Are Private Secondary Markets Detrimental to Startups?*

Luiz Bissoto†

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Abstract

I test whether startups' financing and success likelihood are negatively impacted when their shares are traded in private secondary markets (PSMs). Startups traded in PSMs tend to raise money more slowly, delay IPOs, and face more stringent investors but are also self-selected to be successful, having higher valuations and valuation growth after listing. Additionally, employees' access to PSMs makes them more receptive to equity compensation, extending the time for the startup to obtain financing. Together, my results rationalize the recent PSM activity growth and the viability of these markets as an alternative exit route for private equity investments.

Keywords: Venture Capital, Institutional Investors, Secondary Markets

JEL Codes: G11, G23, G24, G32

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†EPFL and Swiss Finance Institute, Extranef (Unil-Dorigny), Lausanne 1015. Email: luiz.bissoto@epfl.ch

1 Introduction

"I have been working on the startup liquidity problem for almost a decade and spent $150M trying to solve it. After a lost decade (and an unbelievable amount of money), I have concluded that building a secondary private marketplace is an intractable problem that cannot be solved." - Henry Ward (Carta's CEO)[1], June 4th, 2024.

The yearly trading volume of startup shares in private secondary markets (PSMs) in the U.S. surpassed $100 billion for the first time in 2021 (Smith (2023)), following a fast growth trajectory in the preceding decade and accompanied by consistent venture capital (VC) deal volume growth (Figure 1). Unlike public markets, which are open to all, PSMs often restrict access to accredited and institutional investors and operate under different regulatory frameworks with fewer disclosure requirements (SEC (2020)). In the case of PSMs where startup shares are traded[2], a key factor cast doubt on their viability: liquidity and price discovery are plausibly detrimental to startups. The issue was summarized recently by startup Carta's founder Henry Ward in a social media article: *"Marketplace = Liquidity + Price Discovery. Liquidity is a bug (and not a feature) in private markets. Price discovery is also a bug"*. Differently from mature firms, be they public or private, startups are constantly seeking external financing. Exceptions apart, most ventures are not profitable and are still developing a viable business model. Under these circumstances, offering "exit liquidity" for shareholders is frequently against startup founders' interest because, in a PSM, both employees and shareholders compete with the founder for scarce capital. With price discovery enabled, another shortcoming for founders arises: ideally, founders want to *set* the price they ask for their business' shares rather than accept a prevailing market price.

The central question I investigate in this paper is whether trading activity on PSMs

[1]See the full article by Henry Ward here. Carta is a San Francisco, California-based technology company that specializes in capitalization table management and valuation software. As of August 2021, Carta's valuation reached $7.4 billion dollars, following a $500 million financing round (Deutscher (2021)).

[2]I draw this distinction to set them apart from markets where shares in private equity funds are traded.

is detrimental to startups, benefiting some investors at the expense of the startup founder and other investors. If true, then the viability of these markets, a potential alternative exit venue for venture capital (Ibrahim (2012)) and private equity investments in the range of trillions of dollars, is undermined. I seek to answer this question in three parts, working with a selected sample of nearly 400 startups that trade in these markets and whose combined market capitalization is close to $1.9 trillion. This sample includes hand-collected data from several sources on startups trading on major PSM platforms in the U.S., such as EquityZen, ForgeGlobal, Linqto, and Nasdaq Private Market, along with supporting data from the overall U.S. venture capital market from S&P Capital IQ, industry reports (see, e.g., CartaTeam (2024)), and Crunchbase.

First, I characterize which startups trade in these markets in terms of growth and size. The idea is to verify whether the problem laid out is applicable to these firms: do they actually *need* to raise money? Are they unprofitable? Are they still growing fast? If the answer to these questions is negative, then the problem is not even applicable, and PSMs can work fine, provided that the startups trading on them are not "startups" anymore.

Next, I analyze the financing performance of these startups that are "listed"[3] on PSMs. Without aiming to establish causality, I verify whether the time elapsed from founding to listing and from listing to the present (or an IPO, when occurring) has any observable relationship with the startup number of financing rounds, amount of money raised, the time between rounds, and the overall money raised over time. The objective of this analysis is to identify whether startups that have been listed for longer times or that were listed "too early" seem to have difficulties in raising money, surviving, and succeeding.

In the last step, I build a simple listing choice model to estimate whether investors are more or less demanding regarding the expected return from their investments when the startup shares are listed versus when they are not. This listing choice model incorporates key aspects intrinsic to the VC market, namely the anticipated competition for liquidity

[3]Technically, a startup is "listed" in a PSM by shareholders requesting authorization from the startup to trade their shares. I refer to this event as a "listing" for brevity.

with employees and current shareholders faced by the startup and the uncertainty about of securing funding, essential for the startup survival. I show that it can be optimal for founders to opt for a listing *despite* this competition. In my model, the startup founder must choose whether to award shares to employees, how much equity to offer to new investors, how long its initial funds will last, and whether the shares can be traded in a PSM. Combined, these options impact the likelihood that the startup will be able to secure funding, survive, and potentially succeed, impacting the founder's total payoff. While the decision to have shares listed can potentially harm the perception of the startup's prospects toward new investors, e.g., due to asymmetric information (Myers and Majluf (1984)), awarding employees with shares may reduce the rate with which cash is spent, which acts as a *de facto* financing channel that extends the startup's time to secure funding. The founder anticipates that and must weigh the trade-offs between the several scenarios arising from these choices.

The first step of my analysis shows that the startups listed on PSMs are high-growth and large startups, with an average growth that is about 15.8% larger and a valuation $0.63 billion higher for each year they are listed. The vast majority ($\approx$ 83%) of these startups raise money after being listed, albeit less frequently, having about 1.2 financing rounds on average and raising around $270 million on average across these rounds. In the seven years that cover the listing period (the earliest company to list did so in 2016), about 10% of the startups do an IPO, a frequency that is smaller than that observed in the preceding years for similar firms. For instance, in the 2010-2015 period, about 17% of the startups with six or more rounds (the average in the sample) eventually did an IPO. While truncation bias (the fact that these startups might still do an IPO) and time effects (an overall trend toward fewer IPOs, see, e.g., Gao et al. (2013)) partially explain this trend, the lower IPO frequency challenges the idea that these startups are simply "pre-IPO" firms about to go public.

In the second step, my main finding is that startups trading on PSMs are highly engaged in obtaining external financing, suggesting a high *need* for it. These startups have about 0.35 to 0.70 additional rounds per year listed, and the overall number of financing rounds they have after being listed is only minimally influenced by the time elapsed from launch until the listing. Additionally, among the 36 startups that do an IPO, only one is profitable in the two years preceding it. These findings dismiss the idea that founders decide to approve listings only after additional financing rounds are not needed anymore[4]. The total amount of money raised is larger, around \$170 million additional for each round per year that the startup is listed. These effects are amplified by size, growth, and success, such that startups with larger valuations, larger valuation growth, and that eventually do an IPO tend to raise more and have more rounds. This increased financing performance is also observed on a relative basis, with the money raised divided by the time elapsed between rounds being larger. Importantly, across startups, the time between rounds tends to be larger when listed (6 to 9 months per year listed), which supports the hypothesis that once shares have some liquidity, employees are more receptive to equity compensation, partially substituting cash salaries, a key expense for most startups[5]. This hypothesis is reinforced by the finding that startups with larger ownership by employees post-listing are correlated with longer times between rounds. I test this hypothesis further in the next step, where I estimate how receptive to equity compensation employees are in unlisted versus listed startups.

In the last step, I estimate two key sets of parameters from my listing choice model. The first parameter, the minimum payoff risk-adjusted return investors demand to consider investing in a startup, proxies how difficult it is for a startup to obtain financing, given uncertainty about how large it will be if successful. I find that across the sample, this parameter is significantly higher for startups when they are listed, suggesting that, indeed, investors are more stringent when shares are traded on PSMs. This result supports the existence of the problem laid out in the introduction: PSMs are indeed potentially detrimental to startups due to liquidity and price discovery being beneficial for some investors at the expense of the founder. However, I also find that this increased stringency is not the case when estimating it using only ex-post successful startups, defined as those that eventually do an IPO. In the

[4] If that were the case, more years to list would be highly correlated with fewer future financing rounds.

[5] *"For most startups, payroll is the primary driver of cash burn."* (Walker (2022))

case of these firms, investors are, in fact, more likely to consider investing in them when their shares are traded. Therefore, while the "detrimental PSM hypothesis" applies to many startups in general, it can be avoided provided that there is an expectation of quality: for some startups, the listing is beneficial, with the startup being better off when its shareholders can trade their shares. An important channel through which this benefit materializes is equity compensation: I find that employees are, on average, more receptive to equity compensation when shares are traded, an effect that is larger when the startup eventually does an IPO. As such, startups can benefit from a listing by increasing equity compensation, saving cash, and having less frequent rounds, with this benefit increasing with startup quality. Finally, I conclude by investigating the impact of uncertainty about the change in investor stringency. Given that, in practice, founders do not observe the payoff risk-adjusted return investors expect, the impact of the decision to list can be highly uncertain. My model makes predictions regarding the number of years that a startup takes to have its shares listed, given this uncertainty. I find that when investors expect lower stringency when listed, the startup gets listed faster, consistent with the model prediction that stringency impacts the decision to list and that startups tend to list later when founder ownership is higher. The latter suggests that founder sales are expected when the founder has high share ownership, which can be detrimental to the startup, so taking longer to list delays the potentially negative effect.

My main contribution is threefold. First, I characterize startups being traded in PSMs and identify, by looking at a representative sample of these startups, an important obstacle to the functioning of these markets: I show that the startups whose shares are traded are high-growth firms that need frequent external funding rather than mature profitable firms and that the PSM listings interfere with their financing. While public listing models abound in the literature (see, e.g., Mello and Parsons (1998), Chemmanur and Fulghieri (1999)), PSM listings are fundamentally different, with competition between investors, employees, and the startup for capital from other investors affecting the firm's survival itself. Second, I show that this obstacle is not insurmountable. Startup quality, rather than the development stage, can make it beneficial for startups to have their shares traded. I provide descriptive evidence for that, showing an association between being listed and higher growth and better financing and causal, showing that startups that were successful ex-post likely faced less stringent investors when trying to obtain financing. Finally, I provide a framework to better understand these markets, which are increasingly relevant for venture capital investors (see, e.g., Ibrahim (2012), Larcker et al. (2018), and Abuzov et al. (2023)), allowing for an alternative exit route to an acquisition or going public. I do that by incorporating in my model important channels through which trade-offs accrue to the main decision-making agent: investor stringency, impacted when PSM trading occurs and translating into a higher or lower funding likelihood, and the receptiveness to equity compensation by employees, which can prolong the time between rounds, extending the time the startup has to find an investor.

This paper primarily contributes to two streams of literature. First, it adds to the literature on the functioning of VC investing and optimal financing (Hellmann (2002), Hellmann and Thiele (2015), Hugonnier et al. (2014), Gryglewicz et al. (2021), Gryglewicz and Mayer (2023), Sannino (2024)), centered on a particular type of market, PSMs. I add to this literature by describing which sort of firms are traded and by presenting a listing decision model (Pagano and Roell (1998), Mello and Parsons (1998), Chemmanur and Fulghieri (1999), Subrahmanyam and Titman (1999), Boehmer and Ljungqvist (2004), Gupta and Rust (2017), Celentano and Rempel (2020)) incorporating strategic interaction between the shareholders of a startup – the founder, early investors, and employees – competing for capital where key trade-offs are present and can be reasonably estimated. Second, it adds to the literature addressing why firms remain private for longer and the decline in public markets, along with the behavior of late-stage startups (Gao et al. (2013), Doidge et al. (2013), Doidge et al. (2017), Stulz (2018), Stulz (2019), Samimi (2020), Ewens and Farre-Mensa (2020), Davydova et al. (2022)). I add to this literature by showing that PSMs are viable and beneficial for both investors and startups rather than investors only by potentially increasing a startup's chances of securing funding, which in turn may reduce or delay their need to go public.

2 Institutional Background

Private secondary markets (PSMs) differ from public secondary markets (such as stock exchanges) primarily in how regulated they are (SEC (2020)), which in turn impacts who can trade on them and their overall trading activity. In the paper, I focus on U.S. PSMs, for which the restrictions and rules I describe next apply. I stress, however, that while non-U.S. rules may differ, the main problem studied in the paper – whether PSM trading activity interferes with and negatively impacts startup financing – equally applies. I discuss next the most relevant details on the "buying side" (investors) and the "selling side" (investors and startup employees). For brevity, I refer to the companies whose shares are traded in these markets as "startups" throughout the paper.

The main hurdle for investors willing to buy startup shares in PSMs is the "accredited investor status" requirement. Exceptions apart, eligibility for this status requires investors to have an annual income above $200,000 or net worth above $1 million. Importantly, this status requirement is merely an eligibility criterion within PSMs as well, which have full discretion in selecting its participants[6]. In the case of sellers, the main hurdle is obtaining listing and transaction approval. This process is initiated by the seller in the PSM platform, with the platform conducting due diligence to verify the seller's share ownership and market access suitability. The most sensitive step, however, lies at the discretion of the startup, which typically has the right of first refusal (ROFR), being able to buy the shares from the seller even if there is an interested buyer ready to pay the same price, along with transaction approval power. This means that the startup management or its board can block transactions entirely at their discretion. In the paper, I refer to this step as the "listing decision" or simply "listing" and to the agent embodied with this decision as the "founder" for brevity[7].

[6] While similar rules exist outside the U.S., they may be less restrictive. For instance, in the UK equity crowdfunding platform Seedrs, the investor must answer a questionnaire to ensure a minimum knowledge, but there is no net worth requirement. I provide here an example of a contract for an executed transaction, in which the buyer (the author) was not an accredited investor.

[7] In earlier stages of the startup lifecycle, the agent is indeed typically the founder, provided it has board control, but that may shift over time as early investors and the founder itself are diluted, and the board composition and control changes.

Importantly, my analysis considers the listing decision primarily as a one-time event, represented by the moment when the startup shares first started trading on a platform. This assumes that once this occurs, future trades are reasonably expected to happen over time, with the startup having provided the "green light" for investors to trade their shares. As mentioned, however, the board retains transaction approval power until the startup is public, and as such, specific transactions can still be blocked. I provide in Appendix A a summary of the listing and trading process, and in Appendix B a summary of the key processes specific to major U.S. PSM platforms.

3 Hypotheses Development

I test whether a startup having its shares traded in a PSM platform interferes with its financing and whether the impact is negative. The main component in this analysis is the startup's constant necessity of financing: differently from mature firms, startups are constantly raising capital and, exceptions apart, are unprofitable businesses. In a related manner, startup founders ideally want to have the power to *set* the price they ask for their business' shares rather than accept a prevailing market price. Carta's founder Henry Ward summarizes this problem as *"Marketplace = Liquidity + Price Discovery. Liquidity is a bug (and not a feature) in private markets. Price discovery is also a bug"*. As such, I first test whether startups having their shares traded in PSMs are in a development stage where trading activity may interfere with their financing. In particular, I first verify whether financing rounds are still an essential component of their survival at all. I then investigate whether the resulting effects of having their shares traded are, combined, mostly positive or mostly negative, by looking at their performance in terms of growth, survival, and the estimated response by investors and employees to the startup's decision to allow shares to trade in a PSM.

Hypothesis 1: "PSM Listing Irrelevance"

Under this hypothesis, a startup having its shares traded in a PSM is irrelevant to its success and survival. The main consequence of it is that PSMs, in general, can operate normally, contrary to the idea that liquidity and price discovery are obstacles to startups and, therefore a limiting factor to the continued existence of PSMs. This should be observed if the startups being traded in PSMs are profitable and without the need for continued external financing for their success and survival. Whenever taking place, financing rounds for these startups should not be perceived as essential but rather arising primarily from "excess liquidity" from investors looking for private equity investments in venture capital markets.

Hypothesis 2A: "PSM Listing Relevant and Detrimental to the Startup"

This hypothesis entails the idea that a PSM listing interferes with the financing of a startup, with a net negative impact on the startup's performance. As shares become available on the market and a share price is discovered, investors are reluctant to buy newly issued equity at terms that would otherwise be more favorable to the startup. This occurs predominantly for two reasons: first, would-be investors can buy shares directly in the market, where participants compete with the startup founder for capital. Second, early investors offering their shares may convey the signal that the startup prospects are negative. While employees being able to sell their shares may extend how long the startup's funds can last, and early investors selling can also be positively interpreted by new investors (e.g., they might value liquidity, such that observing shares being traded is seen as a positive trait), these effects are insufficient to turn the impact on the startup performance positive. The main consequence of this hypothesis is that PSMs are mostly unsustainable, constrained to a few select firms at best where these negative factors are minimal, and unable to exist in an equilibrium where both investors and startups benefit: PSMs exist to benefit the "exiting" investor at the expense of the startup and "long-term" investors.

Hypothesis 2B: "PSM Listing Relevant and Beneficial to the Startup"

Under this hypothesis, a listing also interferes with the financing of a startup but with an observable positive impact on its performance. Importantly, I do not aim to establish causality: the idea is not that any startup having its shares listed would benefit from it, but that, in general, the startups that are getting listed are benefiting from it (rather than, e.g., getting listed because they succumb to the pressure of shareholders seeking an exit). This net positive impact arises primarily from the financing channel enabled by employees being able to sell their shares and the value attributed to liquidity by prospective new investors. If true, this hypothesis shows that startups opting for a listing are not simply reluctantly allowing it or seeking some sort of regulatory arbitrage by having a "quasi-IPO" through a listing – they actively benefit from it. The main consequence is that, in this case, PSMs are sustainable: some startups eventually reach a stage where a listing is a favorable option, and while still in need of financing and the listing interfering with it, the overall impact is positive, with a resulting equilibrium where startups and investors benefit from these markets.

4 Data

4.1 Sample

I work primarily with a sample of selected startups whose shares are traded on major U.S. PSM platforms: EquityZen, ForgeGlobal, Linqto, and Nasdaq Private Markets. This sample contains 365 startups, with valuations ranging from \$150 million to \$127 billion at the time of their last financing round and a combined market capitalization of around \$1.9 trillion. The reference period for the data is the end of 2023, with the oldest startup being launched in 1998 and the earliest listing on a PSM being 2016. I obtain data about these startups from several sources. A primary supporting source is Crunchbase, an online database providing detailed information on startups and their investors. I extract the datasets on financing rounds, investors, and organizations, covering the 1995-2023 period, for all the startups in the database. The data available on financing rounds include the startup's name, the investors, the announcement date, the amount of funding received, and the startup location. This dataset covers about 22,000 startups in total (including the 365) and is used for obtaining some aggregate parameters that are relevant in the structural model estimation section (Section 6.2). I provide a summary of this dataset's properties in Appendix C.

I also look for information on the selected startups across alternative sources (S&P Capital IQ and online news sources – e.g., CNBC, Forbes, Reuters, TechCrunch, Benzinga), particularly for their approximate valuations (e.g., SpaceX), IPO data, and ownership structure. For the latter, I also rely on estimates based on industry reports[8] and S-1 filings, which provide information on principal stockholders before an IPO. In particular, for the ownership structure when the startup shares start trading on PSMs, the data is estimated from typical ownership distribution and dilution patterns for startups with similar financing histories and sizes (see, e.g., Figure 2). Unless otherwise explicitly stated, all results in the paper are based on the sample of selected startups rather than the larger Crunchbase sample.

