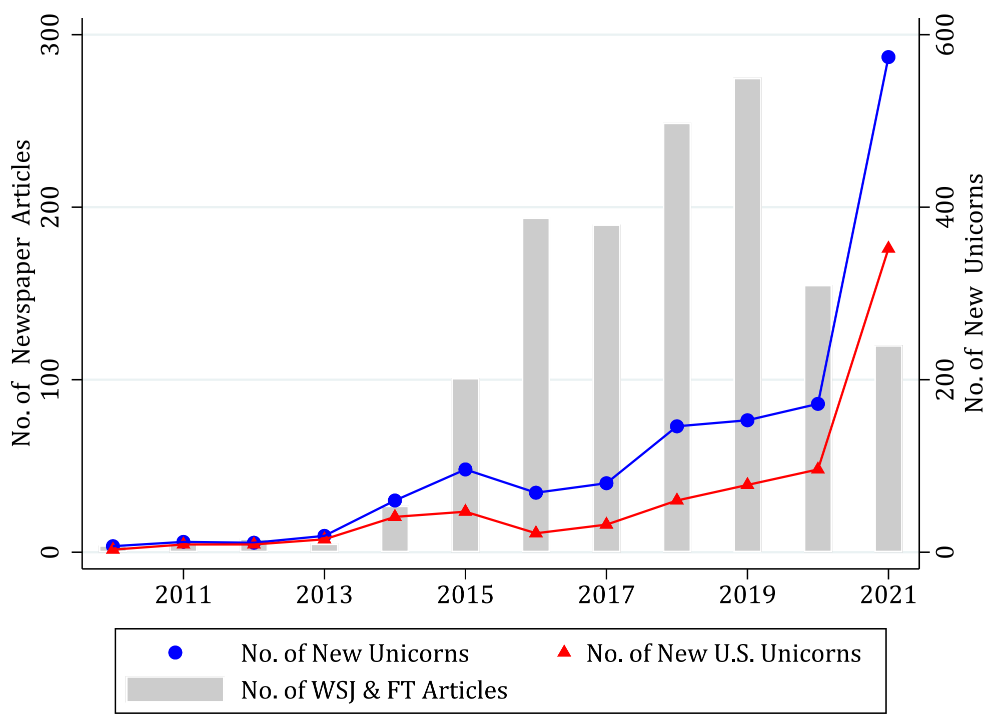


Figure A3. Employee Ratings: Regression Discontinuity Design

Figure A3 shows the average of Glassdoor overall ratings (1: the lowest, 5: the highest) given by employees of California-based startups that raised venture capital financing between January 2014 and December 2014. I restrict reviews written between January 2015 and June 2016. I further restrict the sample to startups that achieve unicorn status (post-money valuation of $1 billion or higher) between 2014 and 2021 to minimize potential selection bias. For example, assume that both startups A and B raised capital in November 2014 with a post-money valuation of $700 million. Startup A conducted subsequent financing round in 2016 with a post-money valuation of $1.2 billion, but startup B did not receive any additional funding until December 2021. In that case, my sample only includes startup A. This figure is associated with equation (4) and Table A2. Each dot represents $100 million. For example, the first dot includes reviews given by employees of startups with post-money valuations of [$700 million, $800 million). Linear lines represent the fitted lines from linear regressions. Curved lines represent the fitted lines from quadratic regressions. Startups with valuations of $1 billion or higher are referred to as 'unicorns' while startups with valuations less than $1 billion are not.

