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Venture Capital Contracts *

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Abstract

We estimate the impact of venture capital (VC) contract terms on startup outcomes and the split of value between the entrepreneur and investor, accounting for endogenous selection via a novel dynamic search and matching model. The estimation uses a new, large data set of first financing rounds of startup companies. Consistent with efficient contracting theories, there is an optimal equity split between agents that maximizes the probability of success. However, VCs use their bargaining power to receive more investor-friendly terms compared to the contract that maximizes startup values. Better VCs still benefit the startup and the entrepreneur, due to their positive value creation. Counterfactual exercises show that eliminating certain contract terms benefits entrepreneurs and enables low-quality entrepreneurs to finance their startups more quickly, increasing the number of deals in the market. Lowering search frictions shifts the bargaining power to VCs and benefits them at the expense of entrepreneurs. The results show that selection of agents into deals is a first-order factor to take into account in studies of contracting.

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A large body of academic work examines the problem of financial contracting, frequently within the context of an entrepreneur negotiating a financing deal with an investor (e.g., Bolton and Dewatripont, 2004; Salanie, 2005). Entrepreneurial firms are key drivers of innovation and employment growth, and the efficient allocation of capital to early stage firms is crucial to their success (Solow, 1957).[1] Financial contracting plays an important role at this stage, as information asymmetries and agency problems are severe (Hall and Lerner, 2010), and the observed contracts between entrepreneurs and venture capitalists (VCs) are quite complex. The predominant explanation in the theoretical literature is that the complex contractual features improve incentives and information sharing (e.g., Cornelli and Yosha, 2003; Kaplan and Strömberg, 2003; Schmidt, 2003; Repullo and Suarez, 2004; Hellmann, 2006). This result is usually derived under the assumption that investors are homogeneous and competitive, and thus earn zero rents.

A contrasting view is that investors negotiate to include certain contract terms not to grow the size of the pie that is divided between the contracting parties, but to change the distribution of the pie in their favor. This is possible because VCs are not homogeneous, as evidenced by the persistence in VC returns (e.g., Kaplan and Schoar, 2005; Hochberg, Ljungqvist, and Vissing-Jorgensen, 2014; Korteweg and Sorensen, 2017) and the positive relation between VC fees and performance (Robinson and Sensoy, 2013). Similar to models of economic superstars (Rosen, 1981), a VC of lesser quality (a shorthand for its experience, network, and other value-added activities) is usually a poor substitute for a greater quality investor. Moreover, VCs are repeat players in the market for startup financing, with a broader view of the market and the distribution of possible outcomes, and a better understanding of the implications of complicated contract terms than entrepreneurs. As a result, they have substantial bargaining power, while lawyers and regulators do not have strong incentives to correct this imbalance. The resulting contracts are favorable to the VC, even if they reduce the startup's value. This comes at the expense of the entrepreneur, who experiences poor returns (e.g., Moskowitz and Vissing-Jørgensen, 2002; Hall and Woodward, 2010; Cestone, 2014). As of yet, there is little empirical evidence that quantifies in which direction, let alone how much, various contract terms impact outcomes and the distribution of value. This paper helps fill that gap.

A key empirical problem is that contracts are related to the underlying qualities of the entrepreneur and investor, which are unobserved. To address the resulting omitted variables problem we specify a dynamic search and matching model. In broad strokes, the model works as follows. Penniless entrepreneurs search for investors in their startups, and vice versa. When two potential

[1]Successful entrepreneurial firms represent a sizable component of the economy. In 2015, public VC-backed firms in the US accounted for 21% of equity market capitalization, 44% of research and development expense, and 11% of employment (Gornall and Strebulaev, 2015).

counterparties meet, the investor offers a contract. The entrepreneur has bargaining power due to the possibility of refusing the contract and resuming the search process in the hopes of meeting a higher quality investor. The model allows for the contract to affect outcomes (the size of the pie) and the split between investor and entrepreneur (the distribution of the pie), and allows for a world with perfectly competitive investors with no bargaining power as a special case. Compared to static matching models, our model is tractable and intuitive despite the addition of dynamics and contracts. Intuitively, the dynamic search feature of the model generates a random component to matches, which helps to identify the impact of contracts on outcomes and value splits, controlling for the qualities of the entrepreneur and the investor.

The second main problem is that startup contracts are private, and data is difficult to find. To take the model to the data, we collect a new data set that contains over 10,000 first round VC financings between 2002 and 2015. After applying reasonable data filters, we have between 1,695 and 2,581 contracts, depending on the outcome variable. This constitutes the largest set of first round contracts studied in the literature to date, and includes data on both cash flow and control rights. Nearly all contracts are some form of convertible preferred equity. We focus on the investor's equity share upon conversion to common stock, participation rights, pay-to-play, and investor seats on the startup's board. Participation is a cash flow right that gives the investor a preferred equity payout with an additional common equity claim. In contrast, in a convertible preferred security without participation, the investor must ultimately choose between receiving the preferred payout or converting to common equity (see Figure 1 for an illustration). Pay-to-play is a term that takes away certain cash flow and/or voting rights if an investor does not participate in a subsequent round of financing. Board seats are an important control right that gives the VC direct influence over corporate decisions.

We find that contracts materially affect startup values, with both value-increasing and decreasing components. Fixing the quality of investor and entrepreneur, the average startup's value increases with the investor's equity share up to an ownership stake (upon conversion) of 15%. Any further increase in the VC's share decreases firm value. An internal optimal equity share is consistent with, for example, theories of double moral hazard in which both the investor and the entrepreneur need to exert effort for the company to succeed. While 15% may appear to be a low stake in the case of common equity contracts, this corresponds to 28% of the average firm's value, due to preferred terms such as liquidation preferences, which shift more value towards the VC. In the data, however, the average deal gives the VC an equity share of 40%, which corresponds to nearly half of the firm's value due to the value of preferred terms and VC board seats. Higher quality investors can bargain for higher ownership stakes, since they add more value to the firm and it is costly for the entrepreneur to search for another investor. Despite the reduction in firm value that results from a suboptimal equity share (and other contract terms), the VC benefits from a higher expected payoff: the average deal value is only 83% of the value under the value-maximizing contract, but receiving nearly half of this value is more than 28% of the maximal value (these numbers include the effects of other contract terms discussed below).

Other contract terms besides equity share also impact firm value and its distribution among agents. Again fixing the agents' qualities, participation significantly lowers the chance that the venture will succeed, while transferring a larger fraction of its value to the VC. The effects of investor board representation go in the same direction for the average startup, but are only about a third as strong as participation, and for some deals can raise rather than lower the firm's success probability. Pay-to-play has the opposite effect, increasing value and moving the split in favor of the entrepreneur, and is slightly weaker in magnitude than VC board seats. Although we cannot make statements about the value impact of terms that are always present (for example, liquidation preferences and anti-dilution protection exhibit virtually no variation in the data), we can estimate their joint effect on the value split. Overall, they move the split in favor of the VC. Since these terms are always present and thus not likely to be contentious, their impact on the startup's value may be positive, such that both VCs' and entrepreneur's benefit.

The equilibrium contract terms negotiated between VC and entrepreneur depend on their respective qualities, and there are important interactions and trade-offs between cash flow and control rights. Entrepreneurs (VCs) match with a range of counterparties between an upper and lower quality threshold. While these ranges generally increase in the entrepreneur's (VC's) quality, endogenous contracting introduces exceptions to this rule, and positively assortative matching does not necessarily hold. An entrepreneur who matches with her lowest acceptable quality VC negotiates a contract with pay-to-play but no participation or VC board seats, and a low VC equity share. As the same entrepreneur matches with a VC of progressively higher quality, the VC's equity share rises. Additionally, the VC has progressively more bargaining power to first drop pay-to-play, then negotiate for board seats, and finally additionally negotiate for participation.

The model does not identify the mechanisms driving these results, but we offer the following observations. The increased VC cash flow rights of participation explains the increase in the fraction of firm value that goes to the VC. But the channel through which participation reduces total value is less clear. The traditional view is that participation induces the entrepreneur to exert more effort, but this may be offset by, for example, asset substitution incentives from the debt-like features of participation rights, or preferences for window-dressing that stem from such features (Cornelli and Yosha, 2003). VC board seats can move a higher fraction of value to VCs through increased control rights. At the same time, they may reduce overall value by reducing incentives for entrepreneurs to exert effort because they have less control over key decisions, and are possibly over-monitored (Burkart, Gromb, and Panunzi, 1997; Zhu, 2019), offsetting value creation effects from improved governance and monitoring. In a large survey by Gompers, Gornall, Kaplan, and Strebulaev (2019), 33% of VCs reported that the board of directors was an important factor contributing to failed investments, slightly higher than the proportion that rates the board as having contributed to success. This explanation is consistent with the observation that VC board seats are not included in every deal, and that they can be value-increasing in deals involving high-quality VCs. Pay-to-play shifts a higher fraction of value to the entrepreneur, because cash flow and/or control rights are returned to the entrepreneur if the VC chooses not to participate in a subsequent financing round, and may increase firm value due to increased incentives to exert effort on the part of the entrepreneur. The above results also speak to the tension in the literature between models that predict that cash flow and control rights should come together to assign control to investors with equity-like claims (Berglöf, 1994, Kalay and Zender, 1997, and Biais and Casamatta, 1999) and models that allocate contingent control to investors with debt-like claims in the presence of costly monitoring (Townsend, 1979, Diamond, 1984, Gale and Hellwig, 1985). In the entrepreneurial finance setting considered here, the evidence favors the latter set of models.

It is important to note that the above results do not imply that a VC investment destroys value in equilibrium. An entrepreneur is still better off with a higher quality VC (consistent with Sørensen, 2007). For example, for an entrepreneur at the 99% quality quantile, moving from the lowest to the highest VC it can match with raises the startup's value by 89% and the entrepreneur's value by 33% (with endogenously determined contracts), even though firm value is not maximized and a larger fraction of it goes to the VC due to a higher equity share, participation and board representation. Also note that even the highest quality VCs still leave almost half of firm value to the entrepreneur, despite their considerable bargaining power.

The estimated link between qualities and contracts also speaks to patterns of persistence and "style" (Bengtsson and Sensoy, 2015; Bengtsson and Ravid, 2009). In equilibrium, VCs offer better entrepreneurs more entrepreneur-friendly contracts that barely vary with entrepreneur quality. This result cannot be driven completely by style (i.e., a VC fixed effect) when VCs encounter entrepreneurs from a range of qualities, of whom at least some have sufficient bargaining power to negotiate entrepreneur-friendly terms. Our model suggests that persistence can at least be partly explained by a market equilibrium in which VCs have much of the bargaining power.

In counterfactual exercises, we explore the effects of eliminating the possibility of using various contractual features implemented by contract terms. If VC-friendly features are removed, counterparties sign contracts that benefit the firm and entrepreneurs, but not the VC. At the same time, many previously unmatched low-quality entrepreneurs sign contracts with low-quality VCs. Combining the two effects, the average startup value decreases but matching rates increase.

However, the magnitude of these effects is modest. In the aggregate, due to the change in values and rates, the value of all deals in the market rises by 1.7%. In a second set of counterfactuals we consider the effects of decreasing search frictions. If the expected time between encounters is halved (an order of magnitude lower), then the value of all deals in the market increases by 1.2% (decreases by 5.1%). If VCs are able to meet new entrepreneurs more frequently, they wield even more bargaining power and claim a higher fraction of the company, negatively affecting its value. The tension between lower average firm value and higher matching rates appears to only favor the market for a small decrease in frictions. We should note that these effects are all on the intensive margin, because we cannot say what happens on the extensive margin in terms of how many entrepreneurs and investors would enter or leave the market.

Finally, we conduct a series of robustness checks and extensions of the model. The results are robust to alternative success outcomes (e.g. follow-on financings or IPOs) and sub-sample splits by industry, location, time, syndication characteristics, and proxies for startup capital intensity. Changes in major theoretical assumptions, such as different discount rates, incorporation of entrepreneur overconfidence, or introduction of match-specific shocks to generate heterogeneity in contracts between pairs do not result in sizable changes to the conclusions. Finally, we informally show that the results are qualitatively similar if we allow for some form of directed search, or for simple one-dimensional asymmetric information about entrepreneur quality.

Our paper is related to a few different strands of literature. First, in the empirical literature on selection in venture capital, our paper is related to Sørensen (2007), who estimates the impact of matching versus observed entrepreneur and VC characteristics on IPO rates. He estimates a static matching model in which the split of firm value between the entrepreneur and VC is exogenously fixed across matches. Our paper differs in two important ways. First, we model the market for venture capital as a dynamic market, instead of a one-shot market, which is more realistic and more tractable. Second, we allow for the endogenous split of total firm value between the entrepreneur and VC via negotiated contracts. These modifications affect the estimated impact of selection on firm value, and allow us to characterize the impact of contract terms on outcomes. Our work is also related to Fox, Hsu, and Yang (2015), who study identification in a one-shot matching model with possibly endogenous terms of trade. Their work is mostly theoretical and their application to venture capital does not include contracts. Outside of VC, Matvos (2013) estimates the impact of contract terms in corporate loans, using a different methodology from ours. Hagedorn, Law, and Manovskii (2017) estimate a dynamic search-matching model of the labor market based on Shimer and Smith (2000). Their identification approach is based on the knowledge of the dollar value of contracts (in their setup, one-dimensional wages) between firms and employees, and the relative ranking of employee wages in different firms as they switch jobs.

Additionally, wages are assumed to not affect the value of the match. The same approach does not work in the VC market as the dollar impact of various contract terms on the value of the startup and its split is unknown and has to be estimated, and most entrepreneurs only match with a VC once. As a result, we estimate the model differently, using aggregate data moments.

Second, our paper is related to the empirical and theoretical literature on VC contracts and, broadly, to the extensive theoretical literature on general contracting. We cite relevant findings from the literature in our discussion of the estimated links between qualities, contracts, and startup values below. Beyond connecting the evidence to the existing theory, our results show that selection of agents into deals is a first-order factor to take into account in studies of contracting.

Third, a complementary paper by Gornall and Strebulaev (2019) also considers the impact of certain contract terms on valuations, using a contingent claims model in the spirit of Merton (1973). Unlike our paper, they can model terms that are always present and provide valuations in dollars, whereas we can only study indirect sensitivities of valuations to contract terms. However, they cannot determine the impact of control terms (such as board seats) on outcomes, or account for the importance of VC and entrepreneur quality and the resulting balance of bargaining powers as drivers of valuations. They also assume that VCs break even, and use a complex option valuation model that is sensitive, amongst others, to the assumption of a geometric Brownian motion process for the value of the underlying asset, ignoring jumps and time-variation in volatility (Peters, 2017).

Fourth, our matching model borrows from the theoretical search-matching literature with endogenous terms of trade. Shimer and Smith (2000) and Smith (2011) characterize the endogenous matching equilibrium in a continuous-time model with a single class of agents meeting each other. Adachi (2007) models endogenous matching with two classes of agents and endogenous terms of trade as a discrete-time game and shows that as the meet rates increase, the model outcomes converge to those in the static model of Hatfield and Milgrom (2005). Our model is continuous-time, but the Poisson process for meetings makes it similar to Adachi (2007). Inderst and Müller (2004) analyze a two-sided exogenous matching model with endogenous contracts in which the supply of venture capital affects the bargaining power of VCs and entrepreneurs. To address such effects, we consider differences across time periods in our robustness tests.[2] Axelson and Makarov (2018) develop a one-sided sequential search model with endogenous contracts where, unlike in our model, entrepreneurs and VCs do not know each other's types, and VCs can observe entrepreneurs' search histories through a credit registry. They show that credit registries lead to more adverse selection and higher VC rents. We leave a more fully developed extension of our two-sided search and matching model to adverse selection and information aggregation to future work.

[2]The importance of a dynamic link between contracts and deal volumes is also recognized by practitioners. See, for example, the Cooley Venture Financing Report, Q1 2017.

1 Identification

To illustrate the identification problem and the source of variation that the model exploits to identify the impact of contracts on outcomes in the data, consider the following example. Entrepreneurs search for an investor to finance their startup company, while at the same time investors are searching for entrepreneurs to fund. Due to search frictions, potential counterparties encounter each other randomly. Upon meeting, the parties attempt to negotiate a contract that is acceptable to both sides. For the purpose of this example, a contract, c, is the share of common equity in the startup received by the investor. If successful, the value of the startup is

$$\pi = i \cdot e \cdot \exp\{-2.5 \cdot c\}. \tag{1}$$

The negative impact of c on the value can be justified by entrepreneurs working less if they retain a smaller share of the startup (in the estimation, we do not restrict the impact to be negative). Suppose there are three types of investors, characterized by $i = 1, 2, 3$, that an entrepreneur is equally likely to encounter. Similarly, suppose there are three types of entrepreneurs, $e = 1, 2, 3$, that an investor is equally likely to encounter. For example, if an $i = 1$ investor and an $e = 2$ entrepreneur meet and agree on $c = 0.4$, then $\pi = 2 \cdot \exp\{-1\}$, the investor receives shares worth $0.8 \cdot \exp\{-1\}$ and the entrepreneur retains an equity stake worth $1.2 \cdot \exp\{-1\}$.