4.2 Definition of Variables

I compute a single set of variables for each startup in the sample (rather than a panel). In general, the variables are computed for two periods: the period between the startup launch and when its shares first start trading on a PSM and the period after the first listing occurs. As the sample ends in 2023, the variables for the post-listing periods are subject to truncation bias, such that these startups might still be listed for more years, have more rounds, raise considerably more money, and related in the future, a concern I address when discussing the results in the next sections. I describe next the main variables.

As performance proxies, I use the valuation when the startup starts trading on a PSM platform ($Valuation$) and the growth in valuation from this moment up to the latest financing round ($ValuationGr$). The average valuation with which startup shares start trading is \$3.2 billion, and the average growth is 18% yearly. I also look at whether these startups eventually

[8]See, e.g., CartaTeam (2024).

do an IPO through an indicator variable equal to one if the startup goes public[9], which is the case for about 10% of the sample, and discuss the IPO performance overall, differentiating between the market capitalization at the share issuance price, at market opening, and at closing. As explanatory variables, I use the number of years elapsed from the startup launch to when it starts trading ($YrsPreListed$) and from this moment until the last round or IPO ($YrsListed$). The average startup starts trading 7.4 years after launch, with the time elapsed post-listing being 1.7 years on average if it does an IPO and two years otherwise.

I measure the financing performance of the selected startups by comparing their financing rounds pre- and post-listing. The average number of financing rounds before a listing ($PreTradingRounds$) is 5.7, and in the post-listing period ($PostTradingRounds$), it is 1.2. On average, startups raise about \$410 million before their shares are traded in any PSM platform ($PreTradingMoney$) and \$270 million afterward ($PostTradingMoney$). To better understand funding performance, I compute the ratio between the money raised during the period the startup shares are listed and the time in years ($\frac{PostTradingMoney}{YrsListed}$), which averages \$140 million per year for each startup. I also measure the average time (in months) between rounds (ΔT). Before the listing period, the average time is 16 months, increasing to 18 months afterward. However, a few startups do not raise any money after being listed, which underestimates this measure. In those cases, I set $\Delta T = 120$ (ten years), which brings the average ΔT post-listing to 44 months.

Finally, I use as ownership structure variables the shares owned by the founder ($w_{founder}$), investors (w_{VC}), and employees (w_{emp}) pre and post-listing. Importantly, in the case of investors, I differentiate between "old" investors, who invested in the pre-listing period, and "new investors," who invested after the listing. The average w_{VC}^{pre} is 50%, and the average w_{VC}^{post} is 12%, indicating that the portion of the startup sold to investors after the listing is typically much smaller. The average share held by founders and employees varies from 24% to 20% and from 14% to 12% from the pre to the post-listing period, respectively. I provide

[9]The use of exit data as a proxy for returns is standard in the venture capital literature (Cumming and MacIntosh (2003), Cochrane (2005), Abuzov (2019), Nanda et al. (2020), Hellmann et al. (2021)).

in Appendix D all the variables definitions along with summary statistics in Table 1.

5 Empirical Methodology

My analysis is made in two steps. I start with a descriptive analysis of the selected startup sample, centered on explaining which kind of startups get listed and what their performance is in terms of growth and financing. I then proceed to an estimation analysis where I evaluate how investors react to the listing, how receptive employees are to equity compensation, and how the startup itself evaluates the decision to invest in the face of uncertainty regarding how investors react to the listing. I describe how I make these two analyses next.

5.1 Descriptive Analysis

I start by verifying whether a startup's valuation growth can be explained by the number of years it has been listed and the number of years it took to list:

$$\mathrm{Y} = \alpha + \beta_1 \mathrm{YrsListed} + \beta_2 \mathrm{YrsPreListed} + \mathrm{Controls} + \mathrm{FE} + \varepsilon \tag{1}$$

where the dependent variable Y is either Valuation or ValuationGr, controls are Valuation and IPO when ValuationGr is the dependent variable and just IPO otherwise. I apply platform, U.S. state, and trading starting year fixed effects, which capture effects related to having shares first traded on a particular platform, being headquartered in a particular state, and starting trading on a particular year.

The main idea behind these regressions is to assess whether a startup being listed for a prolonged period is associated with a lower valuation growth (through β_1) or, alternatively, whether this lower growth can alternatively be explained by having reached a certain development stage (through β_2). When Valuation is the dependent variable, the objective is to check whether the startup size can be determined by the number of years elapsed before and after listing, also with the idea that startups decide on a listing at a particular stage of development. Importantly, using IPO as a control addresses the concern that certain growth levels and size can be explained by highly successful startups that are close to an IPO[10].

I analyze this relationship between IPO and years pre- and post-listing with a similar specification, but using IPO now as the dependent variable, with the idea of understanding how the time pre- and post-listing, size, and growth of the startup are related to the occurrence of an eventual IPO. Specifically, I seek to understand whether being listed delays the occurrence of an IPO or reduces its likelihood, which directly addresses the main hypotheses of the paper. I also look at IPO-day returns to assess the strength of the demand for the startup's stock in public markets. This test addresses the concern that startups might raise money after being listed in a PSM only due to an excess supply of capital for similar startups (private, late-stage, high-growth firms), not out of (survival) necessity. High IPO returns would indicate that the demand for public equity is even higher, with the choice to raise money while private being either suboptimal or motivated by concerns other than maximizing the current startup valuation.

I proceed with an analysis of the financing performance of the startup using as the dependent variables the number of financing rounds after the startup is listed (PostTradingRounds), the total money raised (PostTradingMoney), the funding rate (FundingRate), and the time between rounds (ΔT). The results from this test help explain whether the startup being listed for longer, given all other characteristics, harms its financing prospects, leading to a decreased chance of survival and success.

I conclude by examining how the ownership structure of the startup impacts its financing. In particular, I am interested in knowing whether the share of the startup that is owned by employees (w_{emp}^{pre}, w_{emp}^{post}) changing pre- and post-listing relates to the time elapsed between rounds. The hypothesis being tested is that employees should value more shares that can be sold in PSMs, enabling the startup to finance less often and compensating for possible

[10]Naturally, as an IPO only occurs after the remaining variables can be computed, no sort of causal interpretation can even be considered for it. However, having this variable in the specification allows for a better understanding of how larger ValuationGr is for startups that eventually do an IPO.

negative effects on its financing arising from the listing. For that, I add the variables w_{emp}, w_{VC}, and $w_{founder}$ pre- and post-listing as explanatory variables in the previous specification, using ΔT as the dependent variable.

5.2 Estimation Analysis

In the second part of the paper, I work with a static, three-period listing choice model. I provide a summary of it and how I measure the main parameters in the following.

5.2.1 Model Summary

Consider an economy with M startups and N investors, both fixed, under no asymmetric information such that all parameters introduced are commonly known. Startup i either succeeds or fails. If successful, its payoff is $X_i \sim$ Lognormal(μ, σ^2), and zero otherwise. The choice for a lognormal distribution of payoffs in case of success is motivated by the distribution of the market capitalization of the startups in the sample and in markets in general (e.g., in the S&P500). There are four agents: startup founders, early investors, prospective new investors, and employees. The model timeline is as follows: startup founders make choices at t=0, to which early investors and employees respond at t=1. Between t=1 and t=2, the founder meets prospective new investors who decide whether to invest in the startup. The last period, t=2, is determined by the startup success or failure outcome, after which its payoff (zero if it fails or X_i if it is successful) is revealed.

Startup i has K_i dollars of initial funding and needs to raise a pre-defined amount of Q_i dollars. The amount of time (in months) these initial funds K_i are set to last, T_i, is determined endogenously by the founder at t=0. The probability that startup i survives until receiving investment is given by $\mathbf{P}(K_i, T_i) = \frac{1}{1+e^{-(\beta_0+\beta_1 T_i+\beta_2 log(K_i))}}$. The general idea is that K_i and T_i impact the likelihood of survival. I assume that $\beta_1 > 0$, implying that businesses with high initial funds (K_i) tend to succeed more often. Meanwhile, $\beta_2 < 0$, such that choosing a large T_i implies a larger failure likelihood, suggesting, for instance, an overly risk-averse founder or a project that is in a low-growth industry where large amounts of cash are not actually needed. In general, β_2 can be interpreted as a penalty term for choosing a high T_i. The startup succeeds with probability p_i conditional on receiving investment and receives investment with probability $\mathbf{P}_{\text{inv, i}}$, a one-time event: if it occurs, the timeline ends. Importantly, if the startup does not find an investor and runs out of funds, it fails with certainty. Therefore, startup i succeeds with probability $\mathcal{P}_i = p_i \cdot \mathbf{P}_{\text{inv},i} \cdot \mathbf{P}(T_i, K_i)$:

$$\underbrace{\text{Prob(Success)}}_{\mathcal{P}_i} = \underbrace{\text{Prob(Success | Investment)}}_{p_i} \cdot \overbrace{\underbrace{\text{Prob(Investment | Survive)}}_{\mathbf{P}_{\text{inv},i}} \cdot \underbrace{\text{Prob(Survive)}}_{\mathbf{P}(T_i,K_i)}}^{\text{Prob(Investment)}} \tag{2}$$

This expression reflects the "lifetime" of startup i in which it succeeds if it passes through three key events: surviving until investment occurs ($\mathbf{P}(K_i, T_i)$), investment occurring ($\mathbf{P}_{\text{inv},i}$), and success afterward (p_i).

Prospective new investors meet with startup founders at a rate n per month between t=1 and t=2. They meet them randomly, such that each founder is met by $k_T = \frac{n \cdot N}{M}$ investors per month. For instance, if there are 1,000 startups and 500 investors in the economy and investors can meet 4 startup founders per month, a founder is met 2 times by different investors ($\frac{500 \cdot 4}{1000}$) each month. Prospective new investor j has a skill $S_{ij} \sim \mathcal{U}(0, 1)$ in understanding startup i payoff risk when meeting its founder. When meeting, he is offered a share $w_{i,VC}$ of the startup by the founder and derives a "refined opinion" $\tilde{\sigma}$ about the payoff risk σ such that $\tilde{\sigma} = \sigma^{1-S_{ij}}$[11]. He is (payoff) risk-averse[12] and invests in the startup if:

$$\frac{\mathbb{E}(R_i)}{\tilde{\sigma}} = \frac{(p_i w_{i,VC} \bar{X}_i - Q_i)}{Q_i \sigma^{1-S_{ij}}} \geq S_{VC} \tag{3}$$

[11]Recall that σ is the standard deviation of a payoff, typically a large number, so $\tilde{\sigma}$ decreases with S_{ij}. Whenever necessary, one can consider the technical restriction $\sigma > 1$ to ensure that this is the case. I avoid the alternative form $\tilde{\sigma} = \sigma(1 - S_{ij})$ because that would imply a skilled investor invests in any project with a positive expected return, having no impact on any model equilibria.

[12]This means that if the payoff in case of success is known with certainty, the investor will invest in any startup provided that the expected return is non-negative and larger than S_{VC}.

where S_{VC} represents the investor stringency and $\bar{X}_i = \mathbb{E}(X_i)$. Specifically, S_{VC} is a minimum payoff risk-adjusted return representing how stringent investors are about investing in the startup and is assumed to be common across all potential startup investments and investors and strictly non-negative. Under this setup, $\mathbf{P}_{\text{inv},i}$ is given by:

$$\mathbf{P}_{\text{inv},i} = 1 - \left(1 - \frac{\log\left(\frac{p_i w_{i,VC} \bar{X} - Q_i}{Q_i S_{VC}}\right)}{\log(\sigma)}\right)^k \tag{4}$$

where $k = k_T \cdot T_i = \frac{n \cdot N}{M} T_i$. The value of S_{VC} is contingent on whether employees and early investors sell their shares at t=1. Early investors have a share $w_{i,early}$ of the startup, known at t=0. Employees, on the other hand, have their share offered by the founder (along with that of prospective new investors, $w_{i,VC}$, as described earlier). They accept shares as a cash equivalent in their total compensation if[13]:

$$\mathcal{P}_i \cdot w_{i,emp} \cdot \bar{X}_i \geq S_{emp} \cdot \sigma \tag{5}$$

The term S_{emp} represents the minimum payoff risk-adjusted payoff employees demand to accept shares. Employees discriminate between liquid and illiquid shares, such that $S_{emp} = S^L_{emp}$ when shares can be traded and $S_{emp} = S^U_{emp}$ otherwise. At t=1, both, either, or none among employees and early investors can sell their shares. These actions impact the value of S_{VC}, which changes to either S^{early}_{VC} if only early investors sell, S^{emp}_{VC} if only employees sell, and $S^{emp,early}_{VC}$ if both sell. A full description of the model is provided in Appendix E.

In the model, I focus on the *financing* role of equity compensation rather than any effort-inducing role it may have for two reasons. First, effort-inducing effects are assumed to be not relevant for the listing decision and the financing of the firm, while the financing role has a

[13]In general, employees in early-stage ventures tend to be risk-averse with respect to equity compensation. There is plenty of anecdotal evidence available online that, at least when it comes to early-stage and risky businesses, employees are not receptive to equity compensation, preferring cash instead. I provide some examples in Figure 3. I also provide evidence that the employees tend to have a low (and declining since 2021) rate of exercise of stock options when leaving startups, complementing the idea of lower importance attributed to equity (Figure 4). As startups mature and become less risky, employees become more receptive to equity compensation, an important result in this paper that I discuss in Section 6.2.

direct impact: an employee's total compensation can be considerably higher with equity, by a factor that can be as large as two even in late-stage startups (Truong (2023)). Therefore, compensating employees with stocks and options allows the firm to offer substantially higher salaries without having to use cash for it, effectively financing itself by indirectly issuing stock, which later can be sold when the firm goes public, through a tender offer, or through a PSM. This view is consistent with the literature evidence in which equity compensation for non-executive employees is used to match pay with that of competitors and is persistent over time (Eisfeldt et al. (2021), Eisfeldt et al. (2023)). In the sample, I observe no relationship between either the level of employee ownership or changes in it before and after a listing with startup size or growth, also consistent with the view that its role in boosting firm value is, at best, secondary. Second, in the context of the model (private and unprofitable ventures), equity compensation is a transfer of shares between employees: the founder gives shares that would otherwise be his to employees, so while employees might exert higher effort, the founder might exert lower effort, with an ambiguous net effect over the firm value.

5.2.2 Estimation

The founder's payoff maximization problem can be stated generically as:

$$\underset{T, w_{i,emp}, w_{i,VC}, \text{listing}}{\text{Max}} \mathcal{P}_i \cdot \mathbf{F}_i \cdot X_i \tag{6}$$

where $\mathcal{P}_i = p_i \cdot \mathbf{P}_{\text{inv},i} \cdot \mathbf{P}(T_i, K_i) = p_i \cdot (1 - \left(1 - \frac{\log\left(\frac{p_i w_{i,VC} \bar{X} - Q_i}{Q_i S_{VC}}\right)}{\log(\sigma)}\right)^k) \cdot \frac{1}{1+e^{-(\beta_0 + \beta_1 T_i + \beta_2 log(K_i))}}$. I estimate this problem using proxies for all variables and parameters and by dividing the sample into two groups, one with proxies for the pre-listing period as if these were startups in which the founder decided never to list, and the other with proxies for the post-listing period, as if these were startups in which the founder decided to list the shares.

S_{VC} is estimated by applying a constrained maximum likelihood estimation where the average $\mathcal{P}_i$ must match the average frequency a startup succeeds in the (much larger) Crunchbase sample. The objective of this exercise is to infer whether S_{VC} is higher for the startups in the post-listing period, which supports the hypothesis that the listing interferes with the startup financing such that investors demand a higher payoff risk-adjusted return.

To estimate the acceptance constraints S^U_{emp} and S^L_{emp}, I use the acceptance constraint for employees presented earlier, assuming it is binding in equilibrium so that:

$$w^*_{i,emp} = \frac{\bar{S}^Z_{i,emp}\sigma}{\mathcal{P}_i\bar{X}}, Z \in \{U, L\} \tag{7}$$

where U refers to the pre-listing and L to the post-lising period. I detail all the proxies used in both estimations and the estimation results in Section 6.2.

6 Main Results

I now describe the main results of both analyses, starting with the descriptive section, followed by the estimation results.

6.1 Descriptive Analysis Results

6.1.1 Which Startups Get Listed and When

The results on whether a startup's valuation growth can be explained by the listing period length are in Table 2. In general, startups have a 13.5% to 15.8% larger growth for each year that they have been listed, depending on the platform it was first listed and the headquarters state. They also tend to be larger, with a valuation that is \$0.63 to \$1.012 billion larger. Importantly, the number of years elapsed before the startup is listed (YrsPreListed) seems to not impact its growth or size. This finding weakens the hypothesis that founders wait until the startup reaches some particular milestone, at least in terms of age or size, before its shares can be traded. Finally, eventually doing an IPO is largely correlated with larger growth and larger size. As an IPO can only be observed after ex-post, this characteristic cannot be used to predict startups with larger growth or size, but it is still a relevant variable in explaining that startups that have the characteristics that lead to an IPO are those with the highest growth and size. Additionally, this effect of IPOs being highly correlated with valuation disappears with platform, state, and trading start-year fixed effects, suggesting that within these three levels, there is no correlation between valuation and IPOs, in addition to the correlation between IPO and valuation growth being lower than without these fixed effects. This finding indicates that given a group of startups within the same state, platform, and trading start year, knowing whether it will IPO or not does not help predict its size and is less informative about its growth compared to when looking at the entire sample.

I examine further the relationship between growth, size, and time to list with IPOs in Table 3. The number of years listed has a strongly negative association with IPOs, indicating that the startups that are listed tend to do an IPO relatively quickly. While this relationship is partially mechanical, as YrsListed ceases to increase once an IPO occurs, this is not entirely so: the sample covers a short listing period (2016-2023), and it could be that the startups listed first would be the ones that did an IPO and those recently listed are still private so that the relationship between YrsListed and IPO is positive, but this is not the case. Valuation growth (ValuationGr) is a strong determinant of an IPO in any specification, which is consistent with highly successful startups doing an IPO and, in particular, signals that an IPO tends to occur when the startup is growing rather than maturing or having declining growth. The number of years before the startup is listed has a positive association with IPOs across the sample, such that those that are older are more likely to eventually do an IPO, but this association does not persist with trading start years: within trading start year cohorts, it is not the case that those who took longer to list are more likely to IPO. As in the analysis in the preceding paragraph with growth and size, this finding weakens the hypothesis that founders allow their startup shares to get listed and the startups go public based on time. To the extent that time correlates with startup maturity, these findings that pre-listing years do not correlate with either valuation or growth or doing an IPO indicate that these are not the primary motivating factors behind the decision to list (or to go public).

Finally, I also verify whether these startups are profitable when they decide to go public (Figure 5) and the demand for their equity when public. Apart from one startup (Coinbase in the year before going public), all were unprofitable at the time of their IPO, and only one had a closing price on the IPO day lower than the underwriting price (Robinhood). These findings suggest that these startups are mostly unprofitable businesses, even the successful ones, with a high demand for their equity, public or private, weakening the hypothesis that they are better off raising funds privately. While they might enjoy certain benefits by staying private (see, e.g., Davydova et al. (2022)), these benefits seem unrelated to fundraising ability.