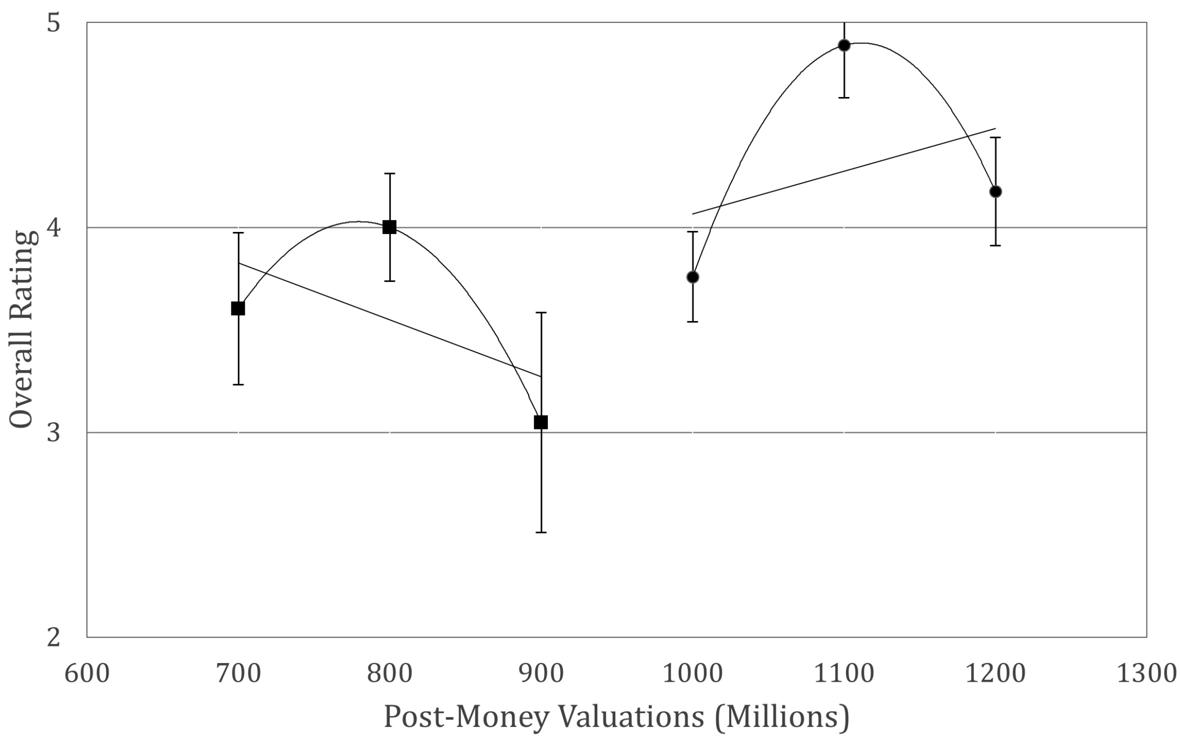
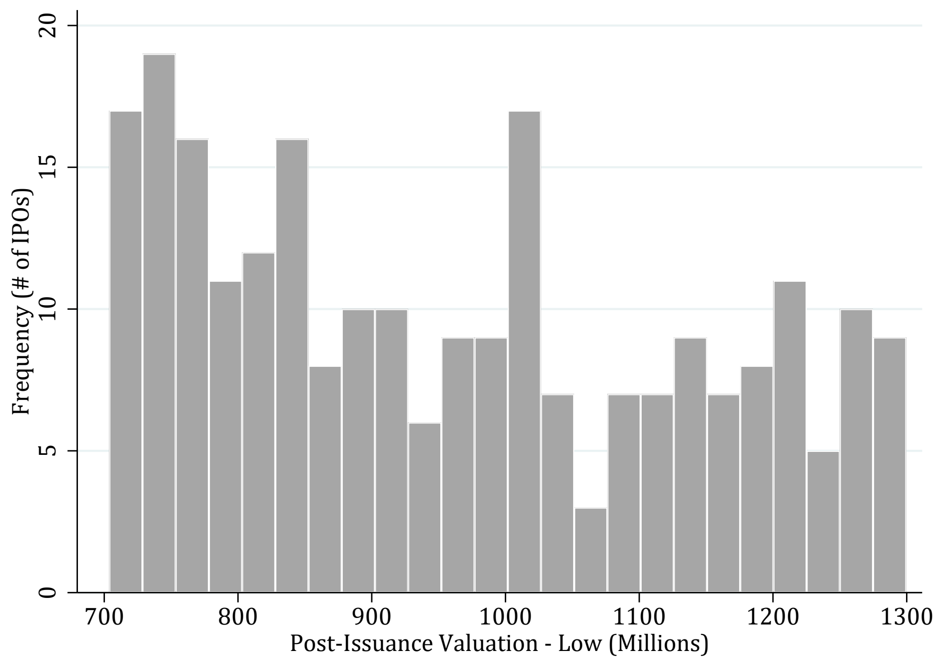