Let feasible matches be as shown in the table below (for simplicity, these outcomes are presented here as given, but they are determined endogenously in the equilibrium of the model for a certain set of parameters). Cells for which a match is feasible, contain the value of the startup, π, and contract that is acceptable to both the investor and entrepreneur, c^*. Empty cells indicate that no contract is acceptable to both agents, relative to waiting for another counterparty to come along. For example, an $i = 3$ investor will match an with $e = 2$ or $e = 3$ entrepreneur, whoever is encountered first, but not with an $e = 1$ type, because the value of waiting for one of the higher type entrepreneurs is higher than the value that could be received from making this match.

		Investor type (i)		
		1	2	3
	3		$\pi = 4.39$ $c^* = 0.13$	$\pi = 5.11$ $c^* = 0.23$
Entrepreneur type (e)	2		$\pi = 2.51$ $c^* = 0.19$	$\pi = 2.92$ $c^* = 0.29$
	1	$\pi = 0.58$ $c^* = 0.21$	$\pi = 0.74$ $c^* = 0.4$	

If we could collect a data set of i, e, c^*, and π for a number of realized matches from this game, then the regression

$$\log \pi = \beta_1 c^* + \beta_2 i + \beta_3 e + \varepsilon, \tag{2}$$

is identified and recovers the true coefficients, $\beta_1 = -2.5$, $\beta_2 = 1$, $\beta_3 = 1$, even though matches and contracts are formed endogenously. In practice, in the VC market the researcher has very limited information about most entrepreneurs and infrequent investors. Suppose e is not observed. The regression using remaining observables,

$$\log \pi = b_1 c^* + b_2 i + \varepsilon, \tag{3}$$

yields the biased estimates $\widehat{b}_1 = -4.16$ and $\widehat{b}_2 = 2.29$. This is an omitted variables problem, as e is in the residual, and is correlated with c^* and i. The bias in $\widehat{b}_1$ is negative because higher type entrepreneurs retain a larger share of their companies, so that e and c^* are negatively correlated. The positive bias in $\widehat{b}_2$ is due to the positive correlation between i and e, as better investors tend to match with better entrepreneurs. Suppose next that both i and e are not observed. A similar regression then yields an even more biased $\widehat{b}_1 = 2.04$, which can lead the researcher to incorrectly conclude that c^* improves the company's value.

To resolve the endogeneity problem, ideally we would have an instrument or natural experiment that generates variation in c that is uncorrelated with i and e, but these are very difficult to find. Another alternative would be to include fixed effects into the regression, which would identify the model in a less statistically efficient manner compared to including agents' types, as there are many investors and entrepreneurs of equal type for whom a separate fixed effect has to be estimated. However, almost all entrepreneurs and some investors only participate in a single startup in our data set, leaving only a small and selected subset of repeat players to identify the model.[3]

The final alternative is to exploit the search friction and endogenous match formation. In the example above, observing only c^* recovers the investor's and entrepreneur's exact types. For example, $c^* = 0.19$ is only agreed upon by investor $i = 2$ and entrepreneur $e = 2$. In practice, however, the number of the investor and entrepreneur types is large, so there will be situations when different combinations of agents sign the same contract. Moreover, the researcher typically does not have a reliable estimate of the startup's value, π, but instead observes only coarse measures of its success (e.g., whether the startup ultimately underwent an initial public offering). These complications mean that recovering the individual agents' types and the value for each match has to be done simultaneously from contracts and an outcome measure that is correlated

[3]Using multiple investment rounds for the same startup is also not helpful because the startup's decision makers and objectives are likely very different across rounds.

with value. This can be imprecise and is extremely computationally intensive. Instead of reverse-engineering individual i, e, and π for each match, we therefore take a more feasible approach and recover aggregate distributions of i, e, and π across all agents present in the market. We do so by matching model-implied moments of the aggregate joint distributions of match frequencies, contracts, and outcomes across matches with their counterparts in the data.[4] For example, if given a random sample of matches from the above game, the theoretical moments of our model best fit the empirical moments when parameters equal their true value (that is, $\beta_1 = -2.5$ and an equal-weighted multinomial distribution of both investor's and entrepreneur's types).

We use a dynamic search and matching model to capture endogenous match variation. As a point of contrast, the prior literature has relied on static matching without search (Sørensen, 2007), where all agents immediately see everyone else in the sample. As a result, each investor type matches with exactly one entrepreneur type (and vice versa). This does not leave enough exogenous variation to separately identify the impact of agent types on contracts, and the impact of types and contracts on values. The literature resolves this problem through the use of subsamples (e.g., by time period), assuming that matching agents only observe the other agents within their own subsample, but not across subsamples. To the extent that subsamples are exogenously different, a given investor type exogenously matches with a different entrepreneur type (and vice versa) across subsamples, resolving the identification problem. Since the model of dynamic search and matching generates randomness in encounters for any given agent's type, the necessary exogenous variation arises naturally, and we can analyze the entire market at once without arbitrarily splitting it. Another advantage of the dynamic search and matching model is that it is computationally more feasible. Static matching models are estimated by comparing realized matches with all unrealized counterfactual matches, choosing parameters that best approximate the set of theoretical matches to the set of observed matches in the sample. In the presence of multiple contract terms, the sheer number of counterfactual matches and contracts makes this approach infeasible. In contrast, the dynamic search and matching model only requires a comparison of observed matches with agents' continuation values, since agents only encounter a single counterparty at a time and they know the distribution of counterparty types. This is relatively fast to compute. We elaborate on the estimation algorithm after we describe our model in more detail.

[4] For reasons similar to ours, distributions rather than point estimates of agents' qualities have previously been estimated in the literatures on mutual funds (e.g., Barras, Scaillet, and Wermers, 2010) and hedge funds (e.g., Buraschi, Kosowski, and Sritrakul, 2014). Similarly, most papers in the empirical auctions literature, starting with Paarsch (1992) and summarized in Paarsch and Hong (2006), focus on distributions of bidders' qualities (or valuations) to analyze the efficiency of the auction format.

2 Model

This section describes the full model, which formalizes the intuition from the previous section. Time is continuous and indexed by $t \geq 0$. There are two populations of agents in the market, one containing a continuum of investors (VCs) and the other a continuum of entrepreneurs. Each investor is characterized by a type $i \in [\underline{i}, \bar{i}]$, distributed according to a continuous cumulative density function $F_i(i)$ with a continuous and positive probability density. Similarly, each entrepreneur is characterized by a type $e \in [\underline{e}, \bar{e}]$, with cumulative density $F_e(e)$ and a continuous and positive probability density. Agents cannot switch populations, and their types do not change over time.

Agents arrive to the market unmatched and search for a suitable partner to form a startup. Search is exogenous: each investor randomly encounters an entrepreneur from the population of entrepreneurs according to a Poisson process with positive intensity λ_i. Similarly, each entrepreneur randomly encounters an investor from the population of investors according to a Poisson process with positive intensity λ_e. The likelihood of meeting a counterparty of a certain type is independent of a searching agent's type, and across agents. Search is costly because agents discount the value of potential future encounters at a constant rate r. Upon an encounter, identities of counterparties are instantly revealed to each other, and they may enter contract negotiations.[5]

During negotiations, an investor offers a take-it-or-leave-it contract $c \in C$ to the entrepreneur, where the contract space C is the set of all possible combinations of contract terms.[6] For example, if the counterparties can only negotiate over the fraction of equity that the investor receives, then the contract space is a one-dimensional set of fractions of equity: $C \equiv [0, 1]$. If the counterparties can additionally negotiate over, say, the participation term, then $C \equiv [0, 1] \times \{0, 1\}$. The second dimension of the contract space captures the absence or presence of the participation term.

If the entrepreneur rejects the offer, the agents separate, receive instantaneous payoffs of zero, and resume their search. In a dynamic model, the ability to walk away from an unfavorable offer thus endogenously gives the entrepreneur a type-specific bargaining power, which the investor internalizes in its take-it-or-leave-it offer. If the entrepreneur accepts the offer, the startup has an

[5] Chemmanur, Krishnan, and Nandy (2011) and Kerr, Lerner, and Schoar (2011) provide evidence that counterparties acquire much information about each other before financing.

[6] The survey evidence from Gompers, Gornall, Kaplan, and Strebulaev (2019) provides empirical support for this assumption, which contrasts with the perfect competition assumption in most previous theoretical work. The authors find that 80% of the contracts (i.e., term sheets) offered by early-stage VCs lead to a closed deal. Some of the remaining 20% likely fall through for reasons unrelated to competing term sheet options for the entrepreneur, such as intellectual property ownership issues or other legal complications. This finding is consistent with the average entrepreneur having few contemporaneous contract alternatives. In addition, we estimated a modified version of the model where the entrepreneur receives more of the surplus over her outside option. The qualitative results do not change.

expected value of

$$\pi(i,e,c) = g(i,e) \cdot h(c). \tag{4}$$

Importantly, π is the expected present value of all future uncertain cash flows generated by the startup, including the exit value, and is obtained over the course of several years. Hence in contrast to models in which the firm value is certain, the agents cannot simply agree on a firm value-maximizing fixed cash transfer from the entrepreneur to the investor, but instead have to sign a contingent contract. The expected value π is affected by the types of counterparties, and by the contract they sign through continuous and bounded functions $g(i,e)$ and $h(c)$.[7] Functional forms that we use for estimation are specified in Section 4 below.

The investor receives a fraction $\alpha(c) \in [0,1]$ of the value, and the entrepreneur retains the remainder,

$$\pi_i(i,e,c) = \alpha(c) \cdot \pi(i,e,c), \tag{5}$$

$$\pi_e(i,e,c) = (1-\alpha(c)) \cdot \pi(i,e,c). \tag{6}$$

If the counterparties can only negotiate over the fraction of common equity that the investor receives, then $\alpha(c) = c$. If they can negotiate over additional contract terms, then $\alpha(c)$ may be different from the investor's equity fraction.

The equilibrium contract $c^* \equiv c^*(i,e)$ offered by investor i to entrepreneur e solves

$$c^*(i,e) = \underset{c \in C: \pi_e(i,e,c) \geq V_e(e)}{\arg\max} \pi_i(i,e,c). \tag{7}$$

Intuitively, the investor offers the contract that maximizes its payoff, subject to the participation constraint of the entrepreneur, who receives the continuation value $V_e(e)$ if she rejects the offer. If $\pi_i(i,e,c^*) \geq V_i(i)$, the investor offers c^*, and the startup is formed. Otherwise, the investor does not offer a contract, walks away, and receives the expected present value $V_i(i)$. Both $V_e(e)$ and $V_i(i)$ are defined below. The counterparties that successfully form a startup exit the market and are replaced by new unmatched agents in their populations.[8]

All unmatched agents maximize their expected present values, or continuation values, $V_i(i)$ and $V_e(e)$. Let $\mu_i(i)$ be the set of types e of entrepreneurs who are willing to accept offer $c^*(i,e)$

[7] Ultimately, i, e, and c interact to impact π in subtler ways because the equilibrium contract depends on matched agents' types.

[8] This assumption ensures that at any time, populations of unmatched agents are characterized by the same density functions. Stationarity of populations implies that, in equilibrium, measures of unmatched agents, m_i and m_e, have to satisfy $\lambda_i m_i = \lambda_e m_e$. These measures do not play any further role in the model and estimation, and only become relevant again when we examine the present value of all potential deals in Sections 4 and 5.

from investor i. Similarly, let $\mu_e(e)$ be the set of types i of investors who are willing to offer $c^*(i,e)$ to entrepreneur e. Because populations of agents remain stationary over time, the model is stationary, so $V_i(i)$ and $V_e(e)$ do not depend on time t. Consider $V_i(i)$. At any time, three mutually exclusive events can happen over the next small interval of time dt. First, with probability $\lambda_i dt \int_{e\in\mu_i(i)} dF_e(e)$, investor i can encounter an entrepreneur with type $e \in \mu_i(i)$, who is willing to accept the investor's offer of $c^*(i,e)$. If $\pi_i(i,e,c^*) \geq V_i(i)$, the agents form a startup and exit the search market, and the investor receives the instantaneous payoff $\pi_i(i,e,c^*)$. Otherwise the investor resumes its search and retains $V_i(i)$. Second, with probability $\lambda_i dt \left(1 - \int_{e\in\mu_i(i)} dF_e(e)\right)$, investor i can encounter an entrepreneur with type $e \notin \mu_i(i)$, who is unwilling to accept the investor's offer. Third, with probability $1 - \lambda_i dt$, the investor may not encounter an entrepreneur at all. In the last two cases, the investor resumes its search and retains $V_i(i)$. Similarly, there are three mutually exclusive events that can happen to any entrepreneur e over the next small interval of time dt, which shape $V_e(e)$. The following proposition (with proof in Appendix A) presents compact expressions for the agents' expected present values:

Proposition 1. *Expected present values admit a discrete-time representation*

$$V_i(i) = \frac{\lambda_i}{r+\lambda_i} \int_e \max\left\{\mathbf{1}_{e\in\mu_i(i)} \pi_i(i,e,c^*), V_i(i)\right\} dF(e), \tag{8}$$

$$V_e(e) = \frac{\lambda_e}{r+\lambda_e} \int_i \max\left\{\mathbf{1}_{i\in\mu_e(e)} \pi_e(i,e,c^*), V_e(e)\right\} dF(i). \tag{9}$$

Proposition 1 shows that our model is equivalent to a discrete-time model in which periods $t = 1, 2, ...$ capture the number of potential encounters by a given agent. These periods are of random length with expected length equal to $\frac{1}{\lambda_j}$, $j \in \{i, e\}$, so that next period's payoffs are discounted at $\frac{\lambda_j}{r+\lambda_j}$. The discrete-time representation allows us to use the results of Adachi (2003, 2007) to numerically solve the contraction mapping (8) and (9).

The model described above is quite general. First, it allows but does not restrict both VCs and entrepreneurs to have bargaining power, due to their option to continue the search process. The model includes, as a special case, perfectly competitive investors as typically assumed in the theoretical literature. Investors become more competitive when there are more of them (λ_e is higher) and when they are more substitutable ($F_i(i)$ has lower dispersion), reaching perfect competition in the limit. The model estimates thus inform us about the split of bargaining power. Second, contract terms impact the expected value of a startup and its split between counterparties in a flexible reduced-form way, via the functions $h(c^*)$ and $\alpha(c^*)$. In Section 4, we flexibly parameterize and estimate these functions. Importantly, we do not explicitly model a multitude of mechanisms through which contracts can impact values. By doing so, we do not commit to a specific microeconomic model that potentially omits or mis-specifies the important mechanisms.[9] Still, our estimates are informative about which mechanisms are likely important in practice. Additionally, by considering the impact of contracts on expected values and evaluating them from agents' revealed preferences at the time of a startup formation (since they make rational negotiation decisions to maximize their own payoffs), we avoid the problem of having to derive values of contracts with a multitude of complicated derivative features on an underlying asset.

3 Data

We construct the initial sample from several sources, starting with financing rounds of U.S.-headquartered startup companies between 2002 and 2015, collected from the Dow Jones VentureSource database. We augment this sample with data from VentureEconomics (a well-known venture capital data source), Pitchbook (a relative newcomer in venture capital data, owned by Morningstar), and Correlation Ventures (a quantitative venture capital fund). These additional data significantly supplement and improve the quality and coverage of financing round and outcome information, such as equity stakes, acquisition prices, and failure dates.

A key advantage of Pitchbook over the other data sets is that it contains contract terms beyond the equity share sold to investors, with reasonable coverage going back as far as 2002. We further supplement this sample with contract terms information collected by VC Experts. Both Pitchbook and VC Experts collect articles of incorporation filings from Delaware and California, and encode key contract terms from the financing rounds described in those documents.[10] We include data from restatements of the articles of incorporation filed after later financing rounds, as supplemental prior-round contract terms can sometimes be identified from such re-filings. Appendix B shows the major elements of an example certificate of incorporation.

Our empirical model considers the first-time interaction between an entrepreneur and a profit-maximizing investor, as the existence of prior investment rounds or alternative objective functions

[9] For example, the mechanisms in Schmidt (2003) and Hellmann (2006) can be used to micro-found our setting, but there may be others (see, e.g., Da Rin, Hellmann, and Puri (2013) for a survey of the theoretical literature on VC contracting and Section 4.2 for a detailed discussion). In a model of covenant contracting for a firm borrowing from a financial intermediary, Matvos (2013) shows how to micro-found a reduced-form impact of covenants on expected outcomes. For reasons similar to ours, he does not explore the additional detail provided by the microeconomic model in his estimation.