Overall, there are two key takeaways from this analysis. The first is that the group of startups being listed consists of firms that are high-growth and that continue to grow once they are listed. This finding contradicts the idea that startups getting listed are (or are becoming) mature firms in which growth has ceased (or is ceasing) to occur and have investors looking for an exit alternative to an IPO. The second is that IPOs tend to occur for the startups with the highest growth, challenging the idea that they occur only after some maturity stage has been attained. In both listing cases (from fully private to PSM listing and from listing to IPO), the listing decision tends to be accompanied or preceded by high growth rather than serving as a "next stage" for the firm to follow as it matures.

6.1.2 How Difficult It Is To Obtain Financing When Listed?

In this section, I analyze how the financing performance of startups is impacted once they are listed. The objective is to test and measure whether the listing has an observable impact on startups' financing at the aggregate level, in particular in terms of financing rounds, amounts raised, and the frequencies with which rounds occur.

The main results are in Table 4. The number of years elapsed from launch to listing (YrsPreListed) is negatively associated with the number of post-listing rounds (PostTradingRounds), consistent with startups that are less reliant on external financing getting listed.

However, the magnitude of this effect is minimal, such that every year pre-listing is associated with ≈0.02 fewer financing rounds. On the other hand, the number of years listed is positively associated with additional financing rounds at a much larger rate: about 0.36 additional rounds per year listed across the sample and 0.71 at the platform, state, and trading start year level. A similar result also holds regarding the total money raised, with startups raising about $0.17 to $0.20 billion additional per year listed. Combined, these results show that listed startups tend to have a larger number of rounds and raise more money in these rounds, contrary to the hypothesis that being listed would be detrimental to their financing ability. Importantly, these results hold with controls for an eventual IPO, growth, and size, weakening the hypothesis that only startups that are highly successful and of high quality can get financing when their shares are traded.

Next, I test whether the rate of financing (FundingRate) slows down once the startup is listed. The results are in Table 5. I find that for each additional year that the startup is listed, the amount of money raised per year, on average, is lower by $105 to 120 million. This result highlights that despite having more rounds in aggregate and raising more money when the time the startups are listed is taken into account, there is indeed a reduction in the rate with which they are financed. This result supports the hypothesis that startups have their financing ability harmed by being listed. Looking at the average time between rounds, I find that the average number of months between rounds is also larger across startups by approximately six to nine months and considerably higher for those that do an IPO[14]. As in the case of the rate of financing, growth (ValuationGr) and size (Valuation) are either not significant in explaining it or do so only at certain levels of fixed effects.

Combined, the key results from this section are that listed startups manage to raise more money and have more financing rounds, although at a sensible reduction in the rate with which the money is raised and an increase in the average time between rounds. In

[14]The coefficients' magnitudes for IPO are largely driven by startups that did an IPO without having any financing round post-trading, the case which I assume a time of 10 years between financing rounds, as described in Section 4. Excluding these startups, the coefficients have magnitudes around 27 and 30.

general, these results are insufficient to show that having shares traded is detrimental to their financing ability, particularly when the startup is successful. Specifically, in the case of the financing rate and time between rounds, an alternative hypothesis is that it is lower and higher, respectively, because these listed startups can afford to raise less money or are less in need of it. I analyze these possibilities next.

6.1.3 How Does Ownership Structure Impact Financing?

In this section, I test whether the time between rounds for listed startups is impacted by changes in the ownership structure occurring when the startup shares are traded. In particular, I am interested in knowing if a higher share in employee ownership once the shares are traded (and hence reasonably more liquid than before) is associated with less frequent rounds. This correlation may suggest that listings enable startups to extend the time their funds are planned to last by paying employees more aggressively in shares rather than cash.

I start by verifying whether valuation growth, an eventual IPO, and the funding rate can be explained by the ownership structure in the pre-listing period, along with the changes once the startup is listed. The results are in Table 6. Apart from a nearly insignificant relationship between an eventual IPO and an increase in employee ownership, none of the dependent variables are explained by ownership structure. This result addresses an important assumption of my model, discussed in the next section, that introducing equity compensation to employees has no effort-inducing effect. While I do not reject the hypothesis of that occurring, my results simply show that whatever the magnitude of these effects, they are not visible across the startups in the sample. Overall, there seems to be no relationship between a startup having more or less founder or employee ownership and its eventual success, growth, and financing, at least as long as this startup is listed.

Next, I examine the impact of ownership structure on the time between rounds (ΔT). The results are in Table 7. Startups with a large increase in employee ownership tend to have a larger time between rounds at a rate of 21 days approximately per percentage point

(2076.9×0.01). This effect, however, is not observed at the platform and state or platform, state, and trading start year level, suggesting the impact of employee ownership on ΔT is better explained by and dependent on these characteristics. I also verify the relationship between changes in employee ownership and growth. Across all fixed effects levels, I find that increases in employee ownership are associated with higher ΔT. The magnitude of this effect, however, is minimal: at the average ValuationGr, 18%, a 1% increase in employee ownership implies a ΔT that is larger by $264.9 \times 0.18 \times 0.01 \approx 0.48$ days approximately. Increases in investor and founder ownership have a larger effect overall across all fixed-effect levels, suggesting an increase in 13 to 27 days in ΔT but no relevant incremental increase based on startup growth. For instance, the coefficient on $w_{VC}^{post} - w_{VC}^{pre} \times$ ValuationGr is 78.6, lower by a factor of three approximately from that on $w_{emp}^{post} - w_{emp}^{emp} \times$ ValuationGr.

In general, larger startups tend to have less frequent rounds, along with those that eventually go public, with these characteristics having a large positive association with ΔT. A startup that does an IPO has from 40 to 90 days longer times between rounds and from 0.79 to 1.05 approximately days per billion dollar valuation (the average valuation being $3.2 billion). Overall, the results point to the existence of differences in the financing of the startup depending on how the ownership structure changes, with a sensible increase in ΔT for large growth startups with increased employee ownership, an effect that is magnified for startups that eventually do an IPO and are large.

6.1.4 How Relevant is Price Discovery for the Founder?

The two main channels impacting a startup's prospects of surviving and succeeding, outlined in the hypotheses development (Section 3), are liquidity and price discovery. In the former, employees and early investors trading their shares impact the chances a founder can obtain funding, with these agents competing for capital from new investors. In the latter, the price formation for a startup stock may alter the funding prospects of a startup by revealing information about its prospects the founder would like to keep private. In this section, I provide empirical evidence for the impact of price discovery on the fundraising activity by startups. In the ideal experiment, one would compare startups for which there is zero trading activity, and hence zero price discovery, with startups for which there is some trading activity with a known volume. I approximate this experiment by looking at price changes and volatility before and after financing rounds, with the assumption that price changes and volatility correlate with trading activity and, therefore, the intensity of price discovery.

I obtain stock prices[15] for the sample startups from notice.co, a database for private companies where users can connect with brokers and trade stocks in PSMs. I provide in Figure 6 an example of the chart available for Udemy, an education technology company. A similar chart is available for most of the startups in the sample (300 out of 365). The pricing algorithm used by notice.co uses both data from brokers and comparable startups, relying more strongly on data from brokers when trading activity is stronger.

For each startup, I compute the monthly returns based on the price on the first day of the month. The average monthly return is 12%, although it is highly skewed: the median monthly return is zero, and the top quartile return is 10.8%. The average annual return is 112% (the median is close to 25%), and most startups are trading (as of the end of 2024) at a price that is lower than their highest price. The average volatility is 73.5% (the median is close to 37%). These figures highlight three key features: i) returns are typically much higher than that of public stock, ii) volatility is even higher, such that the average startup has a (seemingly) low risk-adjusted return, iii) returns and risk-adjusted returns are high only for a small portion of startups, even when considering that the selected sample I use in this paper consists mostly of successful startups that managed to have multiple financing rounds and eventually trade in PSMs. I provide summary statistics in Table 8.

My main result is shown in Figure 7. I compute the average monthly stock price returns during the X-month window preceding a financing round (X= 3, 6, 9, 12) and the monthly-adjusted ($\frac{\text{Final Price}}{\text{Initial Price}}^{\frac{1}{X}} - 1$) return after the round, taking into account the X-month window

[15] The share price is that of *common* shares, which is the most common type of shares that employees are awarded and that are traded in PSMs.

that includes the round and the months succeeding it. For instance, if a round occurs on January 15th, the Post-3M return considers the price change from January 1st to April 1st. The figure highlights two important factors. The first is that earlier rounds tend to have larger price changes before the round occurs, consistent with the hypothesis that price discovery has a higher "intensity" at earlier stages and, therefore, is more relevant in these stages. In the Online Appendix, I provide a variant of this figure using the returns volatility instead of average returns in the X-month windows preceding a round, with a qualitatively similar result. The second is that after the round occurs, the immediate returns (Post-3M) tend to be lower for earlier rounds (e.g., Series A), suggesting that the stocks are typically more "overvalued" in these earlier rounds. This finding supports the hypothesis that founders, more so in early stage rounds, attempt to, and on average succeed, to price the to-be-issued stock at comparatively high prices. I provide in the Online Appendix further tests for this hypothesis, showing that, in general, higher volatility and price changes before a round are associated with a lower return *after* the round occurs (3 to 6, 9, and 12 months).

Overall, the main result from this section is that measures associated with price discovery have an increased role immediately before and after financing rounds in two ways. Firstly, price discovery is more relevant in earlier rounds, where information asymmetries are larger. Second, the founder benefits from having control over the price discovery process, being able to sell stock at higher prices in earlier rounds and therefore facing lower dilution and obtaining higher sale proceeds. These findings support the idea that, in general, prospective new investors adjust their expected risk-adjusted returns according to the intensity of price discovery and, therefore, to the trading activity on PSMs. The extent to which this adjustment is made and how it differs across startups is discussed in the next section.

6.2 Model Estimation

In this section, I provide the results for the estimates of S_{VC}, the payoff risk-adjusted return investors expect from investing in the startup, and (S^U_{emp}, S^L_{emp}), the payoff risk-adjusted return employees demand to accept shares as a cash equivalent in their compensation. The hypothesis being tested for S_{VC} is whether it is higher after the startup shares are traded, suggesting an increase in investor stringency. For (S^U_{emp}, S^L_{emp}), I test whether traded shares are more likely to be accepted as compensation, which is the case if $S^L_{emp} < S^U_{emp}$ so that the acceptance constraint is more easily satisfied for listed vs. unlisted shares. I start by describing the proxies used for the model parameters, followed by the results and a discussion.

6.2.1 Parameters

The founder's payoff is determined by three components: the probability that the startup succeeds, the founder's share, and the payoff conditional on success. The founder's share is given by $1 - w_{emp} - w_{VC}$, that is, the residual share after the share held by investors and employees is deducted. I proxy it by using the estimated (when not publicly available) and observable share of the startup held by investors and employees at the year when the startup shares start trading (for the "pre" period) and at the IPO[16] (for the "post" period). The share of the startup held by early investors pre-listing (w^{pre}_{early}) is assumed to be the share held when the shares got listed, divided by the number of financing rounds the startup had. The idea is that, e.g., if 50% of the startup is owned by investors when the shares start trading, and it had five financing rounds, the share investors bought at the first round was about 10%. w^{pre}_{VC}, the share offered to investors in the unlisted period, is the share held by investors when the shares are listed, minus w^{pre}_{early}. For the post-listing period, the share held by early investors is simply the share held by investors when the listing occurs, $w^{post}_{early} = w^{pre}_{VC} + w^{pre}_{early}$, that is, the early investors for a listed startup are those that invested before the listing. The share offered to investors in the listed period (w^{post}_{VC}) is the incremental share investors obtain from the listing until the IPO or the latest round: $w^{post}_{VC} = w^{\text{IPO or latest round}}_{VC} - w^{pre}_{VC}$. The residual share is then assumed to be the share held by the founders.

I proxy the payoff conditional on success by the approximate valuation of the startup

[16] The shareholder structure for firms doing an IPO in the U.S. is typically provided under a section named "Principal and Selling Shareholders" of their respective S-1 filing.

when the listing starts for the pre-listing period (X_{pre}) and the approximate valuation or market capitalization at the IPO (at share issuance price) for the post-listing period (X_{post}). The idea is these values represent an observable and unambiguous estimated payoff for all shareholders if they were to sell their respective shares of the startup: while returns, for instance, may differ, two shareholders having, e.g., 5% of a startup will get the same payoff if they sell their shares for the same average price.

The probability that the startup succeeds contains an additional set of parameters – p_i, (β_0, β_1, β_2), σ, Q_i, K_i, N, M, and n. I obtain the values for p_i, (β_0, β_1, β_2) by estimating $Y = p_i\mathbf{P}(T_i, K_i)$ where Y is either an IPO, an acquisition, or the occurrence of a subsequent financing round, across the Crunchbase dataset, T_i is the time between a round and the next (I apply the 95th percentile of T_i if there is no next round), and K_i the amount raised in the round. This functional form interprets each investment as successful if the startup has new investors. While Y does not perfectly replicate a successful investment outcome (e.g., having a further financing round does not necessarily imply early investors could exit), it allows for estimates of these parameters across a large sample and is highly correlated with successful investments. I proxy Q_i as the total amount startups raise in each period (pre and post). σ is the standard deviation of the market capitalization or estimated valuation across all startups that were listed or had an IPO (latest round when no IPO) within the three preceding years as those for the startup itself[17]. The parameter N corresponds to the average number of unique investors participating in financing rounds in the five years preceding the listing (pre) or the IPO or latest round across the Crunchbase dataset, where I also obtain M, the average number of startups receiving financing. Finally, I choose n from the 99th percentile of investor participation in financing rounds, with the idea that this number should reflect the maximum "realistic" meeting capacity by investors in the economy. For each startup, I compute the average n across the five years preceding its trading start

[17]For instance, for startup A, assuming it started trading in 2017, σ^{pre} is the standard deviation of the market capitalization or valuation across all sample startups that started trading in 2015, 2016, or 2017. If its last round was in 2023, σ^{post} is the standard deviation of the market capitalization or valuation across all sample startups that had an IPO or their latest round in 2021, 2022, or 2023.

(pre) and its IPO or latest round (post). I provide summary statistics for all the proxies in Table 9, along with a summary of the definitions used for each one in Appendix E.7.

6.2.2 Main Results

I estimate the parameters in two steps. For S_{VC}, I apply a constrained maximum likelihood for the founder's objective function, where the average $\mathcal{P}_i$ across startups should try to match the average frequency startups "similar" to those in the pre and post-listing periods receive subsequent financing, doing an IPO, or being acquired ("success"). I define similar startups in terms of financing rounds, as the probability of financing is the component where S_{VC} appears. Startups in the pre and post-listing period have, on average, 5.7 and 6.9 financing rounds, so I chose six rounds as the "cutoff". The frequency of startups in the Crunchbase sample that are successful and have six rounds or less is 49.3%, and above six rounds, it is 71.83%. The term $\mathbf{P}_{\text{inv},i}$ (the probability that the startup receives investment) in $\mathcal{P}_i$ is highly sensitive to the exponent term $k = \frac{N \cdot n \cdot T}{M}$. To adjust for that, I add a scaling factor a such that the resulting $k^{\text{scaled}} = ak$, to be jointly estimated along S_{VC}. The parameters (S^U_{emp}, S^L_{emp}) are estimated from the expression provided in section 5.2.2, using the estimated values for S_{VC} and a for the pre and post-listing period samples.

The estimation results are in Table 10. Consistent with the hypothesis that investors are more stringent when the startup shares are listed, S_{VC} is substantially higher in the post-listing period. This result suggests that the minimum payoff risk-adjusted return demanded by investors increases, despite an average higher $\mathbf{P}_{\text{inv},i}$ observed for post-listing startups (recall $\mathbf{P}_{\text{inv},i}$ is decreasing in S_{VC}). In general, startups in the post-listing period have characteristics that lead to a higher average $\mathbf{P}_{\text{inv},i}$, like better payoffs ($X$) and lower total money raised (Q), compensating for the increased stringency.

I investigate next whether less successful startups drive this result by estimating S_{VC} again with the sample restricted to startups that did an IPO. In this case, S_{VC} is lower post-listing, suggesting that these startups benefit from a listing, receiving financing more easily when their shares are traded. This result supports the hypothesis that allowing shares to be traded is beneficial when the startup is sufficiently successful, with any potential negative effects arising from the listing being compensated by the increased liquidity. In particular, the increased liquidity can make employees more receptive to receiving equity compensation, which contributes to increasing the cash runway for the startup.

The estimates for S^U_{emp} and S^L_{emp} are consistent with this hypothesis. Both for the pre and post-listing samples, S^L_{emp} is lower than S^U_{emp}, suggesting that employees demand a lower payoff-risk adjusted threshold to accept equity compensation. In addition to that, the reduction in S_{emp} is relatively lower when looking at the sample restricted to startups that eventually did an IPO, decreasing by approximately 75% $(1 - \frac{3.84}{15})$ vs. 52% $(1 - \frac{3.97}{8.23})$ for the entire sample. Finally, the standard errors for S^U_{emp} and S^L_{emp} in the IPO-only sample are such that the hypothesis that $S^U_{emp} = S^L_{emp}$ cannot be rejected. This suggests that, for highly successful startups, employees are indifferent about share liquidity, consistent with the high expected payoffs and lower risk of these firms being sufficient for employees to accept shares.

6.2.3 S_{VC} Uncertainty

I conclude by studying further the impact of S_{VC} in the listing decision. As S_{VC} is, in practice, unobservable, the founder makes the listing decision under uncertainty about it. The founder's decision can then be analyzed under the framework I describe next.

Assume S_{VC} increases when the founder decides to allow his startup shares to be traded with probability q, and decrease with probability $1 - q$. Let the $\uparrow$ superscript denote the parameter values under an increased S_{VC} and $\downarrow$ otherwise. The founder prefers to list the shares if the expected payoff from listing is higher than the expected payoff from not listing, which can be solved for q (see Appendix E.8) and yields that:

$$q < \frac{\mathbf{P}(T_i, K_i)^{\downarrow} \cdot \mathbf{P}^{\downarrow}_{\text{inv},i} \cdot \mathbf{F}^{\downarrow}_i - \mathbf{P}(K_i, T_1) \cdot \mathbf{P}_{\text{inv},i} \cdot \mathbf{F}_i}{\mathbf{P}(T_i, K_i)^{\downarrow} \cdot \mathbf{P}^{\downarrow}_{\text{inv},i} \cdot \mathbf{F}^{\downarrow}_i - \mathbf{P}(T_i, K_i)^{\uparrow} \cdot \mathbf{P}^{\uparrow}_{\text{inv},i} \cdot \mathbf{F}^{\uparrow}_i} = V \tag{8}$$

If q is less than this threshold V, the expected payoff from the listing is higher, making it better for the founder to list. This V can be interpreted as a proxy for the propensity to list: the higher its value, the easier the condition is satisfied, and the more likely the founder is to list. This constraint offers readily testable predictions about the propensity to list for a startup: i) it should increase with the probability of receiving financing when investors become both more or less stringent ($\mathbf{P}^{\uparrow}_{\text{inv},i}$ and $\mathbf{P}^{\downarrow}_{\text{inv},i}$), along with the respective founder's share in each case ($\mathbf{F}^{\uparrow}_{i} = 1 - w^{\uparrow}_{i,VC} - w_{i,emp}$ and $\mathbf{F}^{\downarrow}_{i} = 1 - w^{\downarrow}_{i,VC} - w_{i,emp}$), and ii) it should decrease with the probability of receiving financing pre-listing ($\mathbf{P}_{\text{inv},i}$), along with the respective founder's share $(1 - w_{i,VC})$. These predictions are consistent with a potentially high-value post-listing, irrespective of stringency conditions, and a (comparatively) low-value pre-listing favoring the listing decision. I provide in Appendix E.9 the sign of the correlation between each term with V and V^{-1}, the latter whose use I describe next.