Figure A4. Distribution of IPO Valuations

Figure A4 shows the distribution of all U.S. IPOs' post-money valuations when the post-money valuations are between \$700 million and \$1,300 million. Post-money valuations are defined as *price* $\times$ *the number of basic shares outstanding* after the IPO. *The number of basic shares outstanding* does not include potential conversions, such as options outstanding. **Panel A** reports post-money valuations using the lower bound of the initial price range (low) as *price*. **Panel B** reports post-money valuations using the midpoint of the initial price range (mid) as *price*. **Panel C** reports post-money valuations using the upper bound of the initial price range (high) as *price*. **Panel D** reports post-money valuations using the final offer price as *price*.

Panel A. *Price* = Initial Price Range Low



Panel B. *Price* = Initial Price Range Mid

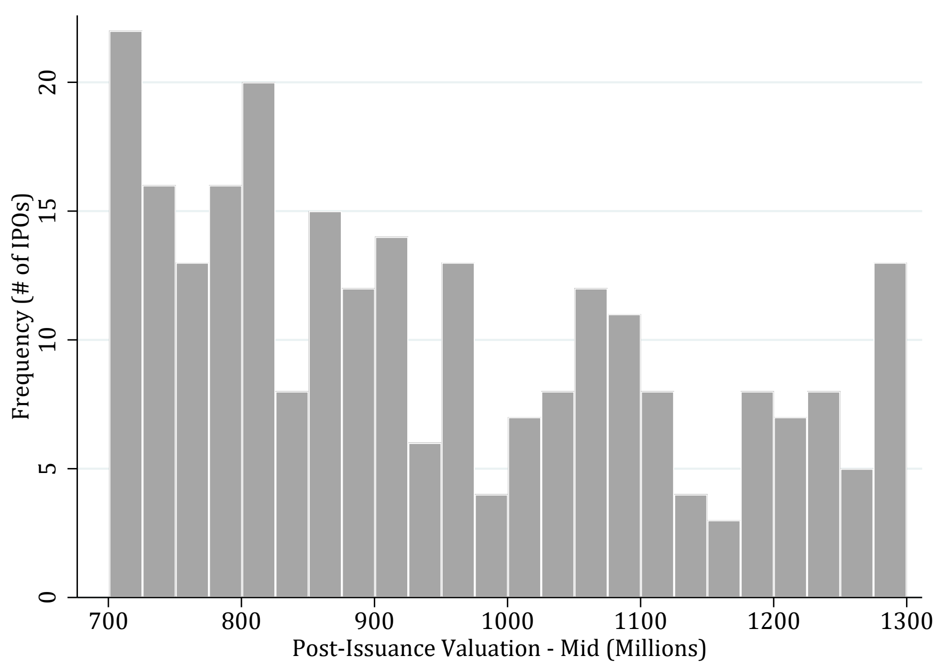
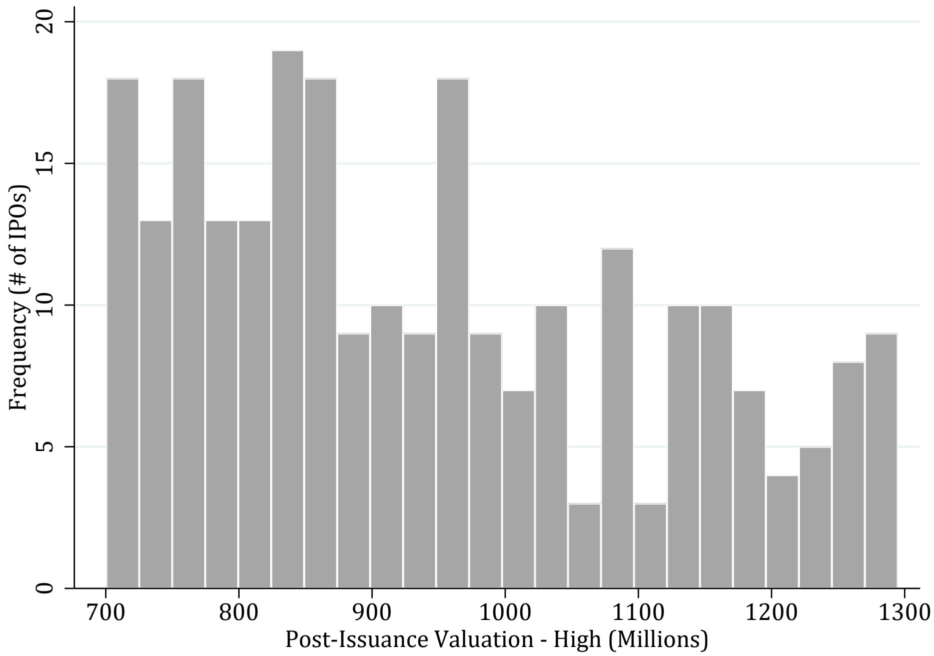