[10] California and Delaware are the preferred choices of states of incorporation. Of all startups in VentureSource, at least 86% are incorporated in one of these two states: 65% are headquartered in California (and 90% of those are incorporated in Delaware during our sample period), and 61% of non-California firms are incorporated in Delaware. These numbers are lower bounds due to noise in matching names to articles of incorporation. The sample bias towards companies founded in those two states is therefore limited.

would significantly complicate the contracting game. To best approximate the model setup in the data, we restrict the sample to a startup's seed-round or Series A financings in which the lead investor is a venture capital firm. Financings greater than $100 million are also excluded as they are more likely to involve non-VC-backed startups. Other early-stage investors, such as friends and family, angels, or incubators, may have objectives other than profit-maximization. Although startups often raise funds from other investors prior to accepting VC money, such funding is usually small relative to the size of the VC round, and is typically in the form of convertible notes, loans or grants whose terms do not materially affect the VC round contracts. The lead investor is the one who negotiates the contract with the entrepreneur, and is identified by a flag in VentureSource, or if missing, by the largest investor in the round. In the 29% of cases where neither is available, we assume the lead investor is the VC with the most experience measured by the years since first investment at the time of financing. We limit the sample to rounds that involve the sale of common or preferred equity, the predominant form of VC securities. This filter drops the 11% of first financing rounds that involve debt financings such as loans and convertible notes that have no immediate impact on equity stakes, or small financings through accelerators or government grants. Our final filter requires that the outcome variable and the main contract terms of interest (equity share, participation, VC board seats, and pay-to-play) are known for each deal. Section 4.2 explains why we restrict ourselves to these specific contract terms. Our main outcome variable is based on initial public offerings and high-value acquisitions, and is defined below. To leave enough time for IPOs and acquisitions to realize, we only consider financing rounds prior to 2011, while we collect information on exit events through March of 2018.

3.1 Descriptive Statistics

The final sample consists of 1,695 first financing rounds between 2002 and 2010. Variable definitions are in Table I, and Table II reports summary statistics. Panel A of Table II reveals that at the time of financing, the average (median) startup is 1.6 (1.1) years old, measured from the date of incorporation. Most startups are in the information technology industry (46% of firms), followed by healthcare (26%). The average (median) time between first financing rounds for a given lead VC is 0.7 (0.3) years. This variable helps to identify the frequency with which investors and entrepreneurs meet.

In the average (median) round, 1.8 (2.0) financiers invest $7.3 million ($5.2 million) in the firm at a post-money valuation of $21.2 million ($13.0 million), in 2012 dollars. Post-money is the valuation proxy of the startup after the capital infusion, calculated from the investors' equity share.[11] The post-money valuation is usually interpreted as the market value of the firm at the time of financing (π in the model), but it is calculated under the assumption that the entrepreneur (and any other investors) own the same security as the investor in the current round, and that the investor breaks even (i.e., no VC bargaining power). However, in virtually all cases in our data (96%), the investor receives preferred equity that is convertible into common stock, whereas the entrepreneur retains common equity. Since we are interested in the impact of contract terms on valuation, the post-money valuation would thus be a poor metric to use.[12] Still, post-money valuations are useful to compute the equity share of the company sold to investors (from post-money valuation and the total capital invested). VentureSource, a traditional data source used in earlier studies, only contains post-money valuations for 553 deals in our sample period, mostly gathered from IPO filings of successful firms. Our additional data collection efforts provide another 1,142 observations in the 2002 to 2010 period (before imposing data filters), resulting in a more complete and balanced sample. Panel B of Table II shows that the average (median, unreported) share sold to the first-round investors is 40% (38.5%), with a standard deviation of 17.5%.

Contract terms beyond the equity share (other than board representation) are not reported in the traditional VC data sets, and the empirical literature on contracts is small. Kaplan and Strömberg (2003) analyze 213 contracts from a proprietary data source. Bengtsson and Sensoy (2011) and Bengtsson and Bernhardt (2014) use the VC Experts data and have 425 and approximately 1,110 first-round contracts, respectively, across all stages of financing rounds. Gornall and Strebulaev (2019) use a sample of contracts for 135 unicorns from VC Experts. We are the first to add the Pitchbook data, which contributes more deals and spans a longer time series than VC Experts (across all rounds the data contain over 21,000 contracts).

We consider two classes of contract terms. The first class involves the cash flow rights of investors. When the startup has a liquidity event (that is, when it is acquired, goes public, or is liquidated in bankruptcy), the investor can either collect the preferred security payoff or convert it into common stock, whichever is more lucrative. In the case of non-conversion, the investor receives a payoff equal to the liquidation preference (or less if funds are insufficient) before common equity receives anything, similar to a debt security payoff. The liquidation preference is typically equal to the invested amount (referred to as "1X") in first round financings, but in 4% of first rounds

[11] The investors' equity share is the share of the company owned by investors upon conversion, assuming no future dilution. For example, suppose the VC invests $2 million by purchasing 1 million convertible preferred shares at $2 per share, with a 1:1 conversion ratio to common stock. The entrepreneur owns 4 million common shares. VCs calculate the post-money valuation to be $10 million (5 million shares at $2 each). The ratio of invested amount to post-money valuation is 20%, which is identical to the ratio of investor shares to total shares upon conversion.

[12] Metrick and Yasuda (2010) show that these additional contract terms lead to a poor connection between firm value and post-money valuation. Gornall and Strebulaev (2019) make a similar point using a sample of over 100 contracts and a contingent claims model framework.

the investor receives a higher multiple of invested capital. This provision serves as additional downside protection for the investor, as conversion to common equity is only attractive when the exit valuation is high. Participation, a term used in 51% of contracts, allows the investor to take the liquidation preference payout, and then convert its shares to common equity and receive its share of the remaining value. This raises the investor's payoff in most outcome scenarios. Figure 1 presents a graphical representation of the investor's payoff at the time of a liquidity event, for both nonparticipating and participating convertible preferred stock.

Other contractual features that involve cash flow rights include cumulative dividends, which are set at a fixed rate (often 8% per year) and cumulate from investment to exit, but are payable only at liquidation. One-fifth of contracts feature this term. Absent the cumulative dividend term, dividends are only paid if the board declares them, which virtually never happens. Full ratchet anti-dilution rights are an investor downside protection term that reduces the conversion price to the price of any future financing round that is lower than the current round. They are only used in 2% of contracts. Approximately 12% of financings have entrepreneur-friendly pay-to-play requirements, which punish investors that do not reinvest in future financings. Finally, 39% of financings have redemption rights, an implicit put option that gives the investor the option to demand their capital back from the startup after 3 to 5 years. If a startup is unable to meet this demand, then the preferred shareholder is given additional control or cash flow rights.

The second class of contract terms involves investor control rights over the startup. The one key control term that we observe is lead investor board seats (sourced from both VentureSource and Pitchbook). At the time of their first investment, 89% of lead investors receive a board seat.

Panel C of Table II summarizes exit outcomes, tracked until March 2018. To treat all firms symmetrically, we set outcomes to zero (i.e., still private) if the exit occurs more than seven years after their first financing. The table shows that 4% of startups went public via an initial public offering (IPO). Acquisitions are more common at 39%. One issue with using acquisitions as a measure of success is that many are hidden failures (e.g., Puri and Zarutskie, 2012). To separate these out, we define our main outcome variable, "IPO or Acq. $> 2X$ capital", as an indicator that equals one if the startup ultimately had an IPO or was acquired at a reported exit valuation of at least two times total capital raised. By this metric, 13% of firms have a successful exit. By the end of March 2018, 43% of startups are still private. The "Out of business" outcome characterizes whether a startup shut down or went into bankruptcy. It appears to be low at 13%, however, this excludes the hidden failures in acquisitions, and many firms that are still private are in fact failed firms. An alternative measure of success that we use in the robustness section is the incidence of follow-on financing rounds. Startups on a good trajectory towards ultimate success typically need follow-on financing within a year to 18 months of their first financing rounds. Using a two-year cutoff, 73% of sample firms had a follow-on financing round. This variable also allows us to extend the sample to include all first financing rounds up to and including 2015, resulting in 2,581 deals.

3.2 Sample Selection

Since contract terms are not always observed, we only exploit a subset of all financings. To assess any sample selection concerns, we compare our sample to the sample of all first-round deals over the same period that does not condition on observing any contract terms. Summary statistics for this broader sample are shown in the columns labeled "All deals 2002–2010" of Table II. Firms in the estimation sample raise capital slightly faster (0.69 vs. 0.85 years), raise more capital ($7.3 million vs. $6.3 million) and have higher post-money valuations ($21.2 million vs. $18.9 million). These differences are expected if the data providers focus their energy on more high-profile startups or investors. Reassuringly, the differences are economically small.

Panel B reveals that our requirement that *all* contract terms are available does not result in major differences in contract usage. With the exception of board seats, the fraction of deals with each contract term is similar between the two samples. Finally, Panel C shows that the sample of firms with full contract coverage are more successful in terms of IPOs (4% vs. 2%) and fewer failures (13% vs. 17%). However, our main variable "IPO or Acq. > 2X capital" is statistically indistinguishable across the samples.

We further address selection in the robustness section by relaxing the filters on contract data availability, resulting in a larger sample of 2,439 deals. Given that our data represent the largest set of both valuation and contracts data, any remaining selection issues are likely to be smaller compared to prior studies that use investment-level returns or contracts.

4 Results

4.1 Regression Analysis

Table III presents regression results that explore the correlations between contract terms and startup outcomes. The dependent variable in columns 1 to 4 is the "IPO or Acq. > 2X capital" outcome. The explanatory variables include various combinations of the four major contract terms, including the squared value of the investor's equity share (we explain the choice of these specific terms in the next section). All regressions include fixed effects for financing year, startup founding year, industry and startup headquarters state.

The results reveal a U-shaped relationship between VC equity share and outcomes. This result is counterintuitive as it suggests that full ownership by either a VC or entrepreneur maximizes the probability of success, in contrast to a hump-shaped relation with an internal optimal equity share predicted by theory (for example, double moral hazard problems that requires both agents to expend effort). We discuss theory in more detail below. Pay-to-play and VC board seats weakly correlate with higher valuations and success probabilities, while participation strongly correlates with lower outcomes. The last two columns of Table III consider the IPO indicator that is standard in the literature, and the (log) post-money valuation as dependent variables. The correlations are similar, with only changes in statistical significance.

4.2 Search Model

The simple regressions of the previous section do not control for the selection issues and omitted variables described in the identification section. We address these problems using the search model. To operationalize the model, we make the following implementation choices.

4.2.1 Empirical Implementation

We assume that the quality distributions, $F_i(i)$ and $F_e(e)$, are Beta distributions on $[0, 10]$ with parameters (a_i, b_i) and (a_e, b_e). The Beta family is very flexible and can generate hump-shaped, U-shaped, skewed, and even uniform distributions. We discretize i and e on a 50 point grid. This grid is fine enough, and the support is wide enough, to find precise solutions to the contraction mapping (8) and (9). More details on these solutions are described in Appendix C.

We assume that the impact of qualities i and e on firm value is captured by a flexible constant-elasticity-of-substitution (CES) function,

$$g(i, e) = (0.5i^\rho + 0.5e^\rho)^{\frac{2}{\rho}}\,. \tag{10}$$

A few special cases are noteworthy. When $\rho \to 0$, the impact of qualities is multiplicative: $g(i, e) = i \cdot e$. When $\rho = 1$, qualities are perfect substitutes, and when $\rho \to -\infty$, they are perfect complements. Note that the qualities are normalized numbers, and they are not comparable across agents (e.g., an $i = 2$ investor is not necessarily the same quality as an $e = 2$ entrepreneur).[13]

Next, we choose a flexible functional form for the impact of contract terms on firm value,

$$h(c^*) = \exp\left\{\beta_1 c_1^* + \beta_2 c_1^{*2} + \beta'_{3:D+1} c_1^*(1 - c_1^*) c_{2:D}^*\right\}, \tag{11}$$

where $D = \dim\{C\}$ is the dimensionality of the contract space. The exponential function prevents

[13] Note also that the more general asymmetric specification $g(i, e) = (si^\rho + (1 - s)e^\rho)^{\frac{2}{\rho}}$, in which one of the parties has a stronger impact on the value (e.g., VC, if $s > \frac{1}{2}$), is subsumed into our model: a stronger (weaker) impact is isomorphic to a left (right) skew of the quality distribution.

negative valuations. Contract terms are generic in principle, but we pay special attention to the fraction of equity retained by the investor, c_1^*. In the case of convertible preferred equity, c_1^* is the share after conversion to common stock. The linear and quadratic terms, $\beta_1 c_1^*$ and $\beta_2 c_1^{*2}$, allow for an internal optimal equity share, as predicted by theory, but it is not assumed.

The other contract terms, collected in the vector $c_{2:D}^*$, are indicators that equal one when the term is present and zero otherwise. We include participation, pay-to-play, and VC board seats. Restricting the set of terms makes estimation computationally feasible. Moreover, liquidation multiples and full ratchet anti-dilution show virtually no variation in the data (see Table II), so we cannot say much about their quantitative impact on value. Redemption rights are not likely to be important, despite their frequent occurrence. While this term might appear relevant if there is value in the startup but it is not successful enough to exit via an IPO or acquisition, the entrepreneur usually does not have the liquidity to buy out the VC. Finally, cumulative dividends are only quantitatively important in a mediocre outcome. We find that they do not materially impact the firm value and its split in a computationally expensive extension of our main model.

The terms in $c_{2:D}^*$ are multiplied by $c_1^*(1-c_1^*)$, because their impact vanishes when investor ownership is very large or very small. For example, in the extreme case of 0% or 100% investor equity ownership, there is no incremental impact of the cash flow terms in $c_{2:D}^*$ on agents' payoffs and hence on their incentive to affect value. Investor board seats are also irrelevant in case of 100% ownership, and their impact is likely greatly diminished when the investor owns no equity.[14]

The distribution of value between investor and entrepreneur is also specified in a flexible way,

$$1-\alpha(c^*) = (1-c_1^*)\exp\left\{\gamma_1(1-c_1^*) + \gamma_{2:D}' c_1^*(1-c_1^*)c_{2:D}^*\right\}. \tag{12}$$

In the simple case of common equity contracts, the value is split according to the agents' equity shares (that is, $\alpha(c^*) = c_1^*$). The exponential term only appears when there are additional contract terms beyond equity share (when $D > 1$). Similar to the firm value function, $c_{2:D}^*$ is multiplied by $c_1^*(1-c_1^*)$, because the impact of these terms on the agents' payoffs vanishes when the investor owns a very large or very small fraction of the company. The value split is bounded between zero and one at estimated parameters.[15] The intercept, γ_1, captures the effect of any terms for which we do not have data, or that are always present. Of these terms, liquidation preference is probably

[14] Our results remain robust if we use a more flexible multiplication term $c_1^{*\zeta_1}(1-c_1^*)^{\zeta_2}$ with $\zeta_1, \zeta_2 > 0$, or if we assume that the impact of board seats does not vanish when $c_1^* = 0$ (i.e., $\zeta_1 = 0$). The same applies to the value split equation discussed in the next paragraph.

[15] To be precise, in the model solution we define any term that is perceived as entrepreneur-friendly in an inverse manner, so that all γ coefficients in equation (12) are less than or equal to zero. The functional form of equation (12) then ensures that $\alpha(c^*) \in [c_1^*, 1]$. But we do not enforce this condition in the estimation and revert signs of entrepreneur-friendly term coefficients to positive in all figures and tables.

the most important. In contrast to other cash flow terms in c^*, its impact is largest when $c_1^* = 0$ but it vanishes when $c_1^* = 1$. Therefore, γ_1 is multiplied by $1 - c_1^*$.

Because equations (11) and (12) are (log-)linear but interactions among contract terms may be important, we slightly expand the definition of the contract space C to also include interactions between pairs of non-equity share terms. Without interactions, contract terms are highly substitutable, such that, for example, participation and board seats almost never coexist in equilibrium. But in practice these terms are often jointly encountered in deals. Intuitively, adding a first generic investor-friendly term has a much larger effect on both firm value and its split compared to adding, say, the fifth such term. Interactions among terms capture this decreasing incremental impact, allowing multiple terms to coexist in equilibrium, and resulting in a better model fit.

Since π is not observed, we add an outcome equation for the probability of success (captured by "IPO or Acq. $> 2X$ capital") using a probit-type specification. Define the latent variable

$$Z(i, e, c^*) = \kappa_0 + \kappa_1 \cdot \pi(i, e, c^*) + \eta, \tag{13}$$

with $\eta \sim \mathcal{N}(0, 1)$. A given startup is successful if $Z \geq 0$, which happens with probability

$$Pr(Success = 1 | i, e, c^*) = \Phi(\kappa_0 + \kappa_1 \cdot \pi(i, e, c^*)), \tag{14}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function.

We calibrate the discount rate, r, to 10%, and use the generalized method of moments (GMM) with efficient weights to estimate all other model parameters. The set of moments include the first and second moments of the equilibrium model outcomes (contract terms, success rates, and investors' time between financings), and their covariances. We exclude the second moments for binary contract terms, because these do not contain additional information beyond their first moments. We also include the third moment of the only non-binary contract term, VC equity share. Appendix D describes the computation of the theoretical moments in detail, and Appendix H provides more detail on the identification of the full model.

Table IV compares theoretical moments at the estimated parameter values to empirical moments. Most first moments and covariance moments are matched well, but the model produces somewhat low second moments of the time between VC deals and VC equity share. The model can easily match these moments in isolation, but the GMM puts more weight on other, more precisely measured moments. Since the model is just identified, a test of overidentifying restrictions is not possible, but the overall fit appears visually sensible.