To verify how these results hold in practice, I derive proxies for each term in the expression for V and work with its inverse V^{-1}, which I proxy by the number of years a startup takes from its launch to list. I proxy the probability of receiving investment pre- and post-listing as the number of financing rounds in these two periods, with an auxiliary indicator variable for stringency that equals one if the average time between rounds post-listing is above 24 months[18]. The results are in Table 11. Consistent with the model prediction, the number of pre-listing rounds ($\mathbf{P}_{\text{inv},i}$) is positively correlated with the years to list (V^{-1}), such that each round implies about one additional year (1.143) before listing when considering the entire sample. The number of post-listing rounds both when investors are less stringent ($\mathbf{P}^{\downarrow}_{\text{inv},i}$) is negatively correlated with the number of years to list, with each reducing the time to list by half a year approximately (-0.413). This is consistent with the model prediction in that V^{-1} increases with $\mathbf{P}^{\downarrow}_{\text{inv},i}$. The correlation between the proxy for $\mathbf{P}^{\uparrow}_{\text{inv},i}$ and V^{-1} is not significant, suggesting that the probability of receiving financing when investors become more stringent has no impact in the propensity to list. A possible explanation for that is selection bias: many startups may have no rounds and fail when investors are more stringent, not appearing

[18] The idea underlying idea is that startups that raised money at such a low frequency (less than once every two years) faced stringent investors.

in the sample, and not contributing toward a predicted negative coefficient.

The pre-listing founder's share of the payoff is negatively correlated with the inverse propensity to list, contrary to the model prediction. A possible reason for that is related to an important model assumption, which is the founder having control over a listing and having its payoff determined by the startup's eventual outcome. In the model, a founder with a higher share pre-listing would prefer the startup to stay unlisted because there is a possibility that the payoff post-listing is smaller. I find, however, that founders with a higher share pre-listing might prefer a listing because they would like to sell their own shares *before* the payoff is realized, which is outside the model scope. As such, the coefficient on "Founder w" of -18.78 implies that each 1 p.p. ownership by the founder is associated with a listing occurring about 68 days earlier. This effect does not change whether investors are more or less stringent after a listing, such that the actual observed correlation with the founder's share post-listing with the number of years for it to occur is zero.

The main takeaway from this section is that the founder's decision to list is predominantly motivated by how well the founder expects the startup to be able to raise money pre-listing, the founder's share of the startup, and the expectation of reduced stringency upon listing, consistent with the model predictions. Overall, my results help explain how the listing decision is impacted by expected changes in investor stringency and, in general, highlight the main drivers behind the listing decision.

7 Conclusion

This paper studies the impact of private secondary market (PSM) listings on startups' performance. Specifically, I test whether startups have their financing impacted by having their shares traded on PSMs and whether this impact is negative, implying that PSMs are inviable at scale. I show that startups whose shares are traded on PSMs ("listed") are typically highly successful firms (e.g., by money raised, valuation, and valuation growth) but that, importantly, are not profitable, are still growing rapidly and still rely on external equity financing: out of those that did an IPO (about 10%), only one was profitable at the IPO, the average valuation growth per year during listed years is 18%, and the average money raised after listing (ex-IPO when occurring) is $270 million. Listed startups have a higher valuation growth the longer they are listed, particularly if they eventually do an IPO, but are less likely to do so the longer they remain listed, particularly if their valuation and valuation growth are not (comparatively) high. These results point to a negative effect on the financing of these startups. I verify this hypothesis further by looking at their financing performance: listed startups have a lower funding rate (money raised over time) the longer they are listed, raising less money and waiting a longer time between rounds.

Using a structural model, I measure the stringency of potential investors in financing these startups before and after a listing. I find that investors demand a significantly higher risk-adjusted payoff to invest after a startup is listed. At the same time, employees become more receptive to equity compensation, which allows startups to extend how long their funds last and partially explains the observed longer time between rounds among listed startups. This increased stringency is not observed when estimated only among startups that eventually do an IPO, suggesting that the result is driven by lower-quality startups.

In general, these results support the hypothesis that when a startup is listed, its financing is impacted, with this impact being highly dependent on quality: provided that the startup is growing comparatively quickly, a listing is beneficial, allowing for better financing rates and a higher likelihood of an eventual IPO. For the remaining startups, their financing is negatively impacted, with that impact being partially mitigated by equity compensation to employees, partially extending the cash runway of the startup. Combined, my results provide evidence that PSMs function under an equilibrium where both certain startups and investors benefit from liquidity and price discovery enabled by these markets, which makes them viable, rather than constrained or unsustainable venues where investors seeking an exit always benefit at the expense of the remaining investors and startup founders.

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Appendix A: Listing and Trading on U.S. PSM Platforms

I provide in Diagrams A and B a summary of how the listing and trading processes work. Notice that, both concerning the listing and trading, the management ultimately retains substantial control over them. For instance, while the listing process itself is initiated by employees or early investors, only the management can approve it, ultimately deciding *if* and *when* the shares can be traded. In practice, management tends to discourage or block trades up until a certain point, after which trades tend to happen with relative frequency. This point is what I refer to as the "started trading" year in the selected sample. Finally, different platforms may also have different specific processes regarding how the listing and trading works. I summarize these key processes in Appendix B.

Diagram A: Company Listing Process

This diagram summarizes how the company listing process works on selected major U.S. PSM platforms – EquityZen, Forge Global, Linqto, and Nasdaq Private Market.

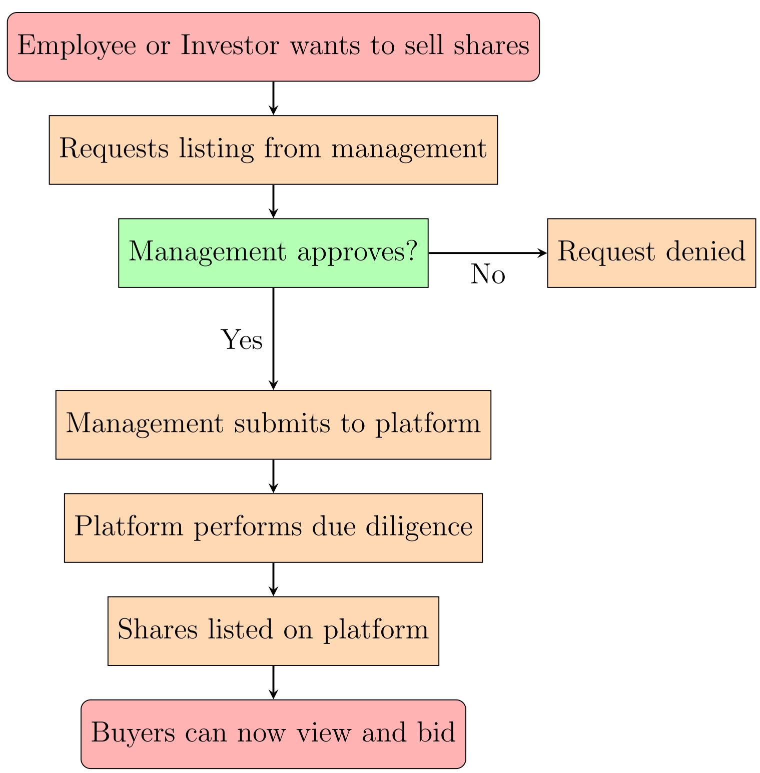
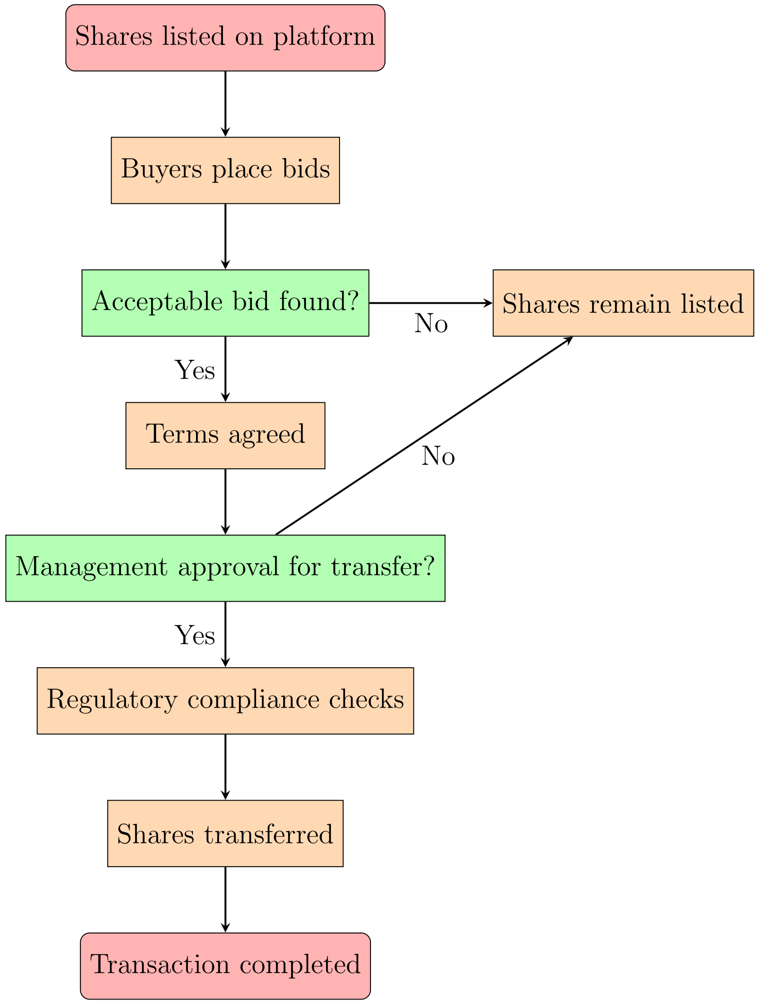


Diagram B: Share Trading process

This diagram summarizes how the share trading process works on selected major U.S. PSM platforms – EquityZen, Forge Global, Linqto, and Nasdaq Private Market.



Appendix B: Key Processes on Selected Major U.S. PSM Platforms

Sources: Platform websites. See EquityZen, Forge Global, Linqto, and Nasdaq Private Market for more information.

Aspect	EquityZen	Forge Global	Linqto	Nasdaq Private Market
Initiation of Sale	Shareholders (employees/investors) initiate by indicating intent to sell.	Shareholders register and indicate intent to sell.	Shareholders select company and view offer from Linqto.	Companies or shareholders initiate liquidity programs.
Proof of Ownership	Required documentation such as stock certificates.	Required documentation to prove ownership.	Required documentation such as stock certificates.	Required documentation as per internal policies.
Company Approval	Required for each transaction to comply with internal policies and ROFR.	Required for each transaction to comply with internal policies and ROFR.	Initially required for listing; subsequent sales depend on company cooperation.	Required for each transaction to ensure compliance with internal policies and ROFR.
Right of First Refusal (ROFR)	Exercised by the company or internal investors before external sale.	Exercised by the company or internal investors before external sale.	Depends on initial agreements; company cooperation needed for each sale.	Exercised by the company or internal investors before external sale.
Due Diligence	Conducted by EquityZen to verify share eligibility and compliance.	Conducted by Forge to ensure eligibility and compliance.	Linqto verifies and provides offer price if interested.	Nasdaq ensures compliance with regulatory and internal requirements.
Listing on Platform	After approval and due diligence, shares are listed.	After approval and due diligence, shares are listed.	After verification, shares are listed if Linqto is interested.	After setup and compliance, shares are listed for matching with buyers.
Buyer Matching	Accredited investors place bids on listed shares.	Forge matches sellers with buyers within its network.	Linqto provides direct offer to buy shares.	Nasdaq matches sellers with buyers within its network.
Transaction Approval	Each trade typically requires company approval.	Each trade typically requires company approval.	Initial company agreement; further approvals based on company cooperation.	Each trade requires company approval and regulatory compliance.
Regulatory Compliance	Ensured by EquityZen before finalizing the transaction.	Ensured by Forge before completing the transaction.	Managed by Linqto, ensuring legal compliance.	Ensured by Nasdaq throughout the transaction process.
Transaction Completion	Shares transferred and funds settled post-approval and compliance checks.	Shares transferred and funds settled post-approval and compliance checks.	Shares sold to Linqto, proceeds deposited to shareholder's account.	Shares transferred and funds settled post-approval and compliance checks.
Platform Fees	Typically around 5% of the transaction value.	Typically around 5% of the transaction value.	No added fees for buyers, variable fees for sellers.	Varies based on transaction specifics and agreements.

Appendix C: Crunchbase Data Summary

This table summarizes the main properties of the Crunchbase dataset. The dataset is constructed using data from financing rounds. I drop all "non-standard" financing rounds (not classified as angel, pre-seed, seed, or Series A to J), together with financing rounds not taking place in the U.S., without information on the money raised or investors, and without USD being the funding currency. For all model estimations, financing rounds of the last five years of the sample (2016-2020) are not included to mitigate truncation bias.

Entry	Value
Number of Financing Rounds Total	34,828
Funding Volume Total (USD billions)	367
Venture Categories	735
Unique Lead Investors	6,088
Unique Ventures	22,343
Period Covered	1995-2016
Financing Rounds Included	Angel, Pre-Seed, Seed, Series A to J
Country	United States

Appendix D: Variable Definitions

Variable	Description
ValuationGr	The arithmetic average valuation growth between the year the startup shares started trading on a platform up to the latest financing round or IPO. Example: Startup A had a 20 billion dollar valuation in 2020 when it started trading on Platform B and raised money the last time in 2023 at an 80 billion dollar valuation. Average (arithmetic) yearly growth = $\frac{80\text{ billion}-20\text{ billion}}{(2023-2020)\times 20\text{ billion}} = 1$ (100%).
YrsListed	Number of years elapsed since the shares first traded on a major platform until 2024.
YrsPreListed	Number of years elapsed from startup launch to the year the shares started trading.
Valuation	Approximate valuation when the shares started trading.
IPO	An indicator variable equal to one if the startup did an IPO (as of 1Q2024).
Platform	The platform the startup shares first started being traded.
State	The U.S. state the startup is headquartered.
PreTradingRounds	The number of financing rounds the startup had from its launch until it first started trading on a platform.
PostTradingRounds	The number of financing rounds the startup had after it first started trading on a platform.
PostTradingMoney	The total amount of money raised by the startup after it first started trading on a platform.
FundingRate	PostTradingMoney divided by the number of years elapsed since the startup started trading on a platform.
ΔT	Average time in months between financing rounds in the period after the startup started trading on a platform.
w^{pre}_{emp}, w^{post}_{emp}	The estimated share of the startup owned by employees in the period before (pre) or after (post) it started trading on a platform.
w^{pre}_{VC}, w^{post}_{VC}	The estimated share of the startup owned by investors in the period before (pre) or after (post) it started trading on a platform.
$w^{pre}_{founder}$, $w^{post}_{founder}$	The estimated share of the startup owned by the founder(s) in the period before (pre) or after (post) it started trading on a platform.

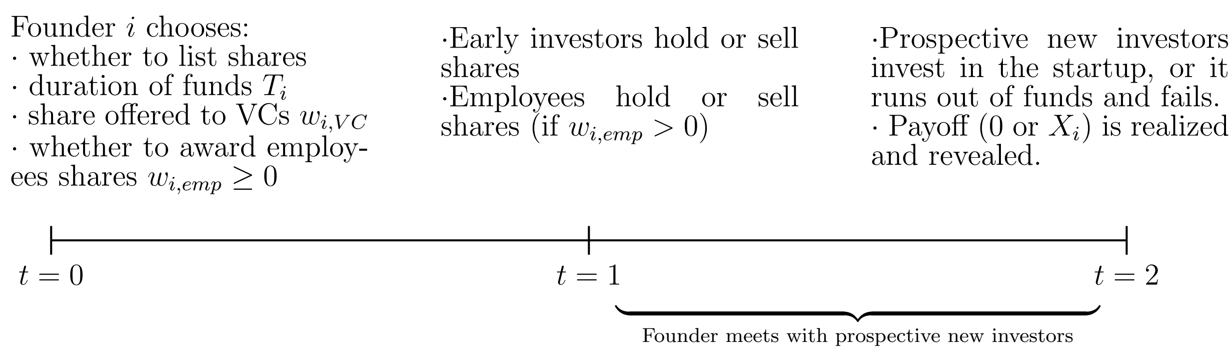
Appendix E.1: Model Description

I describe a model for a startup founder's listing choice in a PSM platform in a setting absent asymmetric information: the founder can fully evaluate the payoffs under each scenario resulting from his choices.

Environment

Consider an economy with M startups and N investors, both fixed. Startup i either succeeds or fails. If successful, its payoff is $X_i \sim \text{Lognormal}(\mu, \sigma^2)$ with μ and σ^2 being known by all agents. Otherwise, their payoff is zero. There are four agents: startup founders, early investors, prospective new investors, and employees. The model has the following timeline: startup founders make choices at t=0[19], to which early investors and employees respond at t=1. Between t=1 and t=2, the founder meets prospective new investors who decide whether to invest in the startup. The last period, t=2, is determined by the startup success or failure outcome, after which its payoff (zero if it fails or X_i if it is successful) is revealed.

Model Timeline



Startups

Startup i has K_i dollars of initial funding and needs to raise a pre-defined amount of Q_i dollars. The amount of time (in months) these initial funds K_i are set to last, T_i, is determined

[19] t=0 represents any point in the startup's lifetime preceding the decision to list.

endogenously by the founder at t=0. The probability that startup i survives until receiving investment is given by $\mathbf{P}(K_i, T_i) = \frac{1}{1+e^{-(\beta_0+\beta_1 T_i+\beta_2 log(K_i))}}$. The general idea is that K_i and T_i impact the likelihood of survival. I assume that $\beta_1 > 0$, implying that businesses with high initial funds (K_i) tend to succeed more often. Meanwhile, $\beta_2 < 0$, such that choosing a large T_i implies a larger failure likelihood, suggesting, for instance, an overly risk-averse founder or a project that is in a low-growth industry where large amounts of cash are not actually needed. In general, β_2 can be interpreted as a penalty term for choosing a high T_i. The startup succeeds with probability p_i conditional on receiving investment and receives investment with probability $\mathbf{P}_{\text{inv, i}}$, a one-time event: if it occurs, the model timeline ends. Importantly, if the startup does not find an investor and runs out of funds, it fails with certainty. Therefore, startup i succeeds with probability $\mathcal{P}_i = p_i \cdot \mathbf{P}_{\text{inv},i} \cdot \mathbf{P}(T_i, K_i)$:

$$\underbrace{\text{Prob(Success)}}_{\mathcal{P}_i} = \underbrace{\text{Prob(Success | Investment)}}_{p_i} \cdot \overbrace{\underbrace{\text{Prob(Investment | Survive)}}_{\mathbf{P}_{\text{inv},i}} \cdot \underbrace{\text{Prob(Survive)}}_{\mathbf{P}(T_i,K_i)}}^{\text{Prob(Investment)}} \tag{9}$$

This expression reflects the "lifetime" of startup i in which it succeeds if it passes through three events: surviving until investment occurs ($\mathbf{P}(K_i, T_i)$), investment occurring ($\mathbf{P}_{\text{inv},i}$), and success afterward (p_i). Finally, startup i shares are held by early investors, and potentially by employees and by prospective new investors, being denoted by $w_{i,early}$, $w_{i,emp}$, and $w_{i,VC}$, with the founder holding the remainder. They are strictly non-negative and sum up to one, with $w_{i,emp}$ and $w_{i,VC}$ being determined endogenously.