Figure A4. Distribution of IPO Pricing (Continued)

Panel C. *Price* = Initial Price Range High



Panel D. *Price* = Final Offer Price

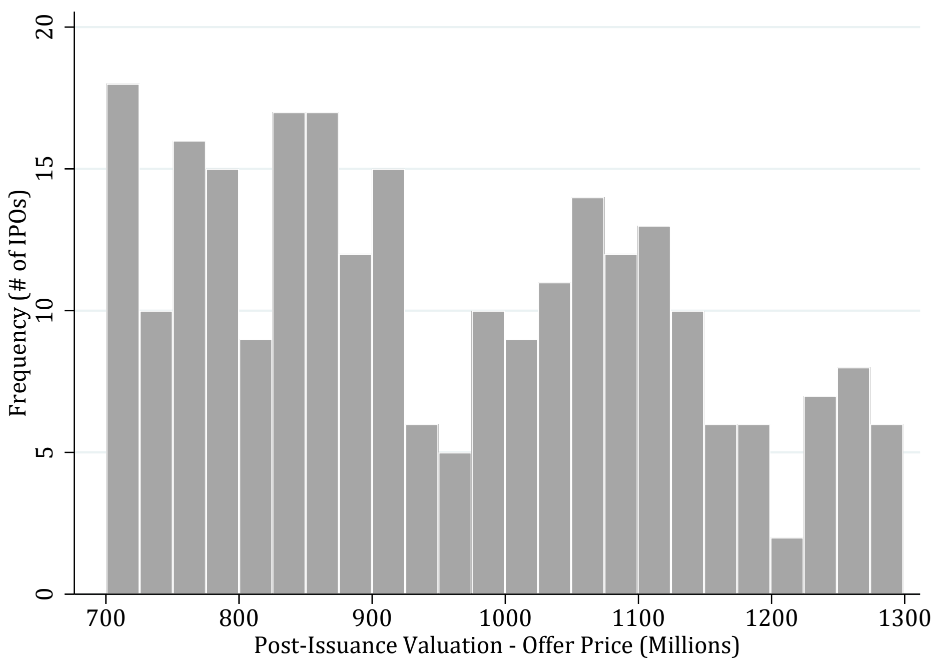
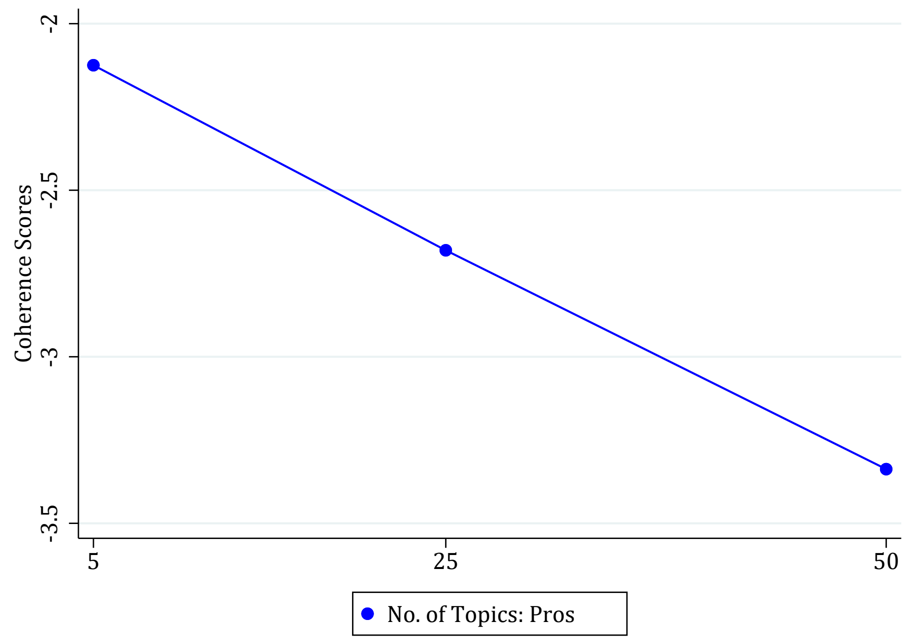