4.2.2 Impact of Contract Terms on Firm Value and Distribution

Table V reports parameter estimates and standard errors. Holding the qualities of investor and entrepreneur constant, the impact of VC equity share on the startup's value is concave ($\hat{\beta}_1 > 0$ and $\hat{\beta}_2 < 0$). This implies that firm value (π) is maximized at an internal VC equity share, in sharp contrast to the naive regression estimates presented above. Inclusion of the participation term lowers firm value ($\hat{\beta}_3 < 0$) but increases the share of the firm that goes to VCs ($\hat{\gamma}_2 < 0$). Conversely, pay-to-play is beneficial to the firm ($\hat{\beta}_4 > 0$) and increases entrepreneurs' share ($\hat{\gamma}_3 > 0$), but the effect is weak compared to participation and its impact on value is not statistically significant. VC board seats work similarly to participation in the absence of other contract terms. Its impact is statistically significant, but small compared to participation and of comparable economic magnitude to pay-to-play (but of opposite sign). However, investor board representation becomes value-increasing and beneficial for both agents when participation is also present (since $\hat{\beta}_5 + \hat{\beta}_7 > 0$ and $\hat{\gamma}_4 + \hat{\gamma}_6 > 0$). This result underscores the importance of including the interactions between contract terms in the model. While the interaction term parameters $\hat{\beta}_7$ and $\hat{\gamma}_6$ are individually not statistically significant, their joint effect is significant (see the "Joint significant tests" panel in Table V).[16]

Taken together, the estimates in Table V imply that the firm value-maximizing contract, c^{Max}, features a 14.7% VC equity share and pay-to-play, but no participation or VC board seats.[17]

4.2.3 Deviations from the Value-maximizing Contract

In equilibrium, the observed contracts between VCs and entrepreneurs depend not only on the impact of contract terms on firm value and its distribution, but also on the frequencies of encounters and the other features of the search and matching process that determine outside options. How close are equilibrium contracts to the value-maximizing contract? Figure 2 shows the contracts for all combinations of VC and entrepreneur qualities for which both parties are willing to match

[16]The impact of contract terms on the first-round expected firm value and its split captures both their direct impact and their indirect impact through contracts signed in follow-on rounds and potential contract renegotiations. Formally, without loss of generality, suppose there are two rounds of financing. Consider the choice of first-round terms c^I by an entrepreneur of quality e and a VC of quality i^I. By backward induction, the choice is made considering the second-round equilibrium, in which, irrespective of the exact mechanism, i^I, e, c^I, and possibly some random between-stage shock ε^{II} with parameters θ_ε determine the set of acceptable second-round investors $i^{II} \in \mu_i^{II}(i^I, e, c^I, \varepsilon^{II})$, second-round terms $c^{II,*}(i^I, e, c^I, \varepsilon^{II}, i^{II})$, and total and agent-specific values $\pi_j^{II}(i^I, e, c^I, \varepsilon^{II}, i^{II}, c^{II,*}(i^I, e, c^I, \varepsilon^{II}, i^{II})) \equiv \pi_j^{II,*}(i^I, e, c^I, \varepsilon^{II}, i^{II})$, $j \in \{\emptyset, i, e\}$. The choice of first-round terms then incorporates first-round expectations of equilibrium second-round values $E\pi_j^{II,*}(i^I, e, c^I, \theta_\varepsilon) = \mathbb{E}_\varepsilon[\pi_j^{II,*}(i^I, e, c^I, \varepsilon^{II}, i^{II})]$ and is fully determined by i^I, e, c^I, and θ_ε. See also Matvos (2013) for a similar argument in a study of the impact of debt covenants on a firm borrowing from a financial intermediary.

[17]Note that we cannot evaluate the value impact of terms that are always present. The maximal value is therefore conditional on the presence of these terms. It is not necessarily the first-best value, as we only model the VC-entrepreneur conflict and omit, for example, the LP-GP conflict within the VC firm.

with each other. Better VCs tend to match with better entrepreneurs, largely driven by the negative estimate of ρ, which implies that VC and entrepreneur qualities are complementary. But this pattern is imperfect: compared to a model with exogenous contracts, lower-quality VCs can sometimes attract higher quality entrepreneurs by offering more entrepreneur-friendly terms.[18] Across all feasible deals, the average VC equity share is 40.6%. For a given entrepreneur, the lowest quality VCs are willing to offer pay-to-play and lower-than-average VC equity share, both of which benefit the entrepreneur. Better VCs remove pay-to-play from their offer and eventually replace it with moderately VC-friendly board seats. The best VCs have sufficient bargaining power to combine board seats with strongly VC-friendly participation and increase the VC equity share up to 44.5%, which is an unconstrained maximizer of $\pi_i(i, e, c)$. In these deals, the entrepreneur-unfriendly impact of participation is somewhat softened by the positive effect of VC board seats.

The large distance between equilibrium contracts and c^{Max} is important. The left panel of Figure 3 shows how a startup's equilibrium value (as a fraction of the maximum value under c^{Max}) changes when we vary the contract terms while holding agents' qualities fixed. We focus on two salient contracts. The first is the representative contract in the data, with an average observed equity share of 39.6%, participation, and VC board seats, but no pay-to-play. With this contract, $c^{*,Avg}$, the firm's value is 82.6% of its maximal value. The second salient contract is the unconstrained contract, $c^{*,Unc}$, offered by the highest quality VC that a given entrepreneur can feasibly attract. This contract has a 44.5% equity share, and is otherwise the same as the representative contract. Firm value is 77.5% of its maximal value under this contract.

4.2.4 Deviations from Common Equity Split

To gain a better understanding of the quantitative impact of contract terms on the split of value between VC and entrepreneur, the right panel of Figure 3 shows how the VC's fraction of total value varies with the terms, holding the parties' qualities fixed. The negative intercept γ_1 in equation (12) means that terms that are always present in contracts (such as 1X liquidation preference), or that are unavailable in our data are on average VC-friendly, resulting in a larger VC fraction of the firm than the VC equity share alone suggests. In particular, while 14.7% of VC equity in the value-maximizing contract c^{Max} may appear low, this contract actually leaves

[18] Positively assortative matching does not necessarily hold in matching models with endogenous contracts. The restrictive theoretical conditions for positively assortative matching in search and matching models are provided in Shimer and Smith (2000) and Smith (2011). Hagedorn, Law, and Manovskii (2017) find violations of assortative matching in the labor market. In their model, contracts (wages) do not impact firm value by assumption. Our result shows that assortative matching also does not generally hold when contracts impact value. Appendix E provides a more detailed discussion.

the VC with 28.2% of the total value. In Appendix G, we use a simple Black-Scholes calibration to show that the 13.5% gap is mainly due to the presence of the 1X liquidation preference in the value-maximizing convertible preferred equity contract. The liquidation preference accounts for approximately 76% of the gap (10.3% of the 13.5% gap). The presence of participation and VC board seats further increases the VC's fraction of the firm. For example, $c^{*,Avg}$ leaves the VC with 49.1% of the total value, while $c^{*,Unc}$ leaves the VC with 52.8% of the value.

The substantial difference between the VC equity share and the fraction of the firm it retains suggests that the post-money valuation, which is calculated under the assumption that the VC equity share is the only relevant contract term, is a poor metric to compute firm value. A sensible practical modification is to use the fraction of the firm retained by the VC instead. For example, because the best VCs for a given entrepreneur offer $c^{*,Unc}$, which has a 44.5% equity share, the post-money valuation per dollar invested is $1/0.445 = $2.25. In contrast, because the best VCs retain 52.8% of the total value, the modified valuation is instead $1/0.528 = $1.89, which is 15.7% lower than the post-money valuation. The difference in valuations is 19.3% in deals with the representative contract, $c^{*,Avg}$. In large first-round financings, the dollar difference between the post-money and modified valuation can easily reach millions of dollars.

4.2.5 Equilibrium Effects of Matching

Figure 3 isolates the impact of contract terms by fixing the qualities of the VC and entrepreneur. However, in equilibrium, contracts differ across deals because they are impacted by the parties' qualities. For example, more investor-friendly contracts are offered to the same entrepreneur by higher-quality VCs. While such contracts reduce firm value relative to that under the value-maximizing contract, the VC's payoff is higher because the contract leaves a larger share to the investor. At first glance this outcome may seem irrational for the entrepreneur, but the entrepreneur in fact benefits from matching with a higher-quality VC. The reason is that the startup's value increases with VC quality, and this value increase offsets the entrepreneur's loss of value from accepting more investor-friendly terms (consistent with the mechanism in Hsu, 2004). Figure 4 illustrates and quantifies this intuition. As a stark example, consider a high-quality entrepreneur at the 99th percentile, $e = 8.32$. The VCs who are willing to match with this entrepreneur are in the quality set $\mu_e(e) = [4.13, 10]$. Moving from the lowest- to the highest-quality VC in this range raises firm value by 89.0%. The entrepreneur's value increases by 32.8%, even though the firm's value is not maximized and a larger fraction of it goes to the VC through a higher equity share and the addition of participation and board representation. As a point of comparison, in the off-equilibrium scenario in which the entrepreneur could retain the contract it signs with the lowest-quality VC, $i = 4.13$, both the firm's and the entrepreneur's value would instead have increased by 141.4%.

Table VI provides additional details on the total value and its split across deals completed by the bottom 10%, 10–50%, 50–90%, and the top 10% of VC and entrepreneur qualities. Deals completed by top-quality VCs (entrepreneurs) are, on average, 33 (144) times larger than deals completed by bottom-quality VCs (entrepreneurs). Overall, there is more heterogeneity in the total value as a function of entrepreneur quality than VC quality. The VC share of total value peaks for top-quality VCs and decreases with entrepreneur quality.

4.2.6 Connections to the Literature

Our paper does not explicitly model mechanisms that link contracts to the value of the firm. By modeling this link in reduced form, our results instead inform about which mechanisms from the theoretical VC contracting literature are likely at work in practice, and to uncover new insights for future work to consider. First, both parties' efforts can be valuable but difficult to verify, setting up the popular double moral hazard problem between VC and entrepreneur in the literature (e.g., Hellmann and Puri, 2002; Schmidt, 2003; Casamatta, 2003; Kaplan and Strömberg, 2004; Inderst and Müller, 2004; Hellmann, 2006). This problem is mitigated by each side retaining a positive equity share, and the internal optimal VC equity share in c^{Max} aligns with this prediction. However, this result is also generally consistent with adverse selection. For example, if VCs are unsure about the entrepreneur's type, they can leave the entrepreneur an equity share to screen out low types. This modeling setup is rarely used in VC contracting theory and it is outside our base model as well. A more detailed discussion is in the robustness section below.

Second, convertible securities and debt-equity mixes have been shown to mitigate inefficiencies related to asset substitution (Green, 1984), exit decisions (Hellmann, 2006), sequential investment (Schmidt, 2003), and sequential investment combined with window dressing (Cornelli and Yosha, 2003). The focus in this literature is on a competitive investor or on the feasibility of optimal contracts that may not necessarily occur in equilibrium. Our results suggest that participation (which effectively makes the contract a debt-equity mix), reduces the contract's effectiveness at dealing with the above inefficiencies compared to a regular convertible equity contract in equilibria without perfect competition.[19] However, this term can still be offered in equilibrium because it increases the payoff value of VCs with substantial bargaining power, even if it is detrimental to

[19]This finding is consistent with Cornelli and Yosha (2003), who point to window dressing as a potential inefficiency. Alternatively, convex incentives provided by participation may force entrepreneurs to gamble for success (e.g., DeMarzo, Livdan, and Tchistyi, 2013, and Makarov and Plantin, 2015) instead of working harder to achieve an IPO or follow-on financing. Gambling can increase the likelihood of a good outcome by increasing the likelihood of high firm value realizations, yet decrease the firm's expected value.

the value of the firm. In contrast, pay-to-play, which affects future investment rounds, appears to improve the ability to deal with the inefficiencies related to sequential investment.

Third, the venture capital literature highlights the value of control terms, for example by giving VCs the power to replace underperforming founders (Ewens and Marx, 2018). In theory these terms may also have drawbacks. For example, firms may face a trade-off between the benefits of VC support and the costs of VC interference in the presence of costly monitoring (Cestone, 2014). Monitoring may also be harmful if it has strong incentive power but is based on weak information (Zhu, 2019). Empirically, Cumming (2008) finds that stronger VC control (measured by board seats) relates to a lower probability of an IPO. Practitioners have also become concerned with the possibility that some VC-driven boards can negatively impact firm value.[20] Relatedly, investor over-monitoring may kill managerial incentives in public firms with large institutional investors, who share many control privileges of VCs, reducing the value of the firm (Burkart, Gromb, and Panunzi, 1997). Put differently, our control term, VC board seats, cannot be unequivocally beneficial for all deals, or else it would always be included in contracts. Instead, this term is absent in 11% of deals in our sample. Since VCs benefit from having more control, the term must sometimes hurt entrepreneurs' value. Indeed we find that VC board seats decrease firm value in the absence of participation. When the contract includes participation (only offered by high-quality VCs), VC board seats improve the firm's value. This result is consistent with Rosenstein, Bruno, Bygrave, and Taylor (1993), who report that startup CEOs rate VC advice no different from outside board members, except for top VC directors, whose advice is considered to be more valuable. It may be that in this case, VC support and interference are both valuable in the presence of distorted incentives and inefficiencies outlined above. In the robustness section we consider an alternative explanation based on heterogeneous effects of board seats.

Finally, cash flow and control terms have been shown to either come together to allocate control to investors with equity-like claims (Berglöf, 1994, Kalay and Zender, 1997, and Biais and Casamatta, 1999) or separately to allocate control to investors with debt-like claims in the presence of costly monitoring (Townsend, 1979, Diamond, 1984, Gale and Hellwig, 1985, and Cestone, 2014). Across all deals, we find a positive correlation between VC board seats and participation, though they do not necessarily appear together. Additionally, these two terms are complements in deals by high-quality VCs. Since participation makes the convertible equity security more debt-like, our results yield more support to the second group of papers.

[20] A data-driven analysis by Correlation Ventures can be found on `https://medium.com/correlation-ventures/too-many-vc-cooks-in-the-kitchen-65439f422b8`.

4.2.7 Encounter Frequencies

In the model and the data, the entrepreneur population of interest is comprised of the "serious" entrepreneurs who possess positive NPV projects and are able to attract at least the lowest-type investor. Such entrepreneurs are quite rare: a VC meets a serious entrepreneur, on average, every $1/\hat{\lambda}_i = 27$ days. A serious entrepreneur arranges a meeting with a VC, on average, every $1/\hat{\lambda}_e = 35$ days.

Meetings only result in deals if both parties fall within the counterparties' acceptable ranges ($\mu_i(i)$ and $\mu_e(e)$). The bottom right graph of Figure 2 shows the quality distributions (recall that qualities are not comparable across investors and entrepreneurs). The investor population is right-skewed, as high-quality VCs are relatively rare. The distribution of serious entrepreneurs is more symmetric, given that even the lowest-quality entrepreneurs are quite promising, lopping off the far left tail.

We combine the frequency of encounters with the quality distributions to compute the frequency of deals. Table VI reports that VCs lead a deal every $1/2.025 = 180$ days on average. Note that this number does not mean that a given VC makes investments at this rate, as VCs regularly participate in deals as non-lead investors. Lower-quality VCs are the most active: for example, VCs in the 10–50th quality percentiles lead a deal every 150 days on average, while the top 10% lead a deal every 350 days.

Entrepreneurs take an average of $1/1.565 = 233$ days to make a deal. The lowest quality decile entrepreneurs rarely sign a deal, while the top 10% contract, on average, in 103 days. Received wisdom is that it can take from 3 to 9 months to raise a first round of financing. High quality entrepreneurs are at the lower end of that range, while lower-quality ones take much longer.

4.2.8 Market Size

We measure total market size as the expected present value of all deals in the market. This present value combines our estimates of total firm values and the frequencies of encounters. A necessary ingredient for this calculation is the measures of VCs and entrepreneurs in the market. In equilibrium, measures of encounters by the parties have to be equal: $\lambda_i m_i = \lambda_e m_e$. The estimated ratio of measures of entrepreneurs to VCs is therefore $\widehat{m_e/m_i} = \hat{\lambda}_i/\hat{\lambda}_e$. On a per-VC basis the present value of all deals in the market is then the sum of $V_i(i)$ and $V_e(e) \cdot \widehat{m_e/m_i}$ across all i and e and with appropriate probability weights. Table VI shows that overall, VCs retain 61.15% of the present value of all deals in the market. The bottom 10% of VCs retain 0.45% of this value, while the top 10% retain 15.60%. In contrast, the bottom 10% of entrepreneurs only retain 0.07% of the value, while the top 10% retain 16.05%.

4.2.9 Persistence in Contracts

Our model produces persistent contracts for a given VC. In equilibrium, the VC offers its most VC-friendly contract to worse entrepreneurs. To better entrepreneurs, the VC offers a set of more entrepreneur-friendly contracts that barely vary with entrepreneur quality. Bengtsson and Bernhardt (2014) associate persistence of VC contracts with VC-specific style. However, style alone is insufficient to generate persistence when VCs encounter entrepreneurs of varying qualities and both parties have sufficient bargaining power to negotiate contracts. Our model suggests that persistence can be at least partly explained by a market equilibrium in which VCs have most of the bargaining power.