Prospective New Investors

Prospective new investors meet with founders at a rate n per month between t=1 and t=2. They meet them randomly, such that each founder is met by $k_T = \frac{n \cdot N}{M}$ investors a month. For instance, if there are 1,000 startups and 500 investors in the economy and investors can meet 4 founders a month, a founder is met 2 times by different investors ($\frac{500 \cdot 4}{1000}$) each month.

This is a key source of uncertainty in the model for the startup seeking investment: there are just so many investments that can be assessed by an investor at a time, and even if the founder is offering very favorable terms, the founder needs to meet an investor first (see Chapter 3 in Strebulaev and Dang (2024) for more details on how that works in practice).

Prospective new investor j has a skill $S_{ij} \sim \mathcal{U}(0,1)$ in understanding startup i payoff risk when meeting its founder. When meeting, he is offered a share $w_{i,VC}$ of the startup by the founder and derives a "refined opinion" $\tilde{\sigma}$ about the payoff risk σ such that $\tilde{\sigma} = \sigma^{1-S_{ij}}$[20]. He is (payoff) risk-averse[21] and invests in the startup if it satisfies:

$$\frac{\mathbb{E}(R_i)}{\tilde{\sigma}} = \frac{(p_i w_{i,VC} \bar{X}_i - Q_i)}{Q_i \sigma^{1-S_{ij}}} \geq S_{VC} \tag{10}$$

Along with the return from the investment, $\mathbb{E}(R_i) = \frac{p_i w_{i,VC} \bar{X}_i - Q_i}{Q_i}$, being non-negative, where $\bar{X}_i = \mathbb{E}(X_i) = e^{\mu + \frac{\sigma^2}{2}}$. S_{VC} is a minimum payoff risk-adjusted return representing how stringent investors are about investing in the startup and is assumed to be common across all potential startup investments and investors and strictly non-negative.

This constraint reflects important factors specific to the VC industry. First, investors typically invest thinking of a "total addressable market", or how large the startup can be *conditional* on success. In general, investors rely on very few high-payoff investments to make up for many losing investments. In this context, the individual risk of an investment is not that important (because they diversify their risk across many investments anyway), but estimating how well it will pay off (if it does pay anything) is extremely important (e.g., see Chapter 2 in Strebulaev and Dang (2024)). As such, I scale the returns by σ, the standard deviation of the payoff conditional on success (rather than investment returns, which differ across investors for the same startup and are difficult to observe): investors

[20] σ here is the standard deviation of a typically "large" payoff, so $\tilde{\sigma}$ decreases with S_{ij}. Whenever necessary, one can consider the technical restriction $\sigma > 1$ to ensure that this is the case. I avoid the alternative form $\tilde{\sigma} = \sigma(1 - S_{ij})$ because that would imply a skilled investor invests in any project with a positive expected return, having no impact on any model equilibria.

[21] This means that if the payoff in case of success is known with certainty, the investor will invest in any startup provided that the expected return is non-negative and larger than S_{VC}.

want to minimize *this* type of uncertainty – preferring investments whose payoffs are large if successful, and more certainly so. Investors who are skilled in estimating it (high S_{ij}) satisfy the constraint and invest more often. Second, while Q_i is exogenous, $w_{i,VC}$ is not, representing the main channel through which bargaining with investors occurs: the founder has to offer a share of the startup that attracts investors[22]. Finally, venture capital investors operate in a competitive environment with relatively no cost of entry (Cochrane (2005)). As such, S_{VC} is better understood as an exogenous parameter for which investors have little to no influence: investors demanding a high S_{VC} will not invest nor raise money, and those demanding a low one will go bankrupt. Under this setup, the probability of receiving investment by startup i can be determined in closed form, given by:

$$\mathbf{P}_{\text{inv},i} = 1 - \left(1 - \frac{\log\left(\frac{p_i w_{i,VC}\bar{X} - Q_i}{Q_i S_{VC}}\right)}{\log(\sigma)}\right)^k$$

where $k = k_T \cdot T_i = \frac{n \cdot N}{M} T_i$, conditional on surviving until meeting an investor willing to invest. The proof is provided in Appendix E.4. Therefore, the probability that a startup receives investment increases with the expected return obtained by the investor $\left(\frac{p_i w_{i,VC}\bar{X} - Q_i}{Q_i}\right)$ and k, and decreases with S_{VC} and σ. As a result, a higher relative fraction of investors to startups $\left(\frac{N}{M}\right)$, along with a longer T_i, increase the chances that the startup receives investment, while startups with a higher risky payoff conditional on success (σ) and facing a more stringent fundraising environment (S_{VC}) are less likely to receive investment.

Employees

The founder can offer employees a share $w_{i,emp} \geq 0$ of the payoff X_i at t=0. These shares are assumed to fulfill a financing role only, extending the duration T_i by $T_i^* = \frac{K_{i,emp} T_i}{K_i}$, where

[22] A convenient simplification: rather than negotiating both Q_i and $w_{i,VC}$, Q_i is fixed, and founders and investors negotiate $w_{i,VC}$. In practice, raised amounts are typically understood as a project requirement, with a narrow margin for bargaining. For instance, see mainstream media headlines about OpenAI and xAI in Field (2024) and Nishant et al. (2024): "OpenAI CEO Sam Altman seeks as much as $7 trillion for new AI chip project" and "Musk's xAI seeking to raise $6 bln in Andreessen Horowitz-backed funding".

$K_{i,emp} = \mathcal{P}_i w_{i,emp} \bar{X}$, the latter representing the equivalent in cash employees receive in the form of shares. For instance, if $K_{i,emp} = K_i$, the startup effectively doubles the duration of its funds by issuing shares equivalent to its initial funds and paying employees. This new $T_i' = T_i + T_i^*$ impacts the term k in $\mathbf{P}_{\text{inv},i}$, such that $\mathbf{P}_{\text{inv},i} = \mathbf{P}_{\text{inv},i}(T_i') > \mathbf{P}_{\text{inv},i}(T_i)$.

Importantly, I do not assume any effort-inducing impact from share compensation. The main reason for that is that the central objective of the model is to answer whether allowing secondary market trading can be optimal even if such impact is non-existent. In general, the effort-inducing impact from equity compensation is ambiguous for a startup: awarding employees with shares may induce their effort but dilutes the founder, potentially reducing his effort[23]. If the net impact is positive and significant, it facilitates the functioning of PSMs, helping the case that these markets can function and operate at scale. If the net impact is negative, then equity compensation acting as a financing channel is even more important than the model assumes. Both alternatives are beneficial to my analysis. Employees are risk-averse and treat cash and shares equally as $w_{i,emp}$ satisfies:

$$\mathcal{P}_i \cdot w_{i,emp} \cdot \bar{X}_i \geq S_{emp} \cdot \sigma \tag{11}$$

The term S_{emp} represents the minimum (payoff) risk-adjusted payoff employees demand to accept shares. Employees discriminate between liquid and illiquid shares, such that $S_{emp} = S_{emp}^L$ when shares can be traded and $S_{emp} = S_{emp}^U$ otherwise. For simplicity, I assume these parameters are known by the founder. If the founder decides to list the shares, then employees can sell their shares at t=1. Employees do not sell their shares if:

$$\mathcal{P}_i \cdot w_{i,emp,market} \cdot \bar{X}_i \geq S_{i,emp,market} \cdot \sigma \tag{12}$$

where $S_{i,emp,market}$ is also assumed to be known by the founder. If employees sell their shares, the investors' stringency parameter S_{VC} changes. The idea is that selling shares

[23]One can add effort-inducing effects by scaling $\mathcal{P}_i$ by the employee's and the founder's share of the payoff.

reveals information to potential investors, who change S_{VC} in response. Importantly, S_{VC} might increase (e.g., because potential investors interpret shareholders selling as a bad signal) or decrease (e.g. because potential investors value liquidity more than the supposed bad signal conveyed by shareholders selling). This new S_{VC} is assumed to be constant, independent of the trading volume, and known by the founder.

Early Investors

Early investors hold a share $w_{i,early}$ of the startup payoff X_i. They are "silent holders" if the shares are unlisted. If the shares are listed, early investors can sell their shares if $\mathcal{P}_i \cdot w_{i,early,market} \cdot \bar{X} < S_{i,early,market} \cdot \sigma$, with $S_{i,early,market}$ also being known by the founder. Similarly, as in the case of employees, the investor stringency parameter S_{VC} changes in response. Specifically, S_{VC} changes to S_{VC}^{emp}, S_{VC}^{early}, or $S_{VC}^{emp,early}$ depending on whether only employees, only early investors, or both sell their shares. The latter term, $S_{VC}^{emp,early}$, is chosen such that $S_{VC}^{emp,early} = \max(S_{VC}^{*}, S_{VC}^{early}, S_{VC}^{emp})$, where S_{VC}^{*} allows for the stringency to be potentially higher than when selling occurs from employees and early investors individually and at least as high as the highest value between S_{VC}^{emp} and S_{VC}^{early}. Finally, these S_{VC} terms are also assumed to be constant and known by the founder.

A summary of the model setup in extensive form is illustrated at the end of this section. I provide in Appendix E.2 a summary of the model constraints.

Solving The Founder's Problem

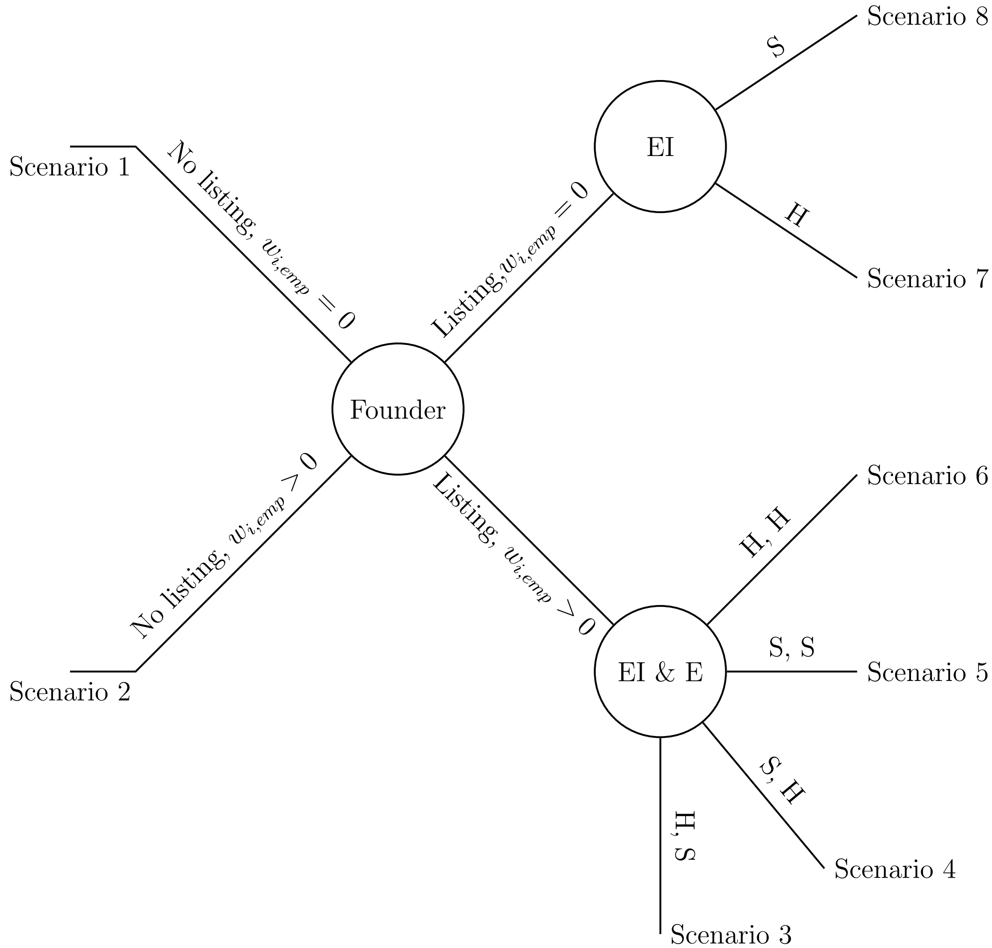
The founder of startup i anticipates other agents' decisions and maximizes his expected payoff by making strategic decisions about the startup's financing: i) the time length T_i the funds should last, (ii) whether to offer a share $w_{i,emp}$ to employees, (iii) the share $w_{i,VC}$ to offer to prospective new investors, and (iv) whether the shares are listed. All decisions are irreversible and made at t=0. Its problem can be generically stated as follows:

$$\underset{T, w_{i,emp}, w_{i,VC}, \text{listing}}{\text{Max}} \mathcal{P}_i \cdot \mathbf{F}_i \cdot X_i \tag{13}$$

The maximization is subject to constraints that are choice-dependent, where $\mathcal{P}_i$ is the total probability that the startup succeeds, $\mathbf{F}_i$ represents the founder's resulting share of the payoff, and X_i is the payoff conditional on success. Appendix E.3 summarizes all possible scenarios arising from the agents' choices, along with their respective constraints. Appendix E.5 provides the proof that a solution exists for each scenario. The model solution involves evaluating the objective function at each attainable (constraint-respecting) scenario and selecting those scenarios for which it is maximized.

Model in Extensive Form

This figure provides the summarized model in extensive form. At t=0, the founder chooses whether the shares will be listed, how long the initial funds are supposed to last (T_i), the share to be offered to prospective new investors $w_{i,VC}$, and whether and how much shares employees are offered, $w_{i,emp}$. At t=1, early investors (EI) and employees (E) decide whether to hold (H) or sell (S) their shares (the former only if they are awarded shares in t=0) based on the constraints indicated in Appendix E.2. Prospective new investors decide whether to invest between t=1 and t=2. The startup payoff X_i is then revealed at $t = 2$. A summary of each scenario, along with the respective investor stringency term S_{VC} and the founder's share of the payoff, is provided in Appendix E.3.



Appendix E.2: Model Constraints

This list contains the constraints faced by employees and early investors. In the first constraint, case (1) refers to the scenarios where there is a PSM listing, and case $(1)^*$ to when there is no listing. I assume that $S^U_{emp} \geq S^L_{emp}$, such that the constraint is never less stringent if the shares are illiquid (i.e., not traded in a PSM).

Constraint	**Description**	**Condition**	**Time**
(1)	Employees Accept Liquid Shares	$\mathcal{P}_i \cdot w_{i,emp} \cdot X_i \geq S^L_{emp} \cdot \sigma$	t=0
$(1)^*$	Employees Accept Illiquid Shares	$\mathcal{P}_i \cdot w_{i,emp} \cdot X_i \geq S^U_{emp} \cdot \sigma$	t=0
(2)	Employees Hold Shares	$\mathcal{P}_i \cdot w_{i,emp} \cdot X_i \geq S_{i,emp,market} \cdot \sigma$	t=1
(3)	Employees Sell Shares	$\mathcal{P}_i \cdot w_{i,emp} \cdot X_i < S_{i,emp,market} \cdot \sigma$	t=1
(4)	Early Investors Hold Shares	$\mathcal{P}_i \cdot w_{i,early} \cdot X_i \geq S_{i,early,market} \cdot \sigma$	t=1
(5)	Early Investors Sell Shares	$\mathcal{P}_i \cdot w_{i,early} \cdot X_i < S_{i,early,market} \cdot \sigma$	t=1

Appendix E.3: Model Scenarios Summary

List of all the scenarios possible given all the agents' decisions, along with the respective founder's share of the payoff in each case, the risk-return threshold demand by prospective new investors, the constraints (listed in the preceding page) to be respected that characterize each scenario.

Scenario	**Description**	**Founder's Share**	S_{VC} **Term**	**Constraints**
(1)	No Secondary Market Listing, No Employee Shares	$1 - w_{i,VC} - w_{i,early}$	S_{VC}	None
(2)	No Secondary Market Listing, Employees Shares	$1 - w_{i,VC} - w_{i,emp} - w_{i,early}$	S_{VC}	(1)*
(3)	Secondary Market Listing, Early Investors Hold, Employees Sell	$1 - w_{i,VC} - w_{i,emp} - w_{i,early}$	S_{VC}^{emp}	(1), (3), (4)
(4)	Secondary Market Listing, Early Investors Sell, Employees Hold	$1 - w_{i,VC} - w_{i,emp} - w_{i,early}$	S_{VC}^{early}	(1), (2), (5)
(5)	Secondary Market Listing, Both Sell	$1 - w_{i,VC} - w_{i,emp} - w_{i,early}$	$S_{VC}^{emp,early}$	(1), (3), (5)
(6)	Secondary Market Listing, Both Hold	$1 - w_{i,VC} - w_{i,emp} - w_{i,early}$	S_{VC}	(1), (2), (4)
(7)	Secondary Market Listing, No Employee Shares, Early Investors Hold	$1 - w_{i,VC} - w_{i,early}$	S_{VC}	(4)
(8)	Secondary Market Listing, No Employee Shares, Early Investors Sell	$1 - w_{i,VC} - w_{i,early}$	S_{VC}^{early}	(5)

Appendix E.4: Derivation of $\mathbf{P}_{\mathbf{inv},i}$

To derive the probability $\mathbf{P}_{\text{inv},i}$ that an investor decides to invest in a startup, we start with the decision rule for an investor j considering startup i. The investor will invest if:

$$\frac{(p_i w_{i,VC}\bar{X} - Q_i)}{Q_i \sigma^{1-S_{ij}}} \geq S_{VC} \tag{14}$$

Rearranging the inequality and taking the logarithm on both sides:

$$\log\left(\frac{p_i w_{i,VC}\bar{X} - Q_i}{Q_i}\right) \geq \log(S_{VC}\sigma^{1-S_{ij}}) = \log(S_{VC}) + (1 - S_{ij})\log(\sigma) \tag{15}$$

Isolating S_{ij}:

$$(1 - S_{ij})\log(\sigma) \leq \log\left(\frac{p_i w_{i,VC}\bar{X} - Q_i}{Q_i}\right) - \log(S_{VC}) \tag{16}$$

$$1 - S_{ij} \leq \frac{\log\left(\frac{p_i w_{i,VC}\bar{X} - Q_i}{Q_i}\right) - \log(S_{VC})}{\log(\sigma)} \tag{17}$$

$$S_{ij} \geq 1 - \frac{\log\left(\frac{p_i w_{i,VC}\bar{X} - Q_i}{Q_i S_{VC}}\right)}{\log(\sigma)} = K \tag{18}$$

Since S_{ij} is uniformly distributed between 0 and 1, the probability that $S_{ij} \geq K$ for a randomly selected investor is simply $1 - K$:

$$P(\text{investor invests}) = 1 - K = 1 - \left(1 - \frac{\log\left(\frac{p_i w_{i,VC}\bar{X} - Q_i}{Q_i S_{VC}}\right)}{\log(\sigma)}\right) = \frac{\log\left(\frac{p_i w_{i,VC}\bar{X} - Q_i}{Q_i S_{VC}}\right)}{\log(\sigma)} \tag{19}$$

As investors meet with startups over time, the number of meetings for which this probability is applied is proportional to the product of the number of investors (N), the number of startups (M), their screening capacity (n), and the duration T in months, given by $k = \frac{N \cdot n \cdot T}{M}$.