Figure A5. Optimal Number of Topics

Figure A5 examines the optimal number of topics in reviews for both Pros and Cons. The horizontal axis is the potential number of topics: 5, 25, and 50 following Glassdoor's classification, Lambert et al. (2021), and Sockin (2022). The vertical axis is the coherence scores calculated using Dirichlet distribution of reviews on topics based on two parameters, α and β following Roder et al. (2015). **Panel A** reports coherence scores for reviews written in Pros category. **Panel B** reports coherence scores for reviews written in Cons category.

Panel A. Reviews Written in 'Pros' Category



Panel B. Reviews Written in 'Cons' Category

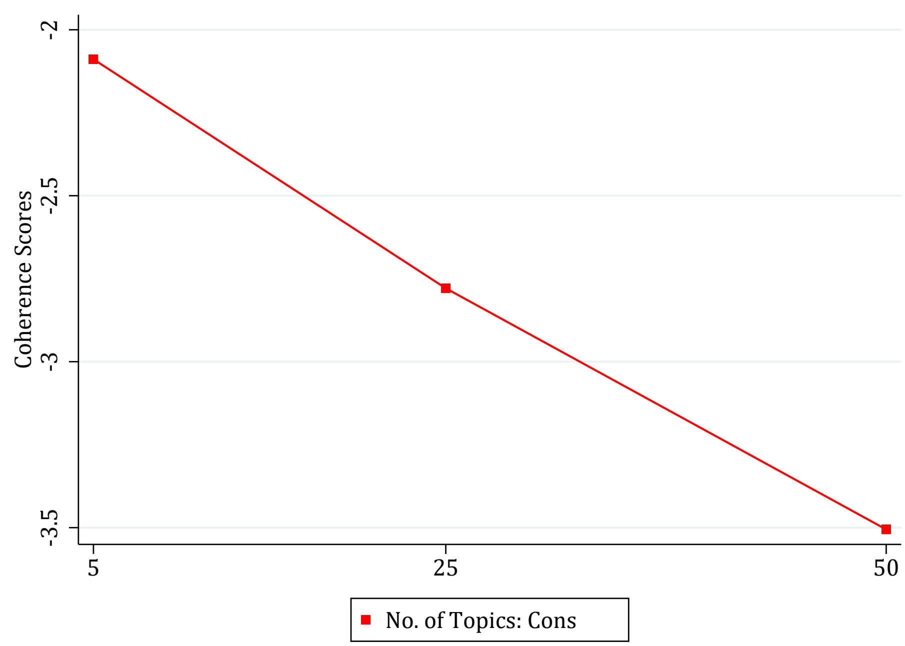


Table A1. Pitchbook Data Verification

Table A1 lists 10 randomly selected deals that Pitchbook reports the post-money valuation is $1 billion and the source of this valuation information is 'estimated' instead of 'actual'. I search online including Factiva to determine whether an independent source reports the same exact $1 billion valuation. I find at least one article for 9 out of 10 deals and 8 of them explicitly mention the post-money valuation of $1 billion. Clicking the independent source column (e.g., Fortune) leads to the actual article. All articles are retrieved as of September 2022.