5 Counterfactual Analysis

5.1 Removing Contractual Features

Because some contractual features appear to benefit VCs at the expense of the startup, we consider the effect of removing certain contract terms that implement these features on deal values, the frequency of deals, and the present value of all deals in the market. A naive approach would be to simply remove a term that implements a particular feature and recalculate the startup value and its split for all deals, but this approach ignores the fact that, in the new equilibrium, agents rebalance the remaining terms that implement the remaining features and they may match differently. Instead, we consider the aggregate equilibrium effect and decompose it into two partial effects. The first effect captures the rebalancing of contract terms, while constraining VCs to compensate entrepreneurs enough to retain the match. This effect is still off-equilibrium, as some VCs who suffer a decrease in their expected value have incentives to rematch. Still, this exercise helps to understand the impact of contracts on the firm in the absence of market effects. The first three columns of Table VII show that the average effect of re-balancing terms on the startup's value and its split is uniformly negative and very small. For example, if contractual features implemented by participation (VC board seats) are removed, rebalancing results in a 0.01% (0.14%) decrease in the startup's value. The VC's value decreases by the same amount (all effects in Panel A are expressed as percentages of the average startup value from our main model).

The second effect captures the rematching that occurs when VCs rebalance the remaining contract terms without constraining them to keep the same matches. If contractual features implemented by participation are removed, the aggregate equilibrium effect is a 2.45% decrease in average startup value, implying that rematching alone is responsible for a 2.44% decrease. The aggregate equilibrium distribution of value to the VC (entrepreneur) decreases by 1.51% (0.94%), so that rematching alone is responsible for a 1.50% (0.94%) decrease. Removing contractual features implemented by VC board seats has comparable effects, decreasing the aggregate equilibrium distribution of value to the VC (entrepreneur) by 1.62% (0.81%). The effects from removing pay-to-play features are much smaller.

One explanation for the modest value effects is that the market for venture capital exhibits a high degree of contractual completeness, so that removed features are easily replicated by the remaining contract terms. Alternatively, it may be that deal-specific effects are large, but they cancel out in the aggregate. We find only limited evidence for this alternative explanation. In unreported analysis, the largest effect from removing participation is for entrepreneurs with qualities in the lowest decile, whose startups increase in value by 41.57%, with VCs (entrepreneurs) gaining 20.40% (21.17%). However, these deals' values are too small to strongly impact the average startup value across all deals. At the same time, the effect is small for startups formed by entrepreneurs with qualities above the median and for startups financed by investors of any quality. The effect from removing VC board seats is similar, while that of removing pay-to-play is small across all qualities.

The fourth column of Table VII Panel B shows the effects on deal frequencies. If features implemented by participation are removed, deal frequency increases by 5.30% on average. Similarly to deal values, this is mainly driven by entrepreneurs of low qualities: for example, entrepreneurs with qualities in the lowest decile match 27.42% more frequently, while entrepreneurs with qualities in the top decile, in fact, match 3.69% less frequently. Additional deals with low-quality entrepreneurs are conducted by low-quality investors: investors with qualities in the 10th to 50th percentiles match 13.85% more frequently, while investors with qualities in the 50th to 90th percentiles lose entrepreneurs and match 2.46% less frequently. Removing VC board seats has a similar effect, while removing pay-to-play does not materially affect deal frequencies.

The combined intuition behind the value and frequency results is as follows. Elimination of VC-friendly terms reduces, in any given deal, value for the VC and improves value for the entrepreneur and startup as a whole. The agents' values of waiting are similarly impacted. As a result, entrepreneurs become more selective and are prepared to wait for investors of higher quality and drop investors of lower quality. The opposite is true for investors. Whether the average startup value across all deals increases or not depends on the eagerness with which investors of high versus low quality are prepared to accept deals with entrepreneurs of lower quality than before. For our estimated parameters, the density of investors of low quality (and hence their competitiveness) is high, so elimination of VC-friendly terms strongly decreases their bargaining power, which leads to an influx of low-value deals signed with entrepreneurs of low quality who were hitherto virtually ignored. This influx positively affects the average deal frequency (despite the counterbalancing impact of entrepreneurs of high quality dropping their worst matches) and negatively affects the average startup value (despite the counterbalancing impact of higher-value deals signed by entrepreneurs of high quality).[21]

The above intuition suggests that even though the average deal value decreases in the absence of VC-friendly terms, there are more deals in the market, which can lead to a larger overall market size. The last three columns of Table VII show how the changes in deal values and frequencies combine to affect the expected present value of all deals in the market (the market size). For example, when participation is removed, the expected present value of all deals increases by 1.70%. VCs (entrepreneurs) on average lose 0.20% (gain 1.90%) (all effects are expressed as a percentage of the expected present value of all deals under estimated parameters). More detailed analysis reveals that entrepreneurs of high quality benefit disproportionately: top decile entrepreneurs capture 15.8% of the total entrepreneurial gain in present value, or 17.7% of the total change in the present value of all deals. When VC board seats are removed, the present value of all deals increases by 1.66%, while VCs (entrepreneurs) on average lose 0.35% (gain 2.00%). Pay-to-play has little impact, since its impact on both values and frequencies is negligible.

To summarize, a removal of VC-friendly features could lead to modest firm value creation, suggesting that the market could benefit from (self-)regulation by restricting some VC-friendly features, such as the "double-dip" of participation. However, attempts to regulate contracts will likely encounter resistance from certain VCs and entrepreneurs (including high quality VCs), because they lose out following the removal of such terms. A few other caveats apply. First, because we do not explicitly model mechanisms through which contractual terms affect values, we cannot examine the effect of including a new feature, or removing a feature that is always present. Second, we cannot control for VCs devising new contract terms that implement the same features as the terms that are taken away, and it is complicated to write legal rules that prevent such contractual engineering. Finally, we do not consider entry and exit into the VC market. Because VC values are less affected than entrepreneurs, removing VC-friendly contract features would likely add more value from newly entering entrepreneurs than what is lost from departing VCs.

[21]For other parameters (i.e., if investors' qualities are more evenly distributed, decreasing competitiveness among investors of low quality), we find that the influx of low-value deals can be dominated, in terms of its impact on the average value of deals and their frequency, by the impact of less frequent high-value deals signed by entrepreneurs of high quality.

5.2 Search Frictions

The introduction of online platforms where agents can easily find each other, like AngelList (which is also used by VCs), may lower search frictions in the market for early-stage financing. We compute the impact of such an event on the present value of all deals in the market by increasing the rate at which investors and entrepreneurs meet each other (λ_i and λ_e, respectively) by a factor of 2, 5, and 10. Table VIII shows that a small reduction in frictions increases the market size, while a large reduction decreases it. A $2X$ increase in encounter frequencies causes a 1.19% increase in the expected present value of all deals. VCs (entrepreneurs) on average gain 2.43% (lose 1.24%) (all effects are expressed as a percentage of the expected present value of all deals under estimated parameters). A $10X$ increase in encounter frequencies results in a 5.14% decrease in the present value of deals, while VCs (entrepreneurs) on average gain 7.25% (lose 12.38%).

The intuition behind this result is as follows. An increase in encounter frequencies has two effects on the present value of deals in the market. The positive effect is that deals with the same counterparties (assuming the agents are still willing to match) occur more frequently. The negative effect is that agents become more selective: intervals of agents' acceptable counterparties $\mu_i(i)$ and $\mu_e(e)$ contract, reducing to a single point if encounters are instantaneous (as in static models of matching). This effect, first, decreases the frequency of deals (although not sufficiently to counterbalance the positive effect), and, second, makes investors less competitive and increases their bargaining power, leading them to offer more VC-friendly contracts that result in lower-valued startups. The positive effect outweighs the negative, resulting in a higher market size for a small increase in encounter frequencies. However, when a reduction in frictions is large, frequent deals encumbered by VC-friendly contracts lead to a smaller market size.

While the mechanism in our paper is different, we note that a result that search frictions should not unambiguously lead to more efficient outcomes has also been explored theoretically in Glode and Opp (2018). This paper finds that more severe frictions in OTC markets (as opposed to centralized limit-order markets) lead to a more cautious and generous pricing, and, as a result, to strategic acquisition of expertise by well-connected traders. Additional expertise, despite causing adverse selection, can improve allocative efficiency.

A caveat to our counterfactual results is that encounter frequencies in our model proxy for both search frictions and the arrival of new agents to replace the matched ones. If search frictions reduce but the arrival rate does not change, the market size may shrink more than our estimates suggest. Moreover, entrepreneurs may depart to seek financing elsewhere, especially if the reduction in search frictions is due to the appearance of new online platforms that allow entrepreneurs to raise financing without a VC intermediary. Overall, our results suggest that benefits from low-cost search in the VC market are not obvious.[22]

6 Robustness and Extensions

Our results are robust to various model modifications and extensions. First, we use IPOs or follow-on financings as alternative outcome variables. The sample using IPOs is the same as the one in the main model (see Table II), but the sample using follow-on financings uses several additional years of contract data, resulting in 2,581 deals, and is described in Table A1 in the appendix. Alternative outcome variables do not materially affect moments and result in similar parameter estimates, as reported in Panels A and B of Table A2 in the appendix. Note that the link between firm value and follow-on financing becomes insignificant, but this is not surprising because 73% of startups receive follow-on financing, and many are likely of low quality.

Second, we check robustness to missing data. Instead of requiring all modeled contract terms to be observed, we impute missing contract terms to be zero for deals with information about the equity share and at least one of the additional terms. This imputation expands the sample to 2,439 deals for our main outcome variable. Panel C of Table A2 in the appendix shows that our parameter estimates are qualitatively unaffected.

Third, we consider whether our results are driven by certain sub-markets, such as the IT or Healthcare industries, California or Massachusetts markets, the time period before or after the release of Amazon's AWS cloud (a structural technological change, see Ewens, Nanda, and Rhodes-Kropf, 2018), and before or during the 2008 crisis. Panels A and B of Table A3 in the appendix show that the parties encounter each other more frequently in IT, compared to Healthcare. Qualities in Healthcare are more complementary, possibly due to higher required VC expertise in this market. The participation term in the IT industry is notably more detrimental to startup value, perhaps because it is easier, for an entrepreneur, to walk away from a project in IT when faced with bad incentives created by VC-friendly terms. Panel C of Table A3 shows that the California market is more similar to the IT market, likely due to the high concentration of IT startups in the Silicon Valley. Unfortunately, we do not have enough data to obtain highly statistically significant results in other geographical markets, but unreported point estimates from the Massachusetts market are very similar to those from our main model.

Panels A and B of Table A4 in the appendix show that the frequency of encounters rises after

[22]The exercise in this section is also useful to assess bias from modeling selection via a static matching model with no search frictions. When λ_i and λ_e are high, our model converges to a static matching model (Adachi, 2003; Adachi, 2007). Estimation of the model when the λ's are very high is difficult, as the system of Bellman equations (8) and (9) converges slowly when the discount factor ($\frac{\lambda_i}{r+\lambda_i}$ and $\frac{\lambda_e}{r+\lambda_e}$) of the next expected encounter is close to one. Since we find that the value is split very differently when λ's change, the estimates obtained from a model with no frictions will likely be very different, underscoring the importance of modeling search frictions in the VC market.

the introduction of Amazon's AWS, reflecting the burgeoning IT startup market. Of additional note is that the average VC quality increases in the post-AWS period, and that the participation term becomes costlier to the startup. The latter result may be due to the higher prevalence of IT startups after the introduction of the cloud.[23] Panels C and D Table A4 show similar results when we compare time periods before and during the 2008 crisis (we split the sample around the Lehman bankruptcy on 9/15/2008). Unfortunately, because the main sample of contracts is limited by 2010, we are unable to examine the post-crisis period.

Fourth, we modify various parameter and model assumptions. Specifically, we change the discount rate from 10% to 20% to capture higher impatience; we allow VCs and entrepreneurs to be overconfident; and we allow for a match-specific shock to the startup value, so that different deals by the same pair of VC and entrepreneur qualities can have different contracts and expected values. Appendix F describes the model extensions in detail. Table A5 in the appendix shows that in all cases, our results remain robust. Appendix F also includes an extension in which the amount of capital raised is an additional endogenous contract term. Due to high computational complexity, this case is not estimated, but uses comparative statics.

Finally, to account for potential sources of unobserved variation other than qualities (e.g., projects with different capital intensity or syndicated rounds can result in different contracts and success probabilities), in unreported results we have also estimated our model in subsamples of seed or series A rounds, syndicated or non-syndicated deals, and high or low capital intensity startups. Our results remained quantitatively unaffected.[24] To account for omitted, ex-ante less important contract terms such as redemption rights or cumulative dividends, in unreported results we have estimated models in which the least important included term, pay-to-play, is substituted with each omitted term, and (at a great computational cost) models in which each omitted term is exclusively added to the set of three included terms. Neither of the newly included terms' impacts is statistically or economically significant in any specification.

Two additional extensions are of interest. First, high-quality VCs and entrepreneurs are more likely to encounter a high-quality counterparty as a result of directed rather than entirely random search. While a full-blown model of optimally conducted directed search is beyond the scope of this paper, we note that the model, in which VCs' and entrepreneurs' qualities in an encounter

[23]An alternative way to account for technological change is to include a technology state in the model, but this comes at the cost of additional model assumptions and substantially higher computational complexity.

[24]These sample splits also help address some alternative interpretations of the main model's findings. For example, an alternative interpretation of the estimated value-improving interaction between participation and VC board seats is that the participation term can change with the deal type. If participation is only offered in certain deal types in which VC control is valuable, then the estimated positive impact of VC board seats in such deals may be unrelated to the presence of participation per se. Our estimates are virtually unaffected in various subsamples of deals that are more homogeneous, alleviating such concerns.

are correlated, produces very similar results to the main model. Given our data, however, it is not possible to statistically disentangle correlation between qualities and the complementarity parameter ρ in the matching function, as the two impact the solution very similarly. Second, even after an encounter, the counterparties may not completely observe each other's type, giving rise to adverse selection concerns. To our knowledge there are no papers on adverse selection in VC contracting specifically (though it is used in some other topics in VC, for example, Winegar, 2018). While we leave estimation of the precise form and impact of asymmetric information for future research, we note that as long as the VCs retain the power to make take-it-or-leave-it contract offers to entrepreneurs, investor quality will remain the main factor affecting endogenous contracts and the positive correlation between contract terms and outcomes.[25] In turn, the extended model will still predict that the OLS regression of outcomes on contracts would overestimate the impact of contracts; once qualities are controlled for, such a model would still lead to qualitatively similar results to the main model (i.e., negative impact of participation and weak or negative impact of board seats).

7 Conclusion

This paper estimates the impact of venture capital contract terms on startup outcomes and the split of value between entrepreneur and investor, using a dynamic search and matching model to control for endogenous selection. Based on a new, large data set of first financing rounds, we find that contracts materially affect the value of the firm, as well as its split between entrepreneur and investor. Consistent with double moral hazard problems that are common in the literature, there is an internally optimal split between investor and entrepreneur that maximizes the probability of success. However, in virtually all deals, VCs receive more equity than is value-maximizing for the startup. All else equal, participation rights and investor board seats reduce company value, while shifting more value to the investors. Pay-to-play has the opposite effect. Conditioning on the entrepreneur's quality, high quality investors receive investor friendly terms, including larger equity shares, board seats and participation, whereas low-quality VCs sign contracts with pay-to-play. Due to the positive impact of VC quality on startup values, having a higher quality VC still benefits the startup and the entrepreneur in equilibrium, though not as much as they

[25]Even the case of one-dimensional asymmetric information (e.g., about entrepreneurs' quality) is difficult to estimate, as this case expands the state space of the model into an additional dimension (true versus perceived quality of the entrepreneur). We have estimated a very simple model with asymmetric information, in which the perceived quality of the entrepreneur e informs the investor that the true quality is either e or a fixed t, where t and its likelihood are the same across investors and entrepreneurs, and t can be, for example, the expected quality or the lowest possible quality. This case is numerically tractable (although far from general) and results in very similar estimates.

could in theory. Eliminating terms like participation makes entrepreneurs (VCs) in a given deal better (worse) off, shifting bargaining power towards them and leading to an influx of deals by low-quality entrepreneurs. As a result, the joint present value of all market participants increases, though it is not clear how such regulation could be implemented in practice.

Overall, our results show that selection of investors and entrepreneurs into deals is a first-order factor to take into account in both the empirical and theoretical literature on financial contracting.