Each meeting is an independent event where an investor may decide to invest, the investment occurring with the probability just derived (P(investor invests)). The probability that the startup does not receive investment after a meeting is $(1 - P(\text{investor invests}))$, or $(1 - P(\text{investor invests}))^k$ after k meetings. Therefore, the probability that the startup receives investment over k meetings can be expressed as:

$$\mathbf{P}_{\text{inv},i} = 1 - (1 - P(\text{investor invests}))^k = 1 - \left(1 - \frac{\log\left(\frac{p_i w_{i,VC}\bar{X} - Q_i}{Q_i S_{VC}}\right)}{\log(\sigma)}\right)^k \tag{20}$$

Appendix E.5: Proof of Existence of Optimal Solutions

I provide a summary of the proof for the existence of solutions to the maximization problem under the various scenarios outlined in Appendix E.3. The main tool is the Weierstrass Extreme Value Theorem, which states that *if a function f is continuous on a compact set K in $\mathbb{R}^n$, then f attains both its maximum and minimum values on K.*

The objective function to maximize in all scenarios is given by:

$$\underset{T, w_{i,emp}, w_{i,VC}, \text{listing}}{\text{Max}} \mathcal{P}_i \cdot \mathbf{F}_i \cdot X_i \tag{21}$$

This function is continuous in T, $w_{i,VC}$, $w_{i,emp}$, and the listing decision. Given that the feasible regions are compact and the objective function is continuous in every case, all requirements are satisfied, and a solution exists for each scenario. I provide below a summary of the feasible regions, defined by the constraints and the natural bounds of the variables.

Feasible Regions and Conditions for Each Scenario

Scenario	**Founder's Share**	**Constraints**	**Feasible Region**
1	$1 - w_{i,VC}$	None	$w_{i,VC} \in [0,1]$, $T \geq 0$
2	$1 - w_{i,VC} - w_{i,emp}$	(1), (2)	$w_{i,VC} \in [0,1]$, $w_{i,emp} \in [w_{i,emp}^{\min}, 1 - w_{i,VC}]$, $T \geq 0$
3	$1 - w_{i,VC} - w_{i,emp}$	(1), (3), (4)	$w_{i,VC} \in [0,1]$, $w_{i,emp} \in [w_{i,emp}^{\min}, w_{i,emp}^{\max}]$, $T \geq 0$
4	$1 - w_{i,VC} - w_{i,emp}$	(1), (2), (5)	$w_{i,VC} \in [0,1]$, $w_{i,emp} \in [w_{i,emp}^{\min}, 1 - w_{i,VC}]$, $T \geq 0$
5	$1 - w_{i,VC} - w_{i,emp}$	(1), (3), (5)	$w_{i,VC} \in [0,1]$, $w_{i,emp} \in [w_{i,emp}^{\min}, w_{i,emp}^{\max}]$, $T \geq 0$
6	$1 - w_{i,VC} - w_{i,emp}$	(1), (2), (4)	$w_{i,VC} \in [0,1]$, $w_{i,emp} \in [w_{i,emp}^{\min}, 1 - w_{i,VC}]$, $T \geq 0$
7	$1 - w_{i,VC}$	(4)	$w_{i,VC} \in [0,1]$, $T \geq 0$
8	$1 - w_{i,VC}$	(5)	$w_{i,VC} \in [0,1]$, $T \geq 0$

Appendix E.6: Proof of Theorem I

Under mild technical restrictions, there is an equilibrium with $S_{VC}^{emp,early} > S_{VC}$ such that the investor is indifferent between not awarding employees with shares and not listing shares in a PSM (Scenario 1) and listing shares, with employees being awarded shares and selling them along with early investors (Scenario 5). In this equilibrium, $T_5 = T_1 + \Delta T$, with $\Delta T > 0$ representing the extra time earned through the effect of employee shares compensation.

Proof

Let $\mathbf{P}(K_i, T_1) = P_1$, $\mathbf{P}(K_i, T_5) = P_5$, and $(w_{i,VC,1}, w_{i,emp,1}, T_1)$ and $(w_{i,VC,5}, w_{i,emp,5}, T_5)$ denote the optimal solutions for Scenario 1 and Scenario 5. The objective functions for the two scenarios are:

$$\text{Scenario 1: } P_1 \cdot \left(1 - \left(1 - \frac{\log\left(\frac{p_i w_{i,VC,1}\bar{X} - Q_i}{Q_i S_{VC}}\right)}{\log(\sigma)}\right)^{k_T \cdot T_1}\right) \cdot (1 - w_{i,VC,1}) \tag{22}$$

$$\text{Scenario 5: } P_5 \cdot \left(1 - \left(1 - \frac{\log\left(\frac{p_i w_{i,VC,5}\bar{X} - Q_i}{Q_i S_{VC}^{emp,early}}\right)}{\log(\sigma)}\right)^{k_T \cdot T_5}\right) \cdot (1 - w_{i,VC,5} - w_{i,emp,5}) \tag{23}$$

Denote $T_5 = T_1 + \Delta T$. The indifference condition between the two scenarios requires equality between the two objective functions above in equilibrium. Let $A = \frac{\log\left(\frac{p_i w_{i,VC,1}\bar{X} - Q_i}{Q_i S_{VC}}\right)}{\log(\sigma)}$ and $B = \frac{\log\left(\frac{p_i w_{i,VC,5}\bar{X} - Q_i}{Q_i S_{VC}^{emp,early}}\right)}{\log(\sigma)}$. This condition can then be written as:

$$P_1 \cdot (1 - w_{i,VC,1}) \left(1 - (1 - A)^{k_T \cdot T_1}\right) = P_5 \cdot (1 - w_{i,VC,5} - w_{i,emp,5}) \left(1 - (1 - B)^{k_T \cdot (T_1 + \Delta T)}\right) \tag{24}$$

Let $C = \frac{P_1 \cdot (1 - w_{i,VC,1})\left(1 - (1 - A)^{k_T \cdot T_1}\right)}{P_5 \cdot (1 - w_{i,VC,5} - w_{i,emp,5})}$, it can be simplified to:

$$C = 1 - (1 - B)^{k_T \cdot (T_1 + \Delta T)} \tag{25}$$

And finally to:

$$k_T \cdot (T_1 + \Delta T) \cdot \ln(1 - B) = \ln(1 - C) \tag{26}$$

Solving for ΔT:

$$\Delta T = \frac{\ln(1 - C) - k_T \cdot T_1 \cdot \ln(1 - B)}{k_T \cdot \ln(1 - B)} \tag{27}$$

For $\Delta T > 0$, consider the technical restrictions:

(i) $0 < C < 1$ and $0 < B < 1$, so $\ln(1 - C)$ and $\ln(1 - B)$ are both negative (undefined otherwise).

(ii) $k_T \cdot T_1 < \frac{ln(1-C)}{ln(1-B)}$. A large enough $k.T_1$ (not respecting this inequality) implies that the startup founder will meet a sufficiently high number of investors, such that the benefit of awarding employees with listed shares (having an extended time to meet investors) never compensates for its negative effects (a lower share of the total payoff).

If satisfied, then there exists an equilibrium with $S_{VC}^{emp,early} > S_{VC}$ such that $T_5 = T_1 + \Delta T$ with $\Delta T > 0$.

Appendix E.7: Model Parameters Proxies Definitions

Parameter	Description
$\bar{X}$	Market Capitalization at IPO (or latest round if no IPO) and at trading start.
σ	Standard deviation of X_i.
$Q_{i,VC}$	Average total money raised per startup.
K	Average money raised per round.
$w_{i,\text{early}}$	Share of the startup owned by investors divided by the number of rounds for the pre-trading start period, the share of the startup owned by investors in the pre-start trading period for the post-trading start period.
M	Number of startups receiving financing over a period.
N	Number of investors participating in the financing rounds over a period.
n	Number of financing rounds the 99th percentile of investors participated in a period.
a	A scaling factor to $k = \frac{n \cdot N \cdot T_i}{M}$ to adjust the sensitivity of $\mathbf{P}_{\text{inv},i}$ to k itself.
p	Estimated from $Y = p_i \mathbf{P}(T_i, K_i)$ using the Crunchbase sample of financing rounds for each year from 2000 to 2020. Then, for each startup, the average value for the parameters in the five years preceding the launch (sample 1, "pre") and start trading date (sample 2, "post") is defined. The resulting value is the average in the combined sample.
β_0	Same as above.
β_1	Same as above.
β_2	Same as above.
T	Time between rounds, in months.
$w_{i,\text{VC}}$	The share of the startup held by investors at trading start minus the share held by early investors for the pre-period, and the share of the startup held by investors at the IPO or latest round minus the share held at trading start for the post-period.
$w_{i,\text{emp}}$	Share of the startup owned by employees at trading start for the pre-period and at IPO or latest round for the post-period.
$\mathbf{P}_{\text{inv},i}$	Share of financing rounds in which the startup obtains subsequent financing.

Appendix E.8: Listing with Uncertainty About S_{VC}

The expected payoff from listing depends on whether S_{VC} increases or decreases:

$$\begin{aligned}\text{Expected Payoff from Listing} = q &\left(\mathbf{P}(T_i, K_i)^{\uparrow} \cdot \mathbf{P}_{\text{inv},i}^{\uparrow} \cdot \mathbf{F}_i^{\uparrow} \cdot X_i \cdot p_i\right) \\ &+ (1-q)\left(\mathbf{P}(T_i, K_i)^{\downarrow} \cdot \mathbf{P}_{\text{inv},i}^{\downarrow} \cdot \mathbf{F}_i^{\downarrow} \cdot X_i \cdot p_i\right)\end{aligned} \tag{28}$$

The payoff from not listing is:

$$\text{Payoff from Not Listing} = \mathbf{P}(K_i, T_1) \cdot \mathbf{P}_{\text{inv},i} \cdot \mathbf{F}_i \cdot X_i \cdot p_i \tag{29}$$

To determine the threshold probability q such that it is better to list, we solve for q in the inequality where the expected payoff from listing is greater than the payoff from not listing:

$$\begin{aligned}q\left(\mathbf{P}(T_i, K_i)^{\uparrow} \cdot \mathbf{P}_{\text{inv},i}^{\uparrow} \cdot \mathbf{F}_i^{\uparrow} \cdot p_i)\right) + (1-q)&\left(\mathbf{P}(T_i, K_i)^{\downarrow} \cdot \mathbf{P}_{\text{inv},i}^{\downarrow} \cdot \mathbf{F}_i^{\downarrow} \cdot p_i\right) \\ &> \mathbf{P}(K_i, T_1) \cdot \mathbf{P}_{\text{inv},i} \cdot \mathbf{F}_i \cdot p_i\end{aligned} \tag{30}$$

Solving for q:

$$q < \frac{\mathbf{P}(T_i, K_i)^{\downarrow} \cdot \mathbf{P}_{\text{inv},i}^{\downarrow} \cdot \mathbf{F}_i^{\downarrow} - \mathbf{P}(K_i, T_1) \cdot \mathbf{P}_{\text{inv},i} \cdot \mathbf{F}_i}{\mathbf{P}(T_i, K_i)^{\downarrow} \cdot \mathbf{P}_{\text{inv},i}^{\downarrow} \cdot \mathbf{F}_i^{\downarrow} - \mathbf{P}(T_i, K_i)^{\uparrow} \cdot \mathbf{P}_{\text{inv},i}^{\uparrow} \cdot \mathbf{F}_i^{\uparrow}} = V \tag{31}$$

If q is less than this threshold V, the expected payoff from listing is higher, making it better for the founder to list.

Appendix E.9: Propensity to List Proxies

This table presents the sign of the correlation between the several terms determining the right-hand side term of the propensity to list inequality, V. I proxy V^{-1}, the inverse listing propensity, by the number of years a startup took to list on a PSM platform, with the idea that longer time proxies for a lower propensity to list.

Term	Description	V	V^{-1}
$\mathbf{P}_{\text{inv},i}$	Probability of receiving investment pre-listing.	(-)	(+)
$\mathbf{P}^{\downarrow}_{\text{inv},i}$	Probability of receiving investment post-listing when investors are **less** stringent after the listing.	(+)	(-)
$\mathbf{P}^{\uparrow}_{\text{inv},i}$	Probability of receiving investment post-listing when investors are **more** stringent after the listing.	(+)	(-)
$\mathbf{F}_i = (1 - w_{i,VC} - w_{i,early})$	Founder's share of the payoff absent a listing.	(-)	(+)
$\mathbf{F}^{\downarrow}_i = (1 - w^{\downarrow}_{i,VC} - w_{i,emp} - w_{i,early})$	Founder's share of the payoff post-listing when investors are **less** stringent after the listing.	(+)	(-)
$\mathbf{F}^{\uparrow}_i = (1 - w^{\uparrow}_{i,VC} - w_{i,emp} - w_{i,early})$	Founder's share of the payoff post-listing when investors are **more** stringent after the listing.	(+)	(-)

Figure 1: Venture Capital Deal Volume and Secondary Market Trading Activity

This figure shows the estimated venture capital deal volume in the U.S. along with secondary market trading activity between 2012 and June/2024. Sources: Hamilton Lane, PitchBook, Crunchbase, ForgeGlobal, and EquityZen yearly reports.

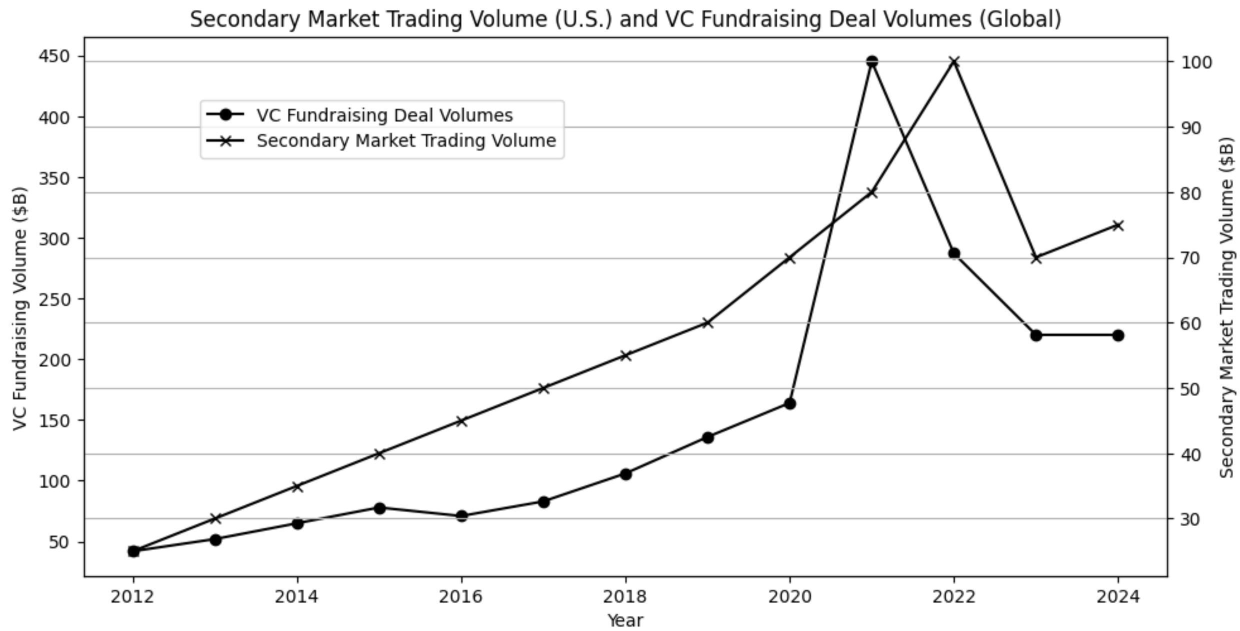


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Figure 2: Dilution Patterns Across Financing Rounds

This figure shows the percentage of startup financing rounds in which a given portion of the startup shares, by brackets ($\leq$ 5%, 5-9.9%, 10-14.9%, 15-19.9%, 20-24.9%, 25-29.9%, and 30%+), is sold to investors for seed, Series A, Series B, and Series C rounds. For instance, in 24% of seed rounds the portion sold to investors is 20-24.9%.

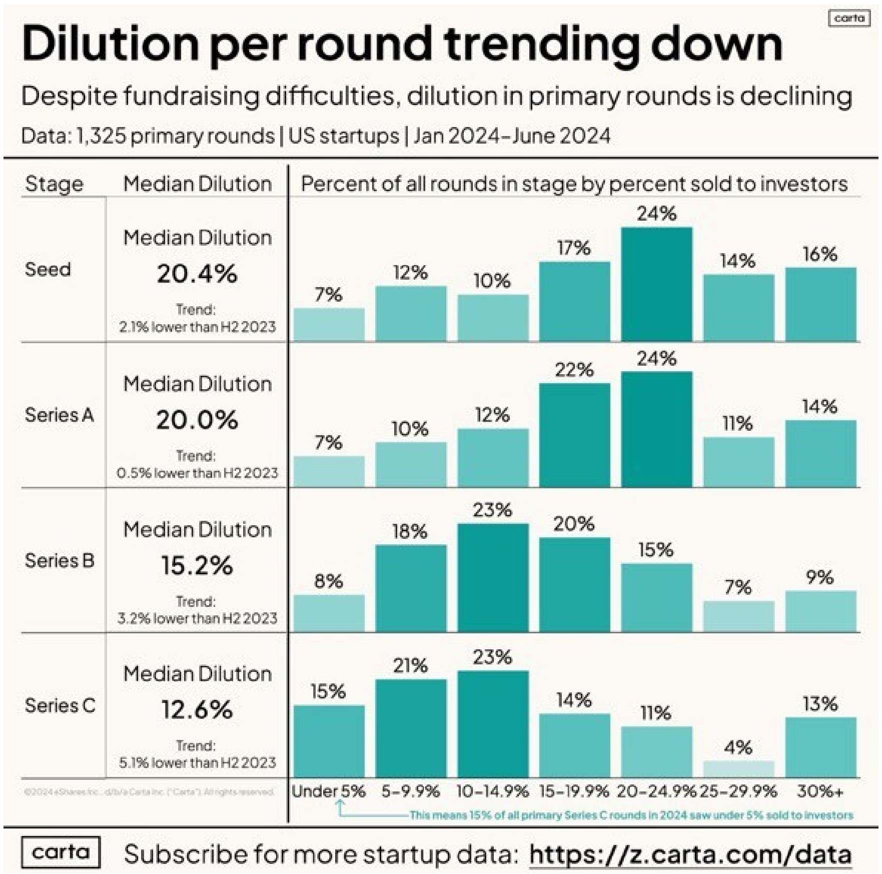

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Figure 3: Receptiveness to Equity Compensation by Prospective Employees

This figure provides anecdotal evidence on how receiving startup shares is seen by prospective employees. In these forum excerpts, software engineers discuss their opinions on receiving shares as partial or total compensation.