Deal Date	Company Name	HQ Location	Valuation	Independent Source
Jun 21, 2021	Amber Group	Hong Kong	exact $1B	Fortune
Dec 6, 2021	Clara	Mexico	exact $1B	Cision PR Newswire
Aug 1, 2021	Haydon	China	exact $1B	Crunchbase
Mar 12, 2018	Kiavi (LendingHome)	United States	exact $1B	Yahoo (based on Pitchbook)
Jun. 12, 2018	Luckin Coffee	China	exact $1B	Radii China
Nov 17, 2021	PLACE	United States	exact $1B	The Real Deal
Apr 9, 2021	SaltPay	United Kingdom	at least $1B	The Times
May 6, 2014	Viridos	United States	N/A	N/A
May 31, 2017	Yuanfudao	China	exact $1B	Private Equity International

Table A2. Employees' Responses to Unicorn Status: Regression Discontinuity Design

Table A2 analyzes the causal impact of achieving unicorn status (post-money valuation of $1 billion or higher) on the startup employees' overall rating of the company. Specifically, it reports results from the regression discontinuity design model defined in equation (4), given by

$$\begin{aligned}\textit{Overall Rating}_i = \beta_1 \textit{Unicorn}_j + \beta_2(\textit{Valuation}_j - \textit{\$1B}) + \beta_3(\textit{Valuation}_j - \textit{\$1B})^2 + \\ \beta_4[\textit{Unicorn}_j \times (\textit{Valuation}_j - \textit{\$1B})] + \beta_5[\textit{Unicorn}_j \times (\textit{Valuation}_j - \textit{\$1B})]^2 + X_j + e_i,\end{aligned}$$

The sample consists of California startups that raised capital with a post-money valuation of $500 million or higher between January 2014 and December 2014 and have non-missing Glassdoor employee review data between January 2015 and June 2016. The unit of observation is review-level *(i)*, which has a specific startup *(j)*. $\textit{Unicorn}_j$ is a dummy variable that equals 1 if the post-money valuation of the financing round is $1 billion (cutoff) or higher. $\textit{Valuation}_j$ is the post-money valuation of the financing round. X_j is a vector of startup-level control variables, including the age of the startup at the time of the capital raising, and the days between the capital raising date and the review written date. Specifications (5) and (6) include quadratic terms but I do not report them for brevity as they are not statistically different from zero. Standard errors are reported in parentheses. Statistical significance levels: *** p-value<0.01, ** p-value<0.05, * p-value<0.10.

	Overall Rating					
	(1)	(2)	(3)	(4)	(5)	(6)
Unicorn	0.449***	0.439***	0.594***	0.550***	0.799**	0.798**
	(0.092)	(0.096)	(0.198)	(0.201)	(0.319)	(0.324)
Valuation			-0.001*	-0.001	-0.003	-0.004
			(0.001)	(0.001)	(0.002)	(0.003)
Unicorn X Valuation			0.001*	0.001*	0.003	0.003
			(0.001)	(0.001)	(0.002)	(0.003)
Constant	3.713***	3.991***	3.610***	3.582***	3.434***	3.351***
	(0.079)	(0.177)	(0.159)	(0.256)	(0.579)	(0.349)
Quatradic Terms	No	No	No	No	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
N. Obsevations	1,123	1,062	1,123	1,062	1,123	1,062
Adj. R-sq	0.023	0.022	0.041	0.040	0.042	0.041

Table A3. Employee Review Topics

Table A3 lists five topics identified by the LDA with labels I created. For each topic, it provides the 15 most frequent Unigrams, and their explanatory power for qualifying the labelled topics (in parenthesis), following Lambert et al. (2021). It also provides examples of actual reviews in the labelled topics. **Panel A** conducts the analysis on reviews written in 'Pros' section. **Panel B** conducts the analysis on reviews written in 'Cons' section. For example, for the first topic in 'Pros' section, I label it as 'Compensation'. The 15 most frequent Unigrams include 'good', 'pay', 'benefit'...'snack' and these 15 Unigrams qualify 35% of the labelled topic.

Panel A: Reviews Written in the Pros Section

Pros 1	Compensation	**Top 15 Unigrams**: good, pay, benefit, free, flexibl, hour, time, lunch, great, food, salari, decent, job, schedul, snack (35%)
		Example: pay is pretty good and slightly above industry, benefits are good (401k match would be nice at any level)
Pros 2	People and Culture	great, peopl, cultur, good, compani, benefit, amaz, product, team, environ, smart, life, place, emplye, balanc, care (50%)
		highly collaborative work environment. extremely sharp, passionate and creative team
Pros 3	Management and Leadership	team, manag, compani, employe, support, cultur, help, feel, care, leadership, good, great, valu, transpar, time, open (22%)
		humble, smart, passionate and human ceo and founders
Pros 4	Employee Benefits	peopl, offic, compani, lot, lunch, great, fun, worker, free snack, team, day, nice, friendli, co (19%)
		free food. each day lunch is served and is generally a meat dish, vegetables and salad. sometimes they have a sandwich bar which is refreshing.
Pros 5	Career Growth	compani, people, opportun, product, team, grow, learn, lot, growth, fast, great, market, new, custom, busi (20%)
		learning is given utmost importance. you try, you learn. whether you fail or succeed, your manager and your team stand by you and gives you a pat on the back for exploring new things.