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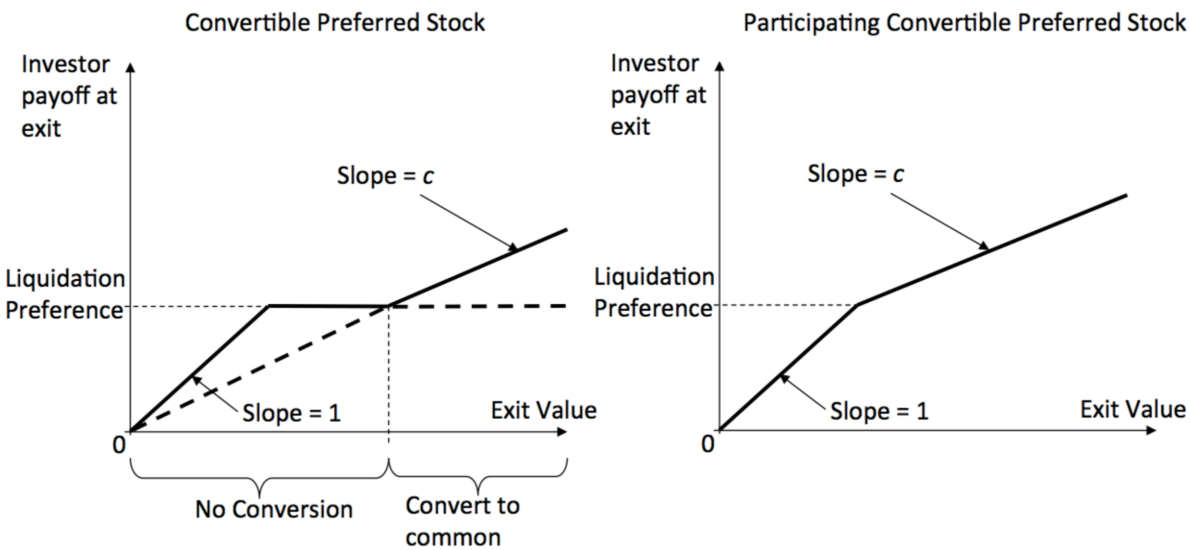

Figure 1: **Exit payoff diagrams.** The left graph shows the final payoff to convertible preferred stock (vertical axis) as a function of the startup's exit value (horizontal axis). The investor has the right to receive a liquidation preference (equal to a multiple of the invested amount, typically 1X for a seed or A round), but may instead choose to convert the preferred shares into a fraction c of the startup's common stock. The right graph shows the payoff for a participating convertible preferred security, in which the investor has the right to receive the liquidation preference, and then participates in the remaining value on an as-converted basis.

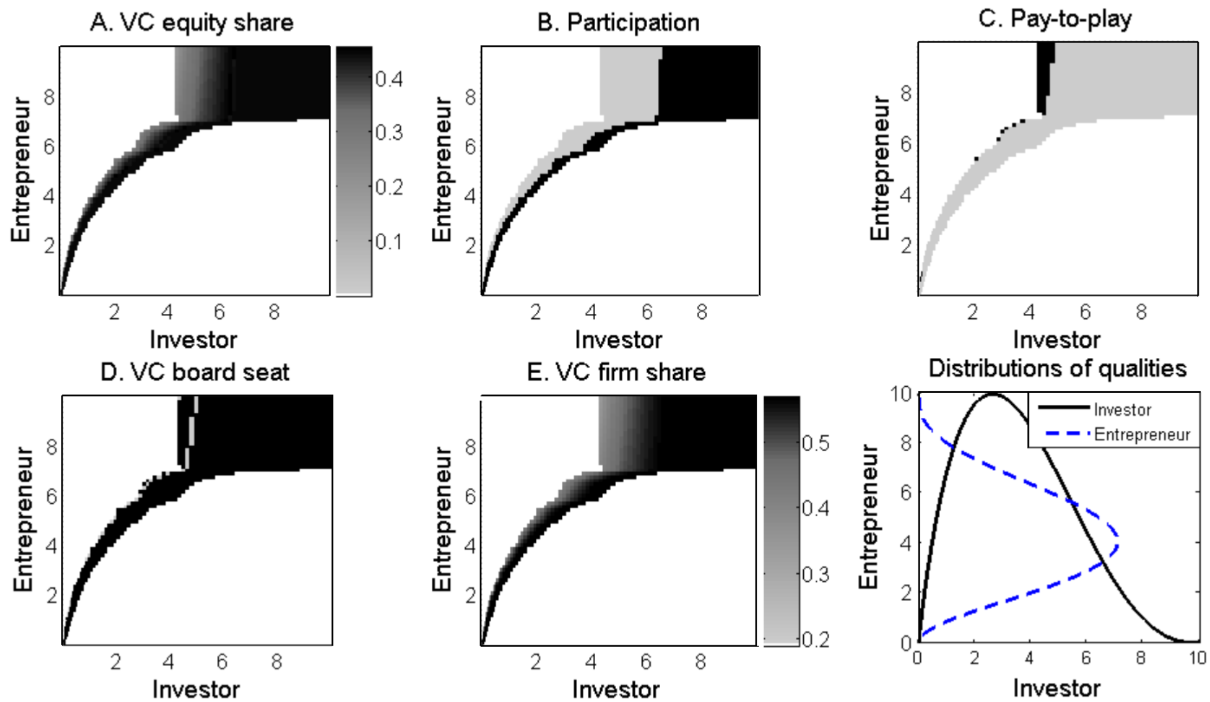

Figure 2: **Equilibrium contract terms at estimated model parameters.** Panel A shows the VC equity share, Panel B shows participation, Panel C shows pay-to-play, Panel D shows the VC board seat, and Panel E shows the resulting VC share of the firm for each combination of investor (VC) and entrepreneur quality. The VC equity share and VC share of the firm take values in $[0, 1]$ and are shown in gray-scale. Participation, pay-to-play and the VC board seat take values in $\{0, 1\}$, and their inclusion is shown in black. Absence of a term is in light gray. Combinations of qualities that do not match are shown in white. Panel F shows the distribution of VC and entrepreneur qualities on the horizontal and vertical axes, respectively.

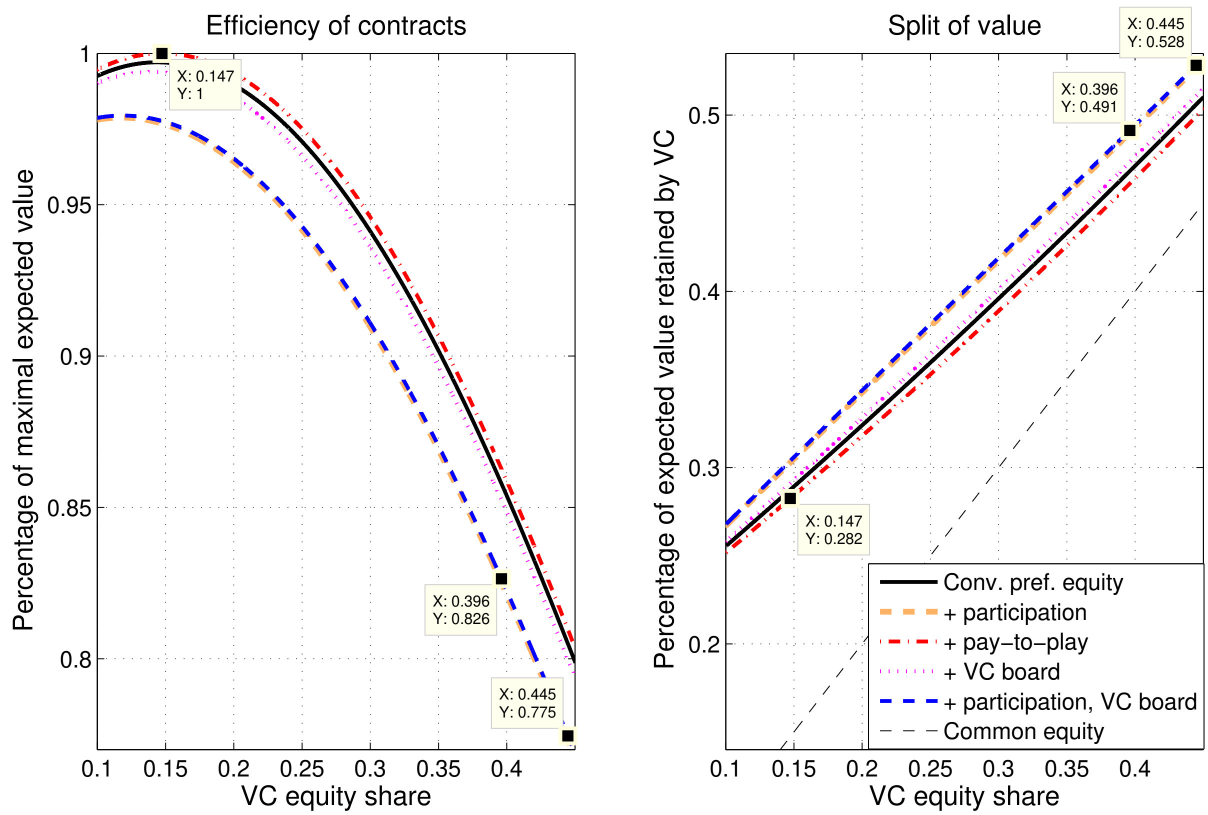

Figure 3: **Impact of contract terms on the startup value and its distribution.** The figure in the left panel shows the ratio of the total startup value to the maximal value, and right side panel shows the fraction of value acquired by the VC, as a function of VC equity share. Qualities of the VC and entrepreneur are kept fixed across contracts. Different lines are shown for the presence of participation, pay-to-play, and VC board representation, as well as for the joint presence of participation and VC board representation. Datatips represent the contract (VC equity share, participation, pay-to-play, board seats) that maximizes the value, $c^{Max} = (0.147, 0, 1, 0)$, the representative contract in the data, $c^{*,Avg} = (0.396, 1, 0, 1)$, and the unconstrained VC-optimal contract, $c^{*,Unc} = (0.445, 1, 0, 1)$, on the startup value and its split. These three contracts achieve 100%, 82.6%, and 77.5% of the maximal value and leave the VC with 28.2%, 49.1%, and 52.8% of the firm, respectively.

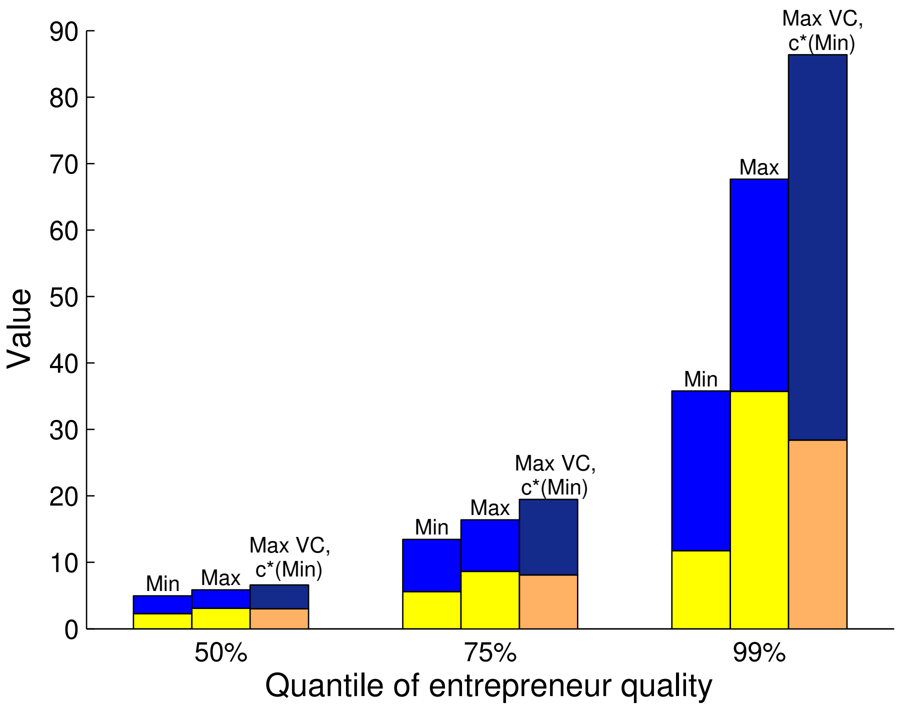

Figure 4: **VC and entrepreneur value creation.** Each bar shows the expected value to the VC (light color) and entrepreneur (dark color) for a given combination of their qualities in the estimated equilibrium. These values add up to the expected value of the startup. The sets of bars refer to entrepreneurs at the 50th, 75th, and 99th quality percentiles, respectively. For a given entrepreneur quality, the first two bars show the expected values for the VC of the lowest (Min) and highest (Max) quality that matches with this entrepreneur quality. The last bar shows the expected values for the VC of the highest quality that matches with this entrepreneur quality in a hypothetical scenario where such VC offers the equilibrium contract of the VC of the lowest quality that matches with this entrepreneur quality.

Table I: Variable definitions.

This table shows the definition of variables used throughout the paper.

Variable	**Definition**
Firm age at financing (yrs)	Years from the startup's date of incorporation to the date of the first round financing.
Information technology	An indicator equal to one if the startup's industry is information technology.
Healthcare	An indicator equal to one if the startup's industry is healthcare, which include biotechnology.
Time since last VC financing (yrs)	The number of years since the lead investors' last lead investment in a first round financing.
Syndicate size	The total number of investors in the first round financing.
Capital raised in round (2012 $m)	Total capital raised (in millions of 2012 dollars) in the startup's first financing rounds (across all investors).
Post-money valuation (2012 $m)	The post-money valuation of the first round financing (capital raised plus pre-money valuation, in millions of 2012 dollars).
Financing year	The year of the financing.
% equity sold to investors	The fraction of equity (as-if-common) sold to investors in the financing round, calculated as the capital raised in the round divided by the post-money valuation.
Participating preferred	An indicator variable equal to one if the stock sold in the financing event includes participation (aka "double-dip").
Common stock sold	An indicator variable equal to one if the equity issued in the financing is common stock.
Liquidation multiple > 1	An indicator variable that is equal to one if the liquidation multiple exceeds 1X. The liquidation multiple provides holders 100% of exit proceeds for sales that are less than X times the original investment amount.
Cumulative dividends	An indicator variable equal to one if the stock sold includes cumulative dividends. Such dividends cumulate each year pre-liquidation and are only paid at liquidation.
Full ratchet anti-dilution	An indicator variable equal to one if the preferred stock includes full ratchet anti-dilution protection. Such protection results in the original share price to be adjusted 1:1 with any future stock offerings with a lower stock price (through a change in the conversion price).
Pay-to-play	An indicator variable equal to ones if the preferred stock sold includes pay-to-play provisions. These provisions penalize the holder if they fail to reinvest in future financing rounds.
Redemption rights	An indicator variable equal to one if the preferred stock sold includes redemption rights. These are types of puts (available after some number of years) that allow the holder to sell back their shares to the startup at a predetermined price.
VC has board seat	An indicator variable equal to one if the VC investor has a board seat at the time of the first financing.
IPO	An indicator variable that is equal to one if the startup had an IPO by March 31st, 2018.
Acquired	An indicator variable that is equal to one if the startup was acquired by March 31st, 2018.
IPO or Acq. $> 2X$ capital	An indicator variable that is equal to one if the startup had an IPO or had an acquisition with a purchase price at least two times capital invested across all its financings by the end of 2018Q1.
Out of business	An indicator variable that is equal to one if the startup had gone out of business by the end of 2018Q1.
Still private	An indicator variable that is equal to one if the startup had not exited by the end of 2018Q1.
Seed round	An indicator variable that is equal to one if the first round financing is a Seed round (other rounds as traditional Series A).

Table II: Summary statistics

Descriptive statistics of startups and their first round equity financings for the samples described in section 3. The "IPO/Good acq. sample" includes financing rounds between 2002 and 2010 where the outcome variable is a dummy variable equal to one if the startup had a successful exit (an initial public offering or an acquisition worth at least twice the invested capital). A financing is in this sample if the outcome variable and contract terms are observed. The "All deals 2002–2010" sample includes all first-round financings between 2002 and 2010 regardless of missing contract data. The variables are as defined in Table I. Only means are reported for indicator variables.