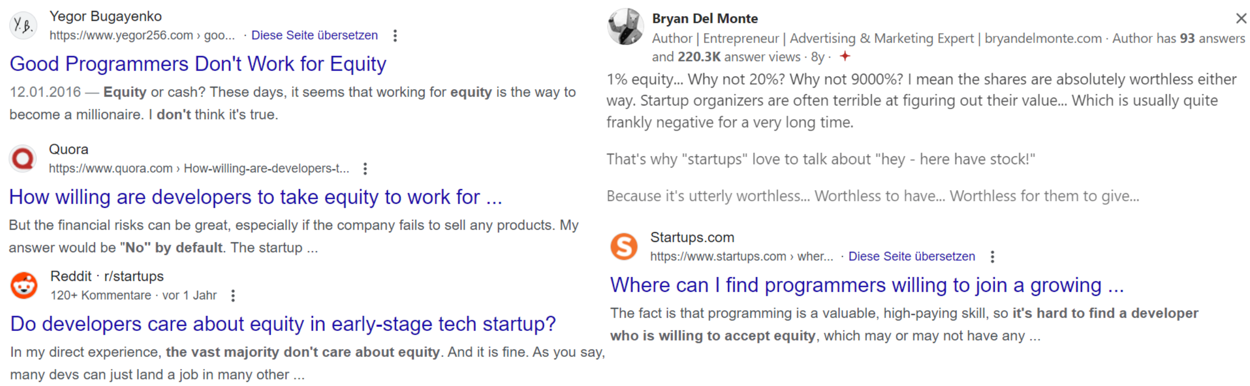

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Figure 4: Employees' Exercise of Options When Leaving Startups

This figure provides the evolution of the average percentage of options exercise by employees when leaving startups, from 2017 to 2024. Source: Carta.

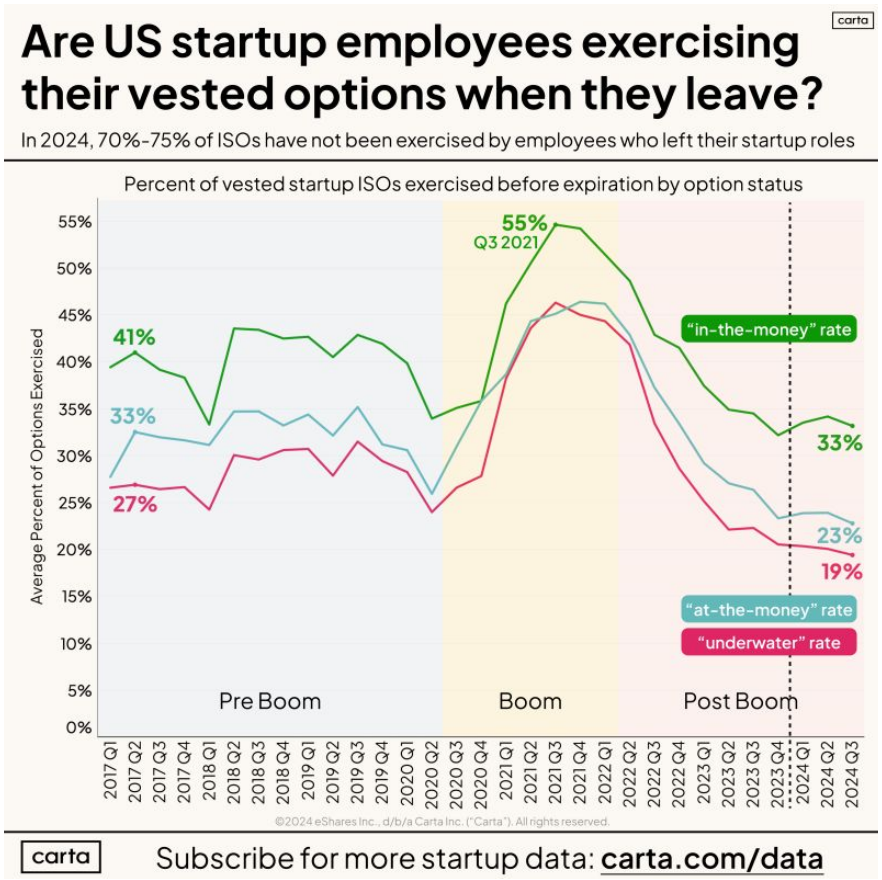

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Figure 5: Profitability Two Years Prior to IPO

This figure shows the reported profit for the startups in the sample that did an IPO in the two years preceding it (Source: S-1 filings).

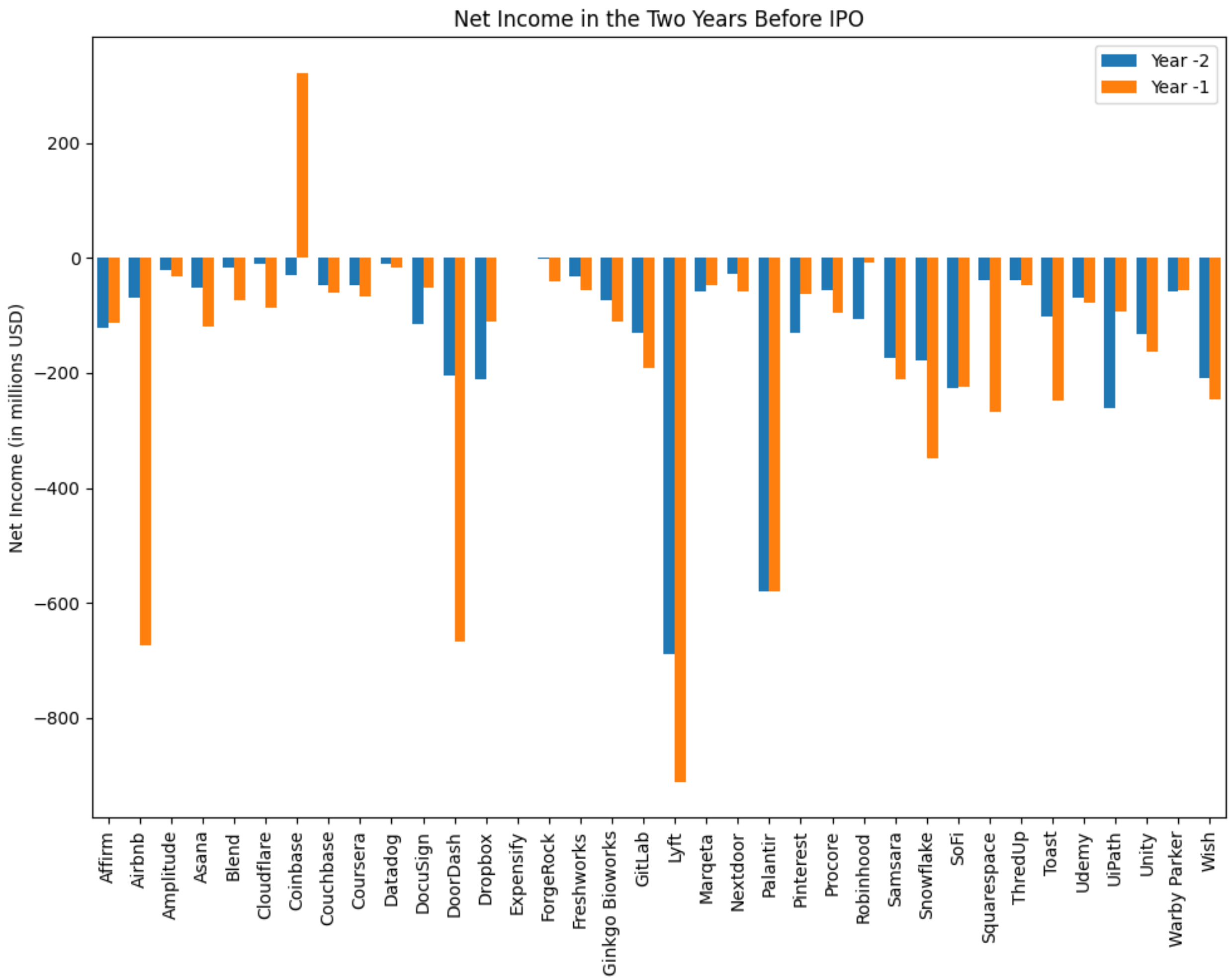

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Figure 6: Startup Stock Price Evolution Example

This figure shows the price chart for the startup Udemy, an education technology company that went public in 2021 (UDMY).

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Figure 7: Average Stock Price Returns Before and After Financing Rounds

This figure shows the average monthly stock price returns before a financing round occurs ("Pre") and the cumulative stock price return, adjusted to a monthly basis, after the financing round ("Post") for different types of rounds.

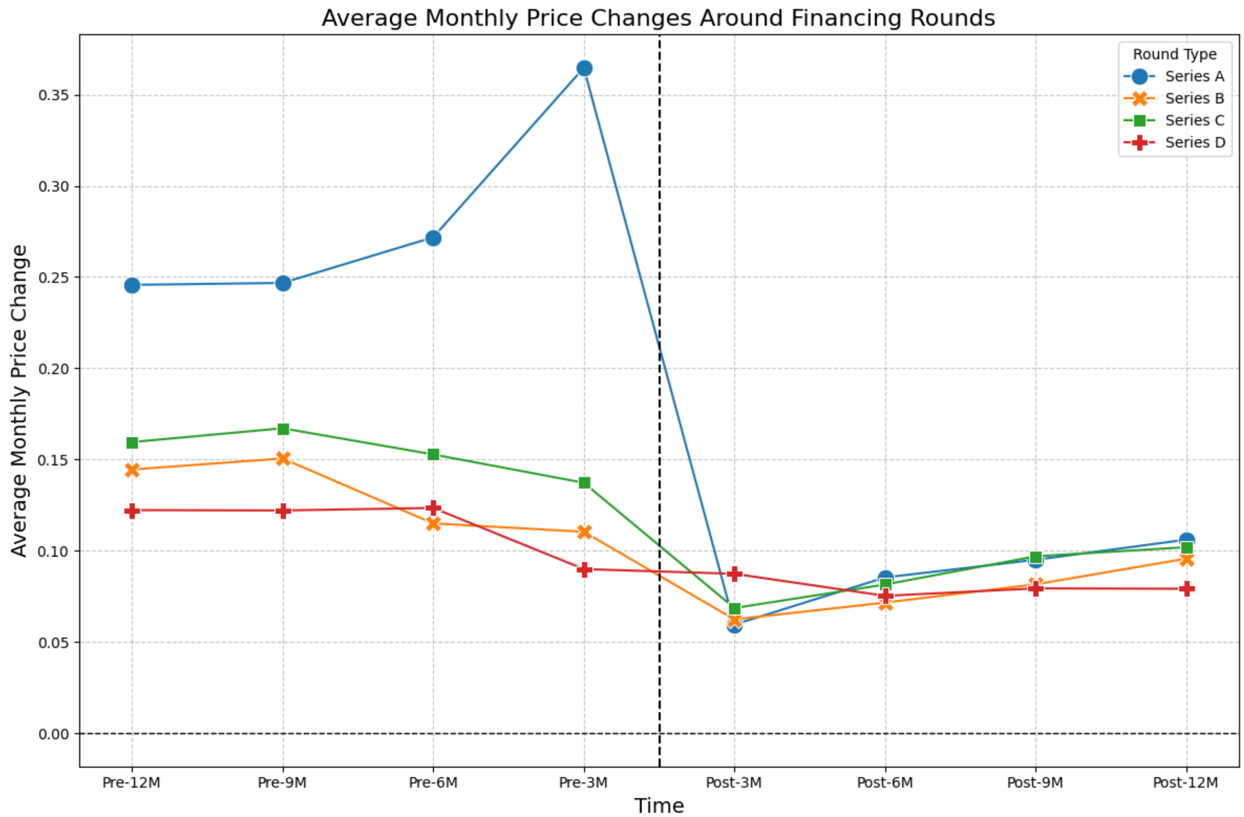

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Table 1: Summary Statistics

This table provides summary statistics for the main variables used in the paper. See Variable Definitions (Appendix E) for their detailed description.

	(1)				
	mean	sd	p25	p50	p75
Valuation	3.2	4.1	1	1.8	3.4
ValuationGr	.18	.66	0	0	0
IPO	.099	.3	0	0	0
Started Trading	2021	1	2021	2021	2021
Year of Launch	2013	3.6	2012	2014	2016
YrsPreListed	7.4	3.3	5	7	9
YrsListed	1.9	.8	2	2	2
PreTradingRounds	5.7	1.6	5	6	6
PostTradingRounds	1.2	.88	1	1	2
PreTradingMoney (in billions USD)	.41	.74	.14	.25	.46
PostTradingMoney (in billions USD)	.27	.45	.075	.12	.22
FundingRate (in billions USD)	.14	.25	.04	.075	.15
Pre-Trading Start ΔT	16	7.6	12	15	19
Post-Trading Start ΔT	18	9	12	12	24
ΔT^*	44	36	18	36	36
w_{emp}^{pre}	.14	.022	.13	.15	.15
w_{VC}^{pre}	.5	.052	.48	.5	.52
$w_{founder}^{pre}$	.24	.045	.2	.25	.25
w_{emp}^{post}	.12	.034	.1	.13	.14
w_{VC}^{post}	.12	.046	.11	.12	.14
$w_{founder}^{post}$	.2	.041	.19	.2	.22
Observations	365				

I apply $\Delta T^* = 120$ for startups with zero post-trading rounds.

Return to Section 4.2

Table 2: Relationship Between Traded Startup Valuations and Listing Time

This table provides the results of OLS regressions studying how the valuation and valuation growth of startups listed in major U.S. PSM platforms relates to the time elapsed from launch to trading start and from trading start to the latest financing round. The precise definition of all explanatory variables is provided in Appendix E. t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) ValuationGr	(2) ValuationGr	(3) ValuationGr	(4) Valuation	(5) Valuation	(6) Valuation
YrsListed	0.135***	0.158***	0.102	0.630**	1.012***	0.634
	(3.64)	(3.52)	(1.21)	(2.41)	(3.06)	(1.06)
YrsPreListed	-0.0123	-0.00966	-0.0115	0.0986	0.0889	0.0819
	(-1.45)	(-1.15)	(-1.38)	(1.54)	(1.37)	(1.29)
Valuation	-0.00143	-0.0107	-0.00899			
	(-0.21)	(-1.50)	(-1.24)			
IPO	1.392***	1.577***	1.318***	2.785***	2.557***	0.980
	(14.60)	(14.24)	(5.72)	(3.91)	(3.01)	(0.59)
Platform FE	No	Yes	Yes	No	Yes	Yes
State FE	No	Yes	Yes	No	Yes	Yes
TradingStartYear FE	No	No	Yes	No	No	Yes
N	350	334	333	365	348	347
R^2	0.0247	0.0710	0.468	0.0245	0.171	0.245

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Return to Section 6.1.1

Table 3: Relationship Between an Eventual IPO and Listing Time

This table provides the results of OLS regressions studying how the occurrence of an eventual IPO for startups listed in major U.S. PSM platforms relates to the time elapsed from launch to trading start and from trading start to the latest financing round. The precise definition of all explanatory variables is provided in Appendix E. t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) IPO	(2) IPO	(3) IPO
YrsListed	-0.0676***	-0.102***	-0.274***
	(-4.15)	(-5.97)	(-22.34)
YrsPreListed	0.0132***	0.00967***	0.000983
	(3.54)	(2.92)	(0.50)
ValuationGr	0.274***	0.248***	0.0726***
	(14.60)	(14.24)	(5.72)
Valuation	0.00937***	0.00882***	0.00109
	(3.10)	(3.16)	(0.64)
Platform FE	No	Yes	Yes
State FE	No	Yes	Yes
TradingStartYear FE	No	No	Yes
N	350	334	333
R^2	0.437	0.620	0.871

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Return to Section 6.1.1

Table 4: Financing Performance of Listed Startups

This table provides the results of OLS regressions studying how startups listed in major U.S. PSM platforms perform in obtaining subsequent financing once their shares are traded, both in terms of the number of financing rounds and the overall money raised volume. The precise definition of all explanatory variables is provided in Appendix E. t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) PostTradingRounds	(2) PostTradingRounds	(3) PostTradingRounds	(4) PostTradingMoney	(5) PostTradingMoney	(6) PostTradingMoney
PreTradingRounds	0.0936***	0.0622**	0.0522*	0.0132	0.0159	0.0115
	(2.95)	(2.20)	(1.96)	(1.03)	(1.18)	(0.91)
IPO	-1.013***	-0.680***	0.507*	0.436***	0.483***	0.358**
	(-5.52)	(-3.53)	(1.66)	(5.89)	(5.26)	(2.47)
YrsListed	0.361***	0.281***	0.712***	0.198***	0.205***	0.171***
	(6.40)	(4.60)	(6.69)	(8.71)	(7.04)	(3.37)
YrsPreListed	-0.0114	-0.0272**	-0.0197*	-0.00823	-0.00504	-0.00475
	(-0.83)	(-2.23)	(-1.74)	(-1.48)	(-0.86)	(-0.88)
ValuationGr	0.145*	0.136*	0.204***	0.125***	0.0633*	0.107***
	(1.79)	(1.80)	(2.85)	(3.84)	(1.76)	(3.14)
Valuation	-0.0145	0.00910	0.00142	0.0443***	0.0380***	0.0334***
	(-1.29)	(0.89)	(0.15)	(9.79)	(7.81)	(7.28)
Platform FE	No	Yes	Yes	No	Yes	Yes
State FE	No	Yes	Yes	No	Yes	Yes
TradingStartYear FE	No	No	Yes	No	No	Yes
N	350	334	333	350	334	333
R^2	0.221	0.341	0.449	0.544	0.550	0.624

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Return to Section 6.1.2

Table 5: Financing Performance of Listed Startups (Continued)

This table provides additional results of OLS regressions studying how startups listed in major U.S. PSM platforms perform in obtaining subsequent financing once their shares are traded, now in terms of the financing rate (money raised over elapsed time between rounds) and the time elapsed between financing rounds. The precise definition of all explanatory variables is provided in Appendix E. t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) FundingRate	(2) FundingRate	(3) FundingRate	(4) ΔT	(5) ΔT	(6) ΔT
PostTradingMoney	0.498***	0.445***	0.464***	-6.534	-16.83***	-14.16***
	(27.80)	(31.62)	(31.30)	(-1.31)	(-3.54)	(-2.86)
IPO	0.0419	0.0428*	0.0505	69.49***	57.73***	12.62
	(1.63)	(1.81)	(1.32)	(9.77)	(7.23)	(0.99)
YrsListed	-0.120***	-0.106***	-0.105***	9.550***	6.419**	-9.926**
	(-14.35)	(-13.58)	(-7.85)	(4.12)	(2.43)	(-2.23)
YrsPreListed	0.000645	0.000772	0.000454	0.267	0.802*	0.625
	(0.38)	(0.57)	(0.35)	(0.56)	(1.77)	(1.44)
ValuationGr	0.0261**	-0.00185	-0.00973	-3.163	-3.796	-5.566*
	(2.36)	(-0.21)	(-1.08)	(-1.03)	(-1.25)	(-1.86)
Valuation	0.00101	0.00138	0.00200	0.713	0.541	0.623
	(0.63)	(1.09)	(1.61)	(1.59)	(1.27)	(1.51)
Platform FE	No	Yes	Yes	No	Yes	Yes
State FE	No	Yes	Yes	No	Yes	Yes
TradingStartYear FE	No	No	Yes	No	No	Yes
N	350	334	333	350	334	333
R^2	0.835	0.889	0.899	0.324	0.483	0.539