Table A3. Employee Review Topics (Continued)

Panel B: Reviews Written in the Cons Section

Cons 1	Career Growth	**Top 15 Unigrams**: grow, compani, chang, work, fast, growth, think, lot, time, pain, need, thing, process, challenge, start (31%)
		Example: fast paced means sometimes feeling overwhelmed at all you need to learn to keep up with the company's needs and desires. it means pushing the edge on your comfort zone, and taking ownership of things you might not feel completely confident in doing.
Cons 2	Wrok Life Balance	work, hour, life, balanc, manag, long, peopl, good, time, bad, hard, day, compani, job, pay (37%)
		the hours are ridiculous, i haven't not worked a 10 hour shift on a weekday or just had a work free weekend in a very long time. management doesn't care as long as you're doing what you're told.
Cons 3	Product and market	compani, product, team, peopl, cultur, leadership, lack, employe, manag, engin, chang, market, year, decis, work (17%)
		when a product is created, you want to make sure customers will want to use your product first, but we were doing the opposite at acorns. we were trying to make a really nice looking product that nobody wanted. but now we were stuck having to make it work because this was the product our ceo had pitched to investors as our secret sauce, our unique proposition.
Cons 4	Leadership and Culture	manag, peopl, sale, team, employe, leadership, compani, lack, promot, hire, know, review, cultur, job, leav (19%)
		the managers they hired during shelter in place did not understand the culture. serious politics where the bros get ahead and are promoted for being the manager's favorite.
Cons 5	Compensation	pay, work, time, offic, compani, day, employe, job, custom, benefit, low, manag, high, expect, posit (16%)
		low reward, pay increases are low compared to inflation and cost of living

Table A4. Employee Review Topic Changes Before and After Achieving Unicorn Status

Table A4 tabulates changes of topic compositions between reviews written prior to achieving unicorn status (up to six months) and written after achieving unicorn status (up to six months). For example, if a startup achieved unicorn status on March 17, 2020, the pre period is between September 17, 2019 and March 16, 2020, and the post period is between March 17, 2020 and September 16, 2020. The '**Topic**' column is based on topics in Table A3. The '**Mean**' column represents the change of the average of document-topic density scores between pre and post periods for each topic. For example, the first 0.3% represents that compared to reviews written in the pre period, the average document-topic density scores for compensation increased 0.3% in post period. The three sub-columns under the '**Document–Topic Density**' column represent the change in percentage of reviews that have document-topic density scores above the given thresholds between pre and post periods for each topic. For example, -6.9% in compensation can be approximately interpreted as compared to reviews written in the pre period, there were 6.9% fewer reviews written in the post period that have document-topic density scores greater than 50%. The final '**Change**' column represents how consistent and significant the changes are based on reported specifications.

	Topic	Mean	Document–Topic Density			Change
			> 50%	> 70%	> 90%	
Pros	Compensation	0.3%	-6.9%	-6.7%	-16.6%	-
	People and Culture	4.7%	7.4%	9.5%	15.0%	weakly positive
	Management and Leadership	-3.0%	-5.7%	-5.7%	-16.9%	weakly negative
	Employee Benefits	5.1%	13.5%	14.6%	28.1%	strongly positive
	Career Growth	-4.7%	-3.6%	-5.3%	2.9%	-
Cons	Career Growth	-0.2%	1.5%	0.4%	-0.6%	-
	Work Life Balance	-5.6%	-10.6%	-13.8%	6.3%	-
	Product and Market	2.6%	1.9%	-1.5%	-3.5%	-
	Leadership and Culture	11.1%	14.1%	22.4%	23.8%	strongly positive
	Compensation	-9.2%	-16.4%	-17.6%	-11.5%	strongly negative