	IPO/Good acq. sample				All deals 2002–2010			
	Obs.	Mean	Median	Std. dev.	Obs.	Mean	Median	Std. dev.
Panel A: Firm and financing characteristics								
Firm age at financing (yrs)	1,695	1.621	1.098	1.703	5,510	1.695	1.084	1.793
Information technology	1,695	0.465			5,510	0.477		
Healthcare	1,695	0.262			5,510	0.230		
Time since last VC financing (yrs)	1,556	0.689	0.279	1.130	4,782	0.849	0.364	1.318
Syndicate size	1,695	1.756	2	0.905	5,510	1.568	1	0.852
Capital raised in round (2012, $ mil.)	1,695	7.261	5.202	8.373	5,185	6.327	4.210	7.988
Post-money valuation (2012, $ mil.)	1,695	21.201	13.014	39.385	3,359	18.905	12.269	31.345
Financing year	1,695	2006.331	2006	2.260	5,510	2006.352	2007	2.403
Seed round	1,695	0.118			5,510	0.162		
Panel B: Contracts								
% equity sold to investors	1,695	0.396		0.184	3,359	0.400		0.181
Liquidation mult. > 1	1,689	0.043			2,731	0.043		
Participating preferred	1,695	0.512			2,737	0.522		
Cumulative dividends	1,694	0.207			2,702	0.220		
Pay-to-play	1,695	0.123			2,022	0.119		
Full ratchet anti-dilution	1,013	0.018			1,816	0.017		
Redemption rights	1,675	0.392			2,199	0.411		
VC has board seat	1,695	0.893			5,510	0.752		
Common stock sold?	1,694	0.038			2,867	0.028		
Panel C: Outcomes								
Went public	1,695	0.045			5,510	0.024		
Acquired	1,695	0.388			5,510	0.397		
IPO or Acq. $> 2X$ capital	1,695	0.127			5,510	0.115		
Out of business	1,695	0.134			5,510	0.170		
Still private	1,695	0.434			5,510	0.408		
Had follow-on within 2 years	1,695	0.727			5,510	0.579		

Table III: Startup outcomes and contract terms

Columns 1 through 4 of this table report probit regression results with the "IPO or Acq. $> 2X$ capital" indicator outcome as the dependent variable for the sample of 1,695 startups described in Table II. "Log Raised" is the log of total capital invested in the financing (2012 dollars). "Year FE" are fixed effects for the financing year, "Year founded FE" are fixed effect for the startup's founding year, "State FE" are fixed effects for the startup's state, and "Industry FE" are fixed effects for industry. All other explanatory variables, and all outcome variables, are defined in Table I. Column (5) shows the same regression specification as in column (4) but using the IPO indicator as dependent variable. The final column reports OLS regression estimates where the dependent variable is the natural logarithm of the startup's post-money valuation. The table reports Pseudo-R^2 for the probit regressions, and R^2 for the OLS. The number of observations varies across dependent variables because the probit regressions drop observations for which the outcome is perfectly predicted by one or more of the explanatory variables. Standard errors are clustered by VC firm, and are reported in parentheses. *, **, and *** indicates significance at the 10%, 5%, and 1% levels, respectively.

	IPO or Acq. $> 2X$ capital				IPO	Log post-money
	(1)	(2)	(3)	(4)	(5)	(6)
% equity sold to investors	-1.589	-1.741*	-1.561	-1.641*	-2.367	-5.004***
	(1.067)	(1.025)	(1.052)	(0.964)	(1.703)	(0.490)
% equity sold to investors^2	2.551**	2.579**	2.375**	2.546**	4.076***	5.252***
	(1.190)	(1.173)	(1.162)	(1.088)	(1.547)	(0.458)
Participating preferred	-0.230***	.	.	-0.238***	-0.201**	-0.0232
	(0.0614)	.	.	(0.0653)	(0.0912)	(0.0432)
VC has board seat	.	0.141	.	0.136	0.280	0.241**
	.	(0.196)	.	(0.198)	(0.219)	(0.103)
Pay-to-play	.	.	0.0871	0.115	0.376***	0.207**
	.	.	(0.124)	(0.133)	(0.135)	(0.0773)
Constant	-4.608***	-4.944***	-4.807***	-4.704***	-4.527***	2.678***
	(0.571)	(0.587)	(0.505)	(0.655)	(0.611)	(0.343)
Observations	1,607	1,607	1,607	1,607	1,549	1,695
Pseudo-R^2, R^2	0.060	0.056	0.055	0.062	0.195	0.129
Year FE	Y	Y	Y	Y	Y	Y
Year founded FE	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

Table IV: Empirical and theoretical moments

This table reports the empirical moments and their model counterparts computed at estimated parameters of the search and matching model described in the paper (Section 4.2). "Success rate" is the fraction of deals that result in a good exit, as measured by the variable "IPO or Acq. $> 2X$ capital". This variable and the contract terms are defined in Table I.

Moment	Data	Model
Avg. time since last VC financing	0.689	0.494
Var. time since last VC financing	1.276	0.420
Avg. VC share of equity	0.396	0.406
Var. VC share of equity	0.031	0.003
Skew. VC share of equity	0.002	-0.000
Cov. VC share of equity and time since last VC financing	0.003	0.001
Avg. participation	0.512	0.465
Cov. participation and time since last VC financing	0.055	0.002
Cov. participation and VC share of equity	0.015	0.018
Avg. pay-to-play	0.122	0.049
Cov. pay-to-play and time since last VC financing	-0.003	-0.001
Cov. pay-to-play and VC share of equity	0.012	-0.001
Cov. pay-to-play and participation	0.018	-0.023
Avg. VC board seat	0.893	0.970
Cov. VC board seat and time since last VC financing	-0.018	-0.001
Cov. VC board seat and VC share of equity	0.006	0.003
Cov. VC board seat and participation	0.004	0.014
Cov. VC board seat and pay-to-play	0.005	0.000
Avg. success rate	0.127	0.093
Cov. success rate and time since last VC financing	-0.014	0.024
Cov. success rate and VC share of equity	0.004	-0.001
Cov. success rate and participation	-0.012	-0.008
Cov. success rate and pay-to-play	0.005	0.005
Cov. success rate and VC board seat	0.002	-0.000

Table V: Parameter estimates

The first panel reports the parameters of the dynamic search and matching model (Section 4.2), estimated using the Generalized Method of Moments (GMM) with the efficient weight matrix. The second panel – "Joint significance tests" – reports results from a set of hypothesis tests about the interaction coefficient estimates. *, **, and *** indicates significance at the 10%, 5%, and 1% levels, respectively.

Parameter and Description		Estimate	Standard error
a_i	Distribution of investor qualities	1.927***	0.257
b_i	Distribution of investor qualities	3.602***	0.760
a_e	Distribution of entrepreneur qualities	3.142***	0.334
b_e	Distribution of entrepreneur qualities	4.152***	0.573
λ_i	Frequency of investors meeting entrepreneurs	13.443**	6.096
λ_e	Frequency of entrepreneurs meeting investors	10.393***	2.739
ρ	Substitutability of qualities	-1.370***	0.078
κ_0	Probability of success, intercept	-4.056**	2.066
κ_1	Probability of success, total value	0.104*	0.061
β_1	Total value, share of VC equity	0.679***	0.220
β_2	Total value, share of VC equity squared	-2.362***	0.233
β_3	Total value, participation	-0.163***	0.027
β_4	Total value, pay-to-play	0.024	0.048
β_5	Total value, VC board seat	-0.026***	0.006
β_6	Total value, participation × pay-to-play	0.016	0.102
β_7	Total value, participation × VC board seat	0.033	0.026
β_8	Total value, pay-to-play × VC board seat	0.019	0.064
γ_1	Split of value, intercept	-0.211***	0.076
γ_2	Split of value, participation	-0.174***	0.027
γ_3	Split of value, pay-to-play	0.055*	0.029
γ_4	Split of value, VC board seat	-0.040***	0.007
γ_5	Split of value, participation × pay-to-play	0.015	0.113
γ_6	Split of value, participation × VC board seat	0.029	0.027
γ_7	Split of value, pay-to-play × VC board seat	0.012	0.107
	Number of observations	1,695	

Joint significance tests

Null hypothesis	F-stat
Total value and split: $(\beta_6, \beta_7, \beta_8) = \mathbf{0}$ and $(\gamma_5, \gamma_6, \gamma_7) = \mathbf{0}$	14.838**
Participation & pay-to-play interaction: $\beta_6 = 0$ and $\gamma_5 = 0$	0.028
Participation & VC board seat interaction: $\beta_7 = 0$ and $\gamma_6 = 0$	9.106**
Pay-to-play & VC board seat interaction: $\beta_8 = 0$ and $\gamma_7 = 0$	0.332
Total value: $(\beta_6, \beta_7, \beta_8) = \mathbf{0}$	1.571
Split of value: $(\gamma_5, \gamma_6, \gamma_7) = \mathbf{0}$	1.150

Table VI: Startup values, deal frequencies, and present values of deals in the VC market

The first column of this table reports the average expected startup value across deals completed by quality subgroups of VCs and entrepreneurs, $\pi^*(Sub)$, as a percentage of the average expected startup value across all deals, $\pi^*(All)$. Columns 2 and 3 show how the expected value in column 1 is distributed between investors and entrepreneurs, respectively. The percentages in these two columns add to 100%. The fourth column reports expected deal frequencies (expected number of deals per year), $\Lambda^*(Sub)$, across all deals and by quality subgroups of VCs and entrepreneurs. The last column shows the present value (PV, a properly discounted combination of deal values and frequencies) that accrues to the two types of agents and their subgroups, as a percentage of the combined PV of all deals. The percentages for the subgroups add up to the PV percentage of all deals for each agent type. The PV percentages of all deals across the two agent types sum up to 100%. All numbers in this table are equilibrium numbers generated from the search and matching model with the parameter estimates from Table V.

	Percentage of startup value			Deal frequencies	PV of deals
	$\frac{\pi^*(Sub)}{\pi^*(All)}$	$\frac{\pi_i^*(Sub)}{\pi^*(Sub)}$	$\frac{\pi_e^*(Sub)}{\pi^*(Sub)}$	$\Lambda^*(Sub)$	$\frac{PV^*(Sub)}{PV^*(All)}$
Investor					.
All deals	100	48.40	51.60	2.025	61.15
0–10th percentile	8.51	49.39	50.61	2.213	0.45
10th–50th percentile	57.60	48.10	51.90	2.435	12.49
50th–90th percentile	166.80	47.40	52.60	1.788	32.62
90th–100th percentile	279.30	52.60	47.40	1.043	15.60
Entrepreneur					.
All deals	100	48.40	51.60	1.565	38.85
0-10% percentile	1.55	51.11	48.89	0.158	0.07
10-50% percentile	15.34	50.99	49.01	0.721	3.24
50-90% percentile	82.37	49.35	50.65	2.370	19.49
90-100% percentile	223.68	47.32	52.68	3.559	16.05

Table VII: Counterfactuals: Elimination of contract features

This table reports the results of counterfactual exercises that disallow the use of one of three contract features: participation preference, pay-to-play, or VC board seats. The first column shows the change in the average expected startup value across all deals when moving from the unrestricted model equilibrium (at the parameters shown in Table V) to the restricted contracts counterfactual, $\Delta\pi^{cf}(All) = \pi^{cf}(All) - \pi^*(All)$, as a percentage of the average expected startup value across all deals in the unrestricted model, $\pi^*(All)$. The "rebalanced terms only" rows report the partial effect of VCs rebalancing the remaining contract terms such that the set of matches does not change, while the "equilibrium" rows report the total effect of rebalancing and rematching in the new equilibrium. The second and third columns show the change in the average expected value for the VC and entrepreneur, respectively. Both are computed as a percentage of $\pi^*(All)$, such that columns 2 and 3 add up to the numbers in column 1. The fourth column reports the change in equilibrium expected deal frequencies (expected number of deals per year) in the market, $\Delta\Lambda^{cf}(All) = \Lambda^{cf}(All) - \Lambda^*(All)$, as a percentage of the expected deal frequency in the unrestricted equilibrium, $\Lambda^*(All)$. The final three columns report the change in the present value of all deals in the market, $\Delta PV^{cf}(All) = PV^{cf}(All) - PV^*(All)$, and the change in present values of all VCs and entrepreneurs. All present value changes are computed as percentages of the unrestricted equilibrium present value of deals in the market, $PV^*(All)$, so that columns 6 and 7 add up to the numbers in column 5.

	Change in percentage of startup value			Change in deal frequencies	Change in PV of deals		
	$\frac{\Delta\pi^{cf}(All)}{\pi^*(All)}$	$\frac{\Delta\pi_i^{cf}(All)}{\pi^*(All)}$	$\frac{\Delta\pi_e^{cf}(All)}{\pi^*(All)}$	$\frac{\Delta\Lambda^{cf}(All)}{\Lambda^*(All)}$	$\frac{\Delta PV^{cf}(All)}{PV^*(All)}$	$\frac{\Delta PV_i^{cf}(All)}{PV^*(All)}$	$\frac{\Delta PV_e^{cf}(All)}{PV^*(All)}$
No participation preference							
Rebalanced terms only	-0.01	-0.01	0	–	–	–	–
Equilibrium	-2.45	-1.51	-0.94	5.30	1.70	-0.20	1.90
No pay-to-play							
Rebalanced terms only	-0.01	-0.01	0	–	–	–	–
Equilibrium	-0.29	-0.05	-0.24	-0.31	-0.002	-0.002	-0.000
No VC board seats							
Rebalanced terms only	-0.14	-0.14	0	–	–	–	–
Equilibrium	-2.43	-1.62	-0.81	5.30	1.66	-0.35	2.00

Table VIII: Counterfactuals: Search frictions

This table reports the results of counterfactual exercises that increase the frequency at which investors and entrepreneurs meet each other by 2, 5, and 10 times the estimated frequency of Table V. The table shows the change in the present value of all deals in the market, $\Delta PV^{cf}(All) = PV^{cf}(All) - PV^{*}(All)$, and the change in present values of all VCs and entrepreneurs. All present value changes are computed as percentages of the unrestricted equilibrium present value of deals in the market, $PV^{*}(All)$, so that columns 2 and 3 add up to the numbers in column 1.

	$\frac{\Delta PV^{cf}(All)}{PV^{*}(All)}$	$\frac{\Delta PV_i^{cf}(All)}{PV^{*}(All)}$	$\frac{\Delta PV_e^{cf}(All)}{PV^{*}(All)}$
2X more frequent encounters	1.19	2.43	-1.24
5X more frequent encounters	-2.74	5.42	-8.16
10X more frequent encounters	-5.14	7.25	-12.38

Appendix

A Proof of Proposition 1

The agents' expected present values are

$$V_i(i) = \frac{1}{1+rdt}\left(\lambda_i dt\left(\int_{e\in\mu_i(i)}\max\{\pi_i(i,e,c^*),V_i(i)\}dF(e)+\int_{e\notin\mu_i(i)}V_i(i)dF(e)\right)+(1-\lambda_i dt)V_i(i)\right), \quad (15)$$

$$V_e(e) = \frac{1}{1+rdt}\left(\lambda_e dt\left(\int_{i\in\mu_e(e)}\max\{\pi_e(i,e,c^*),V_e(e)\}dF(i)+\int_{i\notin\mu_e(e)}V_e(e)dF(i)\right)+(1-\lambda_e dt)V_e(e)\right) \quad (16)$$

Consider the expression for $V_i(i)$ ($V_e(e)$ is symmetric). Multiply both sides by $1+rdt$, cancel out the two terms that contain $V_i(i)$ but not dt, and divide by dt to obtain

$$rV_i(i) = \lambda_i\int_{e\in\mu_i(i)}\max\{\pi_i(i,e,c^*),V_i(i)\}dF(e)+\lambda_i\int_{e\notin\mu_i(i)}V_i(i)dF(e)-\lambda_i V_i(i).$$

Move $\lambda_i V_i(i)$ to the left-hand side and divide everything by $r+\lambda_i$. Equation (8) follows.

B Example contract terms: Reata Pharmaceuticals (NAS: RETA)

Sections of Reata Pharmaceuticals 2003 Series A certificate of incorporation that contain contract term information.

B.1 Equity sold and share price

The Series A investors purchased 1,751,000 shares at \$1.00/share at an approximate \$8.25m pre-money, \$10m post-money valuation (17.5% of equity):

> The total number of shares of capital stock that the Corporation shall have authority to issue is 90,000,000, consisting of 55,000,000 shares of common stock, par value \$0.001 per share (the "Common Stock"), and 35,000,000 shares of preferred stock, par value \$0.001 per share (the "Preferred Stock"). [...] 1,751,000 shares of Preferred Stock are designated as the Corporation's Series A Convertible Preferred Stock (the "Series A Preferred Stock"). [...] for each share of Series A Preferred Stock then held by them equal to \$1.00 (as adjusted for any stock splits, stock dividends, recapitalizations, combinations, or similar transactions with respect to such shares after the filing date of this Certificate, the "Original Issue Price").

The equity stake sold is calculated by data providers Pitchbook and VC Experts using a proprietary model that estimates the total number of issued shares out of the total shares authorized. Pitchbook estimates that a total of 10 million shares were issued at the time of the Series A financing.[26]

[26] See `https://my.pitchbook.com/profile/44160-31/company/profile#deal-history/19114-57T`.

B.2 Cumulative dividends

The following details the cumulative dividends available to the Series A investors:

> The holders of the outstanding shares of Series A Preferred Stock shall be entitled to receive dividends from time to time out of any assets legally available for payment of dividends equal to $0.08 per annum per share [...] Dividends on each share of Series A Preferred Stock shall be cumulative and shall accrue on each share from day to day until paid, whether or not earned or declared, and whether or not there are profits, surplus, or other funds legally available for the payment of dividends.

B.3 Liquidation preference and participation

This section details the liquidation preference for the Series A shareholders:

> The Series A Preferred Stock ranks senior with respect to distributions on liquidation to any Equity Securities that do not by their terms rank senior to or on a parity with Series A Preferred Stock, including the Common Stock. In the event of any liquidation, dissolution, or winding up of the Corporation, either voluntary or involuntary, the holders of the Series A Preferred Stock shall be entitled to receive, after payment or distribution and setting apart for payment or distribution of any of the assets or surplus funds of the Corporation required to be made to the holders of Liquidation Senior Stock (the "Liquidation Senior Stock Preference"), but prior and in preference to any payment or distribution and setting apart for payment or distribution of any of the assets or surplus funds of the Corporation to the holders of the Common Stock and to the holders of any other Equity Securities ranking junior to the Series A Preferred Stock with respect to distributions on liquidation, an amount for each share of Series A Preferred Stock then held by them equal to $1.00. [...] plus all accrued or declared but unpaid dividends on the Series A Preferred Stock up to and including the date of payment of such Liquidation Preference (the "Liquidation Preference").