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Return to Section 6.1.2

Table 6: Relationship Between Performance and Ownership Split

This table provides the results of OLS regressions studying how startups listed in major U.S. PSM platforms perform in terms of valuation growth, having an eventual IPO, and obtaining financing depending on the estimated share of it owned by investors, the founder, and employees. The precise definition of all explanatory variables is provided in Appendix E. t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) ValuationGr	(2) ValuationGr	(3) IPO	(4) IPO	(5) FundingRate	(6) FundingRate
$w_{emp}^{post} - w_{emp}^{pre}$	25.07	22.82	7.729	10.31*	-6.167	-1.885
	(1.23)	(1.20)	(0.99)	(1.73)	(-0.82)	(-0.30)
$w_{VC}^{post} - w_{VC}^{pre}$	20.41	19.98	2.907	5.469	-8.025	-2.977
	(1.02)	(1.07)	(0.38)	(0.94)	(-1.09)	(-0.49)
$w_{founder}^{post} - w_{founder}^{pre}$	17.32	16.87	1.799	4.009	-8.617	-3.498
	(0.86)	(0.90)	(0.23)	(0.68)	(-1.17)	(-0.57)
w_{emp}^{pre}	15.37	13.39	5.115	5.372	-2.948	-0.0575
	(1.30)	(1.21)	(1.13)	(1.54)	(-0.68)	(-0.02)
w_{VC}^{pre}	31.49	29.72	4.756	7.857	-10.26	-3.152
	(1.06)	(1.07)	(0.42)	(0.90)	(-0.94)	(-0.35)
$w_{founder}^{pre}$	5.098	8.003	-1.803	1.333	-5.812	-1.716
	(0.43)	(0.74)	(-0.40)	(0.39)	(-1.35)	(-0.48)
Platform FE	No	Yes	No	Yes	No	Yes
State FE	No	Yes	No	Yes	No	Yes
TradingStartYear FE	No	Yes	No	Yes	No	Yes
N	350	333	356	338	350	333
R^2	0.208	0.386	0.437	0.730	0.274	0.476

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Return to Section 6.1.3

Table 7: Relationship Between Financing Rate and Ownership Split

This table provides the results of OLS regressions studying how startups listed in major U.S. PSM platforms perform in terms of obtaining financing depending on changes in the estimated share of it owned by investors, the founder, and employees, along with other characteristics. The precise definition of all explanatory variables is provided in Appendix E. t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) ΔT	(2) ΔT	(3) ΔT	(4) ΔT	(5) ΔT	(6) ΔT
$w^{post}_{emp} - w^{pre}_{emp}$	2076.9**	1292.3	855.3	1424.3*	1091.8	475.8
	(2.44)	(1.56)	(1.03)	(1.71)	(1.29)	(0.56)
$w^{post}_{VC} - w^{pre}_{VC}$	2516.0***	1853.4**	1363.2*	2110.6***	1734.4**	1120.2
	(3.01)	(2.29)	(1.67)	(2.61)	(2.12)	(1.36)
$w^{post}_{founder} - w^{pre}_{founder}$	2665.9***	1961.8**	1489.5*	2335.9***	1951.3**	1345.5
	(3.18)	(2.41)	(1.81)	(2.85)	(2.34)	(1.60)
w^{pre}_{emp}	1320.0***	880.7*	694.2	1030.4**	745.0	455.4
	(2.68)	(1.83)	(1.43)	(2.16)	(1.53)	(0.93)
w^{pre}_{VC}	3698.9***	2775.7**	2024.7*	3114.5***	2597.7**	1670.8
	(2.98)	(2.31)	(1.67)	(2.60)	(2.15)	(1.38)
$w^{pre}_{founder}$	1350.3***	1050.2**	786.4*	1186.8**	1041.4**	704.1
	(2.78)	(2.24)	(1.66)	(2.52)	(2.19)	(1.47)
PostTradingMoney	-9.961**	-18.24***	-16.83***	-16.73***	-19.65***	-21.17***
	(-2.34)	(-4.36)	(-3.76)	(-4.01)	(-4.73)	(-4.68)
IPO	79.17***	79.47***	39.54***	91.57***	78.19***	38.46***
	(11.23)	(10.06)	(3.10)	(12.39)	(9.49)	(3.01)
YrsListed	2.389	0.562	-13.85***	2.753	-0.969	-15.78***
	(1.07)	(0.23)	(-3.15)	(1.26)	(-0.39)	(-3.64)
YrsPreListed	0.101	0.247	0.238	0.122	0.293	0.292
	(0.23)	(0.58)	(0.57)	(0.30)	(0.69)	(0.71)
ValuationGr	-3.801	-7.451***	-7.547***	4.446	24.56	32.12
	(-1.44)	(-2.75)	(-2.76)	(0.22)	(1.18)	(1.48)
Valuation	0.822**	0.811**	0.790**	0.872**	1.001***	1.054***
	(2.05)	(2.10)	(2.06)	(2.29)	(2.61)	(2.76)
$w^{post}_{emp} - w^{pre}_{emp}$ × ValuationGr				238.3***	211.7***	264.9***
				(4.03)	(2.78)	(3.28)
$w^{post}_{VC} - w^{pre}_{VC}$ × ValuationGr				28.19	66.67*	78.57*
				(0.74)	(1.70)	(1.93)
$w^{post}_{founder} - w^{pre}_{founder}$ × ValuationGr				-116.6*	-107.3	-101.9
				(-1.75)	(-1.63)	(-1.54)
Platform FE	No	Yes	Yes	No	Yes	Yes
State FE	No	Yes	Yes	No	Yes	Yes
TradingStartYear FE	No	No	Yes	No	No	Yes
N	350	334	333	350	334	333
R^2	0.522	0.612	0.632	0.576	0.629	0.652

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Return to Section 6.1.3

Table 8: Startup Stock Prices Summary Statistics

This table provides summary statistics for stock prices and returns data for the startups in the sample. The table includes only data for stocks whose prices were available on notice.co, a database with historical prices for startups and private firms.

	mean	sd	p25	p50	p75	N
Avg Monthly Return (%)	12.0	132.7	-6.0	0.00	10.8	25209
Avg Quarterly Return (%)	24.7	210.5	-7.2	2.6	27.3	24609
Avg Yearly Return (%)	112.6	537.3	-6.2	24.8	103.0	21909
Avg Monthly Volatility (%)	73.5	110.7	26.8	36.5	59.2	300*
Avg Bottom-to-Peak Return (%)	24061.2	145668.1	1785.4	4722.2	14301.3	300
% Below 50%+ from Peak	63.0	-	-	-	-	300

* Computed for each startup using monthly returns, then averaged across 300 startups.

Return to Section 6.1.4

Table 9: Model Estimation Summary Statistics

This table provides summary statistics for the variables used in the estimation section (Section 6.2). See Appendix F for their detailed description.

Period: Pre	Mean	Std. Dev.	p(25)	p(50)	p(75)
p	0.76	0.04	0.73	0.77	0.80
b_0	15.58	8.16	9.14	13.73	22.12
b_1	-0.38	0.23	-0.65	-0.49	-0.17
b_2	2.90	0.80	2.26	2.55	3.49
X	$3.17 \cdot 10^9$	$4.07 \cdot 10^9$	$1.00 \cdot 10^9$	$1.80 \cdot 10^9$	$3.40 \cdot 10^9$
w_{early}	0.12	0.03	0.10	0.11	0.13
w_{emp}	0.14	0.02	0.13	0.15	0.15
w_{VC}	0.50	0.05	0.48	0.50	0.52
Q	$4.09 \cdot 10^8$	$7.40 \cdot 10^8$	$1.40 \cdot 10^8$	$2.50 \cdot 10^8$	$4.60 \cdot 10^8$
K	$6.85 \cdot 10^7$	$1.34 \cdot 10^8$	$2.50 \cdot 10^7$	$4.50 \cdot 10^7$	$7.50 \cdot 10^7$
M	4521.84	125.11	4544.00	4544.00	4544.00
N	6681.12	276.77	6761.20	6761.20	6761.20
n	23.33	0.55	23.09	23.09	23.25
σ	$5.09 \cdot 10^9$	$8.75 \cdot 10^7$	$5.07 \cdot 10^9$	$5.07 \cdot 10^9$	$5.07 \cdot 10^9$
T	16.14	7.59	12.00	15.00	19.20
Observations	365				

Period: Post	Mean	Std. Dev.	p(25)	p(50)	p(75)
p	0.63	0.02	0.62	0.62	0.62
b_0	18.98	1.67	18.43	18.43	18.43
b_1	-0.01	0.03	-0.01	-0.01	-0.01
b_2	4.69	0.15	4.70	4.70	4.70
X	$4.94 \cdot 10^9$	$1.06 \cdot 10^{10}$	$1.00 \cdot 10^9$	$2.00 \cdot 10^9$	$4.20 \cdot 10^9$
w_{early}	0.40	0.10	0.38	0.38	0.39
w_{emp}	0.08	0.02	0.07	0.09	0.09
w_{VC}	0.12	0.05	0.11	0.12	0.14
Q	$2.71 \cdot 10^8$	$4.89 \cdot 10^8$	$7.50 \cdot 10^7$	$1.20 \cdot 10^8$	$2.00 \cdot 10^8$
K	$1.49 \cdot 10^8$	$2.81 \cdot 10^8$	$4.50 \cdot 10^7$	$7.50 \cdot 10^7$	$1.43 \cdot 10^8$
M	4702.37	76.36	4734.00	4734.00	4734.00
N	6997.54	146.01	7053.00	7053.00	7053.00
n	23.06	0.22	23.00	23.00	23.00
σ	$8.75 \cdot 10^9$	0.00	$8.75 \cdot 10^9$	$8.75 \cdot 10^9$	$8.75 \cdot 10^9$
T	18.30	9.02	12.00	12.00	24.00
Observations	326				

Return to Section 6.2.2

Table 10: Estimates of S_{VC} and S_{emp} in a Sample of Selected Startups

This table provides the estimates of a (scaling factor), S_{VC} (investor stringency), and S_{emp} (share acceptance threshold) obtained through a constrained maximum likelihood estimation where $\mathbf{P}_{\text{inv},i}$ is fixed for the pre and post-listing periods to match the average observed frequency of startups in the U.S. receiving subsequent financing, eventually doing an IPO, or being acquired, conditional on having fewer (pre) or more (post) than six financing rounds. This amount corresponds roughly to the threshold between the average number of rounds startups had pre-listing (5.6) and post-listing (6.8). Standard errors are given in parentheses.

Parameter	Pre	Post	Pre	Post
a	0.348	-	0.0092	-
	(0.044)	-	(0.00231)	
S_{VC}	3.57×10^{-10}	4.7×10^{-5}	0.485	8.37×10^{-11}
	(5.17×10^{-28})	(1.7×10^{-6})	(0.056)	(5.98×10^{-17})
$S^{U}_{i,emp}$	8.23×10^{-5}	-	1.5×10^{-4}	-
	(6.5×10^{-6})	-	(3.97×10^{-3})	-
$S^{L}_{i,emp}$	-	3.97×10^{-5}	-	3.84×10^{-5}
	-	(3.36×10^{-6})	-	(6.5×10^{-6})
Sample	Full	Full	IPO Only	IPO Only
N	365	326	72	72

Return to Section 6.2.2

Table 11: Inverse Listing Propensity Determinants

This table provides the results of OLS regressions studying the inverse listing propensity (V^{-1}) determinants. I proxy it by the number of years it took for a startup to list and use proxies for each of the terms in the listing constraint derived in Appendix C.8. Stringent is an indicator variable equal to one if the time between rounds when listed is in the top quartile (T $\geq$ 24 months). t-statistics are in parentheses.

	(1) Years To List	(2) Years To List	(3) Years To List
Pre-Listing Rounds	1.329***	0.620	1.143***
	(6.66)	(1.59)	(6.97)
Stringent=0 $\times$ Post-Listing Rounds	-0.222	-1.697**	-0.413*
	(-0.82)	(-2.42)	(-1.72)
Stringent=1 $\times$ Post-Listing Rounds	0.0172	1.052	-0.396
	(0.03)	(0.65)	(-0.73)
Founder w	-17.47**	-32.62	-18.78**
	(-1.98)	(-1.68)	(-2.46)
Stringent=0 $\times$ Founder w Post-Listing	14.67	6.404	12.32*
	(1.47)	(0.60)	(1.72)
Stringent=1 $\times$ Founder w Post-Listing	11.32	8.428	9.380
	(1.26)	(0.75)	(1.44)
Did IPO?	No	Yes	Full Sample
N	320	36	356
R^2	0.198	0.312	0.179

t statistics in parentheses

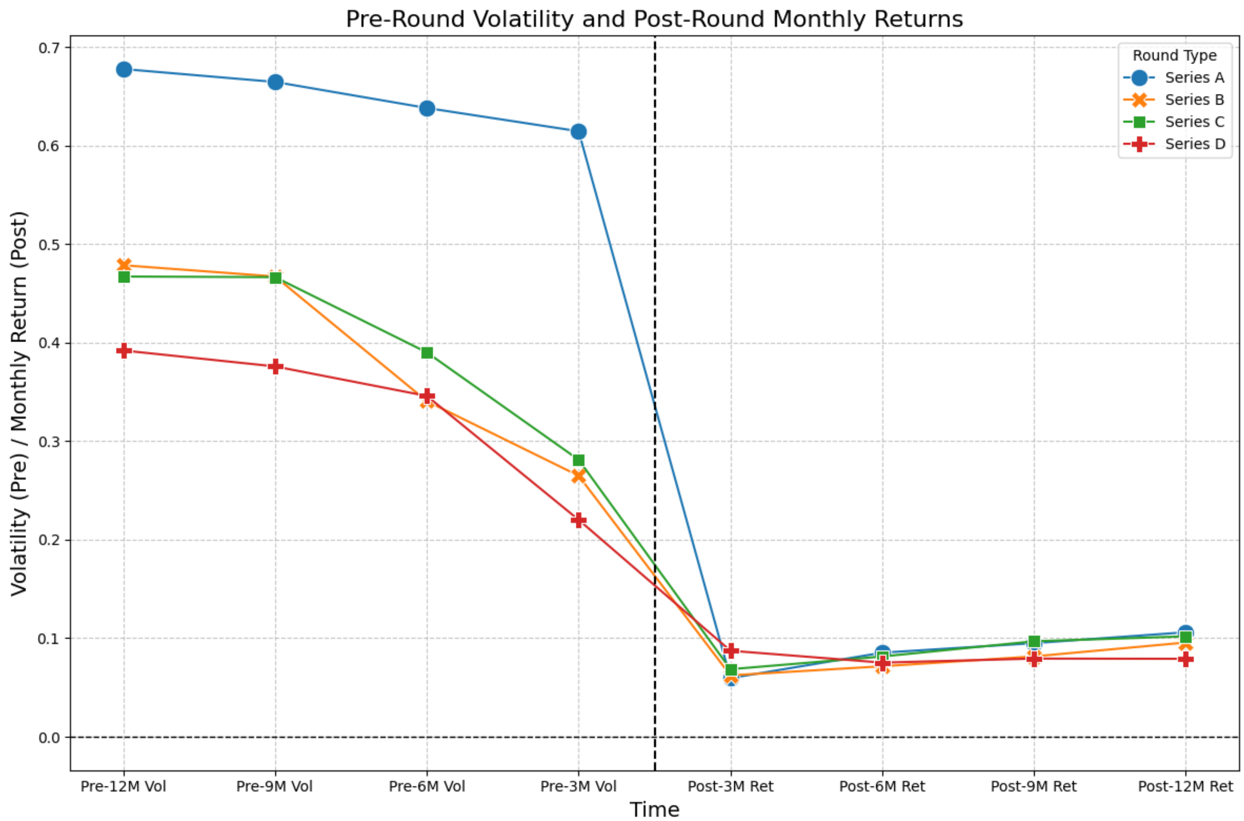
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Return to Section 6.2.3

Online Appendix

Figure 8: Average Stock Price Volatility and Returns Before and After Financing Rounds

This figure shows the average monthly stock price returns' volatility before a financing round occurs ("Pre") and the cumulative stock price return, adjusted to a monthly basis, after the financing round ("Post") for different types of rounds.



Online Appendix

Table 12: Impact of Pre-Round Price Changes on Post-Round Stock Price Returns

This table provides the results of OLS regressions studying the stock price returns between the three months that follow a financing round to the six, nine, and twelve months that follow that round. The dependent variable corresponds to the total stock price return $R_{x\text{-}y \text{ mos.}}$ between x and y months after a financing round, with the reference point being the first day of the month when the financing round occurs. The main explanatory variable is the average stock price change in the three months preceding a round. t-statistics are in parentheses.

	(1)	(2)	(3)
	$R_{3\text{-}6 \text{ mos.}}$	$R_{3\text{-}9 \text{ mos.}}$	$R_{3\text{-}12 \text{ mos.}}$
Pre 3-Month Avg. Ret.	-1.765***	-1.919***	-2.226***
	(-8.39)	(-4.41)	(-4.22)
Log(PreMoneyValuation)	-0.00888	0.125	0.205*
	(-0.20)	(1.35)	(1.77)
Log(MoneyRaised)	0.0355	-0.0796	-0.206
	(0.71)	(-0.76)	(-1.61)
N	493	482	472
R^2	0.167	0.104	0.117

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Online Appendix

Table 13: Impact of Pre-Round Price Change Volatility on Post-Round Stock Price Returns

This table provides the results of OLS regressions studying the stock price returns between the three months that follow a financing round to the six, nine, and twelve months that follow that round. The dependent variable corresponds to the total stock price return $R_{x\text{-}y \text{ mos.}}$ between x and y months after a financing round, with the reference point being the first day of the month when the financing round occurs. The main explanatory variable is the stock price change volatility in the three months preceding a round. t-statistics are in parentheses.

	(1)	(2)	(3)
	$R_{3\text{-}6 \text{ mos.}}$	$R_{3\text{-}9 \text{ mos.}}$	$R_{3\text{-}12 \text{ mos.}}$
Pre 3-Month Vol.	-0.362**	-0.334	-0.197
	(-2.01)	(-0.94)	(-0.46)
Log(PreMoneyValuation)	-0.0138	0.118	0.205*
	(-0.29)	(1.25)	(1.74)
Log(MoneyRaised)	0.0282	-0.0854	-0.218*
	(0.53)	(-0.80)	(-1.66)
N	493	482	472
R^2	0.0509	0.0680	0.0827

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$