This text details the participation rights of the Series A investors:

> If, after full payment of the Liquidation Senior Stock Preference, if any, the assets and funds of the Corporation legally available for distribution to the Corporation's stockholders exceed the aggregate Liquidation Preference payable pursuant to Section 2.2(a) [i.e, see quote above] of this Article Four, then, after the payments required by Section 2.2(a) of this Article Four shall have been made or irrevocably set apart for payment, the remaining assets and funds of the Corporation available for distribution to the Corporation's stockholders shall be distributed pro rata among (i) the holders of the Common Stock, (ii) the holders of the Series A Preferred Stock (with each such holder of Series A Preferred Stock being treated for this purpose as holding the greatest whole number of shares of Common Stock then issuable upon conversion of all shares of Series A Preferred Stock held by such holder pursuant to Section 2.5 of this Article Four), and (iii) among the holders of any other Equity Securities having the right to participate in such distributions on liquidation, in accordance with the respective terms thereof.

B.4 Board rights

Along with data collected by data providers such as VentureSource and Pitchbook, the certificate of incorporation shows that the Series A investors also have at least one board seat:

> [I]ncluding at least one member of the Board appointed by the holders of the Series A Preferred Stock.

C Contraction mapping details

The discrete-time representation derived in Proposition 1 allows us to numerically solve the contraction mapping (8) and (9) as a system of interdependent Bellman equations. Specifically,

1. We assume that $F_i(i)$ and $F_e(e)$ are flexible Beta distributions on [0,10]. We discretize qualities $i \sim F_i(i)$ and $e \sim F_e(e)$ by using a quadrature with 50 points for each distribution, resulting in 2,500 possible combinations of partner qualities. This fine grid proves more than sufficient to adequately approximate continuous distributions. The technical role of the support normalization is to allow for a sufficiently wide support of qualities so that the tails of the Beta distributions disappear at the boundaries. If the support is too narrow so that the density of qualities is positive at its boundaries, this would indicate that some qualities are not captured by the distribution. Our results are robust in the presence of wider and slightly narrower supports.

2. For any i and e, we set the initial guess of continuation values equal to $V^0 = (V_i^0(i), V_e^0(e)) = (0, \bar{V})$, where $\bar{V}$ is sufficiently large. For example, if the only contract term is the fraction of equity that the investor retains, then $\bar{V} = v_e(\bar{i}, \bar{e}, 0)$: the entrepreneur is guessed to retain the entire firm.[27] For any i and e, we set the initial guess of qualities of those agents from the opposite population, who are willing to match, equal to $(\mu_i^0, \mu_e^0) = (\mu_i^0(i), \mu_e^0(e)) = (\mathbf{1}_{i=\bar{i}}[\underline{e}, \bar{e}], [\underline{i}, \bar{i}])$. This choice implies that few agents are initially guessed to match, so the initial update to V^0, explained below, is smooth.

3. For every $n \geq 1$, we obtain $V^n = (V_i^n(i), V_e^n(e))$ and $(\mu_i^n, \mu_e^n) = (\mu_i^n(i), \mu_e^n(e))$ by inputting V^{n-1} and $(\mu_i^{n-1}, \mu_e^{n-1})$ into the right-hand side of the system of equations (8)–(9) and solving for the left-hand side. Because the system is a contraction mapping, $V = \lim_{n\to\infty} V^n$ is the equilibrium. We stop the process when $\|V^n - V^{n-1}\| < \varepsilon$, where $\varepsilon > 0$ is sufficiently small.

While theoretically there can be multiple equilibria in the search and matching game, we were unable to find parameters for which the equilibrium is not unique, despite examining a very broad parameter set.

[27] The static matching literature shows that this initial guess is consistent with an entrepreneur making an offer to match with a sufficiently good investor, and leads to computation of the so-called “entrepreneur-friendly” equilibrium. This terminology is somewhat confusing in the dynamic setting with contracts, as, once encountered and offered to match, it is an investor who offers the contract to an entrepreneur. The situation where the entrepreneur approaches the investor but is offered a take-it-or-leave-it contract in return is consistent with practice in the venture capital market. Our robustness checks explore the situation when the entrepreneur has extra bargaining power in addition to its threat to walk away from the deal and match with a different investor in the future.

D Derivation of theoretical moments

Let w_e be the discretized probability that an investor meets an entrepreneur of quality e; w_i be the discretized probability that an entrepreneur meets an investor of quality i; and the match indicator $m(i,e) = 1$ if i and e form a startup, and zero otherwise.

D.1 Contract-related moments

The expected value of contract term $c_k^*(i,e)$, $k \in \{1..D\}$ across all deals is

$$E(c_k^*) = \frac{\sum_i \sum_e w_i w_e m(i,e) c_k^*(i,e)}{\sum_i \sum_e w_i w_e m(i,e)}. \tag{17}$$

The variance of $c_k^*(i,e)$ across all deals is

$$V(c_k^*) = \frac{\sum_i \sum_e w_i w_e m(i,e)(c_k^*(i,e) - E(c_k^*))^2}{\sum_i \sum_e w_i w_e m(i,e)}. \tag{18}$$

For terms that only take values of zero or one, the variance does not contain additional, compared to the expected value, information, so we do not use it in the estimation. Finally, the covariance between any two contract terms $c_k^*(i,e)$ and $c_l^*(i,e)$, $k,l \in \{1..D\}$ across all deals is

$$Cov(c_k^*, c_l^*) = \frac{\sum_i \sum_e w_i w_e m(i,e)(c_k^*(i,e) - E(c_k^*)) \cdot (c_l^*(i,e) - E(c_l^*))}{\sum_i \sum_e w_i w_e m(i,e)}. \tag{19}$$

D.2 Moments related to expected time between deals

Recall that after a successful deal, the distribution of the number of new encounters for investor i is a Poisson random variable with intensity λ_i. Each encounter, in equilibrium, results in a deal with probability $p_i = \sum_e w_e m(i,e)$. The distribution of the number of deals, conditional on k meetings, is therefore an independent Binomial distribution with number of trials k and success probability p_i. This implies that the distribution of the number of deals is a Poisson distribution with intensity $\lambda_i p_i$. Therefore, the time between deals, τ, for investor i has mean and variance equal to

$$E(\tau|i) = \frac{1}{\lambda_i p_i}; \quad V(\tau|i) = \frac{1}{(\lambda_i p_i)^2}. \tag{20}$$

Across all deals done by investors with different qualities, the expected time between deals is, from the law of iterated expectations,

$$E(\tau) = E[E(\tau|i)] = \sum_i w_i^* E(\tau|i),$$

where $w_i^* = w_i \frac{\sum_e w_e m(i,e)}{\sum_i \sum_e w_i w_e m(i,e)}$ is the equilibrium share of deals done by investor i among all deals. This is different from w_i, the probability distribution of investors, because some investors match more frequently than others. Inserting w_i^* into the above equation and using (20),

$$E(\tau) = \frac{\sum_i \sum_e w_i w_e m(i,e) \frac{1}{\lambda_i p_i}}{\sum_i \sum_e w_i w_e m(i,e)}. \tag{21}$$

Because τ is random for any given deal, its variance is, from the law of total variance,

$$V(\tau) = E[V(\tau|i)] + V[E(\tau|i)]. \tag{22}$$

Using (20), the first term of (22) is

$$E[V(\tau|i)] = \frac{\sum_i \sum_e w_i w_e m(i,e) \frac{1}{(\lambda_i p_i)^2}}{\sum_i \sum_e w_i w_e m(i,e)};$$

additionally using (21), the second term is

$$V[E(\tau|i)] = \sum_i w_i^* (E(\tau|i) - E(\tau))^2 = \frac{\sum_i \sum_e w_i w_e m(i,e) \left(\frac{1}{\lambda_i p_i} - E(\tau)\right)^2}{\sum_i \sum_e w_i w_e m(i,e)},$$

The covariances between τ and contract term $c_k^*(i,e)$, $k \in \{1..D\}$ across all deals can similarly be derived from the law of total covariance,

$$Cov(\tau, c_k^*) = E[Cov(\tau, c_k^*|i)] + Cov[E(\tau|i), E(c_k^*|i)] \tag{23}$$

The first term of (23) is zero, because the time between deals does not vary with contract terms for a given investor. Using (17), (20), (21), and $E(c_k^*|i) = \frac{\sum_e w_e m(i,e) c_k^*(i,e)}{\sum_i \sum_e w_i w_e m(i,e)}$, the second term is

$$\begin{aligned} Cov[E(\tau|i), E(c_k^*|i)] &= \sum_i w_i^* (E(\tau|i) - E(\tau)) \cdot (E(c_k^*|i) - E(c_k^*)) \\ &= \frac{\sum_i \sum_e w_i w_e m(i,e) \left(\frac{1}{\lambda_i p_i} - E(\tau)\right) \cdot (c_k^*(i,e) - E(c_k^*))}{\sum_i \sum_e w_i w_e m(i,e)}. \end{aligned}$$

D.3 Success outcome-related moments

Recall that the probability of success for a given deal is

$$Pr(Success = 1|i,e) = \Phi(\kappa_0 + \kappa_1 \cdot \pi(i,e,c^*(i,e))), \tag{24}$$

with Φ the standard normal c.d.f. The expected success rate across all deals is then

$$\begin{aligned} E(Success) &= E\left[E(Success = 1|i,e)\right] \\ &= E\left[Pr(Success = 1|i,e)\right] \\ &= \frac{\sum_i \sum_e w_i w_e m(i,e) \Phi(\theta_0 + \theta_1 \cdot \pi(i,e,c^*(i,e)))}{\sum_i \sum_e w_i w_e m(i,e)}. \end{aligned} \tag{25}$$

Similarly to (22), because *Success* is random for any given deal, its variance is, from the law of total variance,

$$
\begin{aligned}
V(Success) &= E(V(Success|i,e)) + V(E(Success|i,e)) \qquad (26)\\
&= E(Pr(Success=1|i,e)\cdot(1-Pr(Success=1|i,e))) + V(Pr(Success=1|i,e))\\
&= \frac{\sum_i \sum_e w_i w_e m(i,e)\Phi(\theta_0+\theta_1\cdot\pi(i,e,c^*(i,e)))\cdot(1-\Phi(\theta_0+\theta_1\cdot\pi(i,e,c^*(i,e))))}{\sum_i\sum_e w_i w_e m(i,e)}\\
&\quad + \frac{\sum_i\sum_e w_i w_e m(i,e)(\Phi(\theta_0+\theta_1\cdot\pi(i,e,c^*(i,e))) - E(Success))^2}{\sum_i\sum_e w_i w_e m(i,e)},
\end{aligned}
$$

where we use (24) and (25) to arrive at the final expression.

The covariances between $Success$ and contract term $c_k^*(i,e)$, $k \in \{1..D\}$ across all deals are

$$
\begin{aligned}
Cov(Success, c_k^*) &= E(Cov(Success, c_k^*|i,e)) + Cov(E(Success|i,e), E(c_k^*|i,e)) \qquad (27)\\
&= Cov(Pr(Success|i,e), c_k^*(i,e))\\
&= \frac{\sum_i\sum_e w_i w_e m(i,e)(\Phi(\theta_0+\theta_1\cdot\pi(i,e,c^*(i,e))) - E(Success))\cdot(c_k^*(i,e)-E(c_k^*))}{\sum_i\sum_e w_i w_e m(i,e)},
\end{aligned}
$$

where $E(Cov(Success, c_k^*|i,e))$ is zero because the contract is deterministic for a given pair of investor and entrepreneur, and therefore does not vary with the startup's success outcome. To arrive at the final expression, we use (17), (24), and (25).

Finally, the covariance between $Success$ and τ across all deals is

$$
\begin{aligned}
Cov(\tau, Success) &= E[Cov(\tau, Success|i)] + Cov[E(\tau|i), E(Success|i)] \qquad (28)\\
&= Cov[E(\tau|i), E(Success|i)]\\
&= \sum_i w_i[E(\tau|i)-E(\tau)]\cdot[E(Success|i)-E(Success)]\\
&= \frac{\sum_i\sum_e w_i w_e m(i,e)\left(\frac{1}{\lambda_i p_i} - E(\tau)\right)\cdot(\Phi(\theta_0+\theta_1\cdot\pi(i,e,c^*(i,e))) - E(Success))}{\sum_i\sum_e w_i w_e m(i,e)},
\end{aligned}
$$

where $E[Cov(\tau, Success|i)]$ is zero because the time between deals does not vary with the startup's success outcome for a given investor. To arrive at the final expression, we use (20), (21), (24), (25), and $E(IPO|i) = \frac{\sum_e w_e m(i,e) Pr(IPO|i,e)}{\sum_i\sum_e w_i w_e m(i,e)} = \frac{\sum_e w_e m(i,e)\Phi(\theta_0+\theta_1\cdot\pi(i,e,c^*(i,e)))}{\sum_i\sum_e w_i w_e m(i,e)}$.

E Positively assortative matching in matching models with contracts

Figure 2 shows that better VCs tend to match with better entrepreneurs, but this pattern is imperfect. The following proposition shows that if the contracts were, instead, exogenous, and the matching function $g(i,e)$ exhibited a sufficient degree of complementarity, we would obtain positively assortative matching (e.g., good VCs would always match with good entrepreneurs):

Proposition 2. *Suppose that $\rho \le 0$ in specification (10) for $g(i,e)$, and that $c^*(i,e) \equiv const$ is exogenous. Then, the model solution admits positively assortative matching.*

Proof: The result follows from Shimer and Smith (2000) and Smith (2011). Specifically, when $\rho = 0$ and $c^*(i,e) \equiv const$, $\pi(i,e,c^*)$ depends on types i and e multiplicatively and is therefore log-modular. As a result, the model solution admits block segregation, in which VCs within a certain band of qualities only match with entrepreneurs within a certain band of qualities and never with anyone else, and vice versa. Formally, for $k \geq 1$, any VC quality $[\hat{i}_k, \hat{i}_{k-1}]$ matches with any entrepreneur quality $[\hat{e}_k, \hat{e}_{k-1}]$, where $(\hat{i}_0, \hat{e}_0) = (\bar{i}, \bar{e})$ and $(\hat{i}_k, \hat{e}_k)$, $k \geq 1$ are endogenous functions of model parameters. Block segregation immediately implies positively assortative matching. Further, when $\rho < 0$ and $c^*(i,e) \equiv const$, $\pi(i,e,c^*)$ is log-supermodular, which implies strict positively assortative matching.

When contracts are endogenous, there is no guarantee that the model solution admits positively assortative matching. In particular, Figure 2 shows that this matching pattern does not occur under our parameter estimates. This pattern is even more distorted in settings, in which qualities are weaker complements (e.g., in the IT market, as shown in Table A3). Intuitively, because contracts are chosen endogenously, it can pay, for a lower-quality VC who otherwise would have been excluded by the best entrepreneurs, to offer a larger fraction of the startup to these entrepreneurs to make a deal. The lower the VC quality, the higher is the fraction it has to offer to a given entrepreneur, and the higher is the cut-off on the entrepreneur quality, at which this VC can benefit.[28] This result suggests that it may be risky to simply assume positively assortative matching in settings that are affected by contracts (e.g., Cong and Xiao, 2018; Sannino, 2019).

F Robustness and extensions

F.1 Overconfidence

There is ample evidence that entrepreneurial individuals are overconfident, i.e., assign a higher precision to their information than the data would suggest.[29] Our model easily extends to allow for overconfidence on the part of agents. Modify (5) and (6) as

$$\pi_i^j(i,e,c^*) = \alpha(c^*) \cdot \pi^j(i,e,c^*), \tag{29}$$
$$\pi_e^j(i,e,c^*) = (1-\alpha(c^*)) \cdot \pi^j(i,e,c^*), \tag{30}$$

where superscript $j \in \{i,e\}$ indicates that VCs and entrepreneurs compute the total value and its split using potentially different beliefs. Let counterparty $j \in \{i,e\}$ believe that with probability p_j, signal e about entrepreneur quality is correct, and with probability $1-p_j$, the signal is completely uninformative, so that entrepreneur quality is a random draw from $F_e(e)$. Then, $\pi^j(i,e,c^*) = i \cdot (p_j e + (1-p_j)\bar{e}) \cdot h(c^*)$. For example, the case of entrepreneurs entirely relying on the signal about their quality but VCs doubting it is $p_e = 1$ and $p_i < 1$. In the presence of the difference in

[28] Formally, the VC's payoff may not be log-supermodular in the deal, in which an entrepreneur of the highest quality matches with a VC of the lowest quality allowed for such an entrepreneur in equilibrium: $\frac{\partial \pi_i\left(i,e,c^*(i,e)\right)}{\partial i \partial e} < 0$ (see Theorem 1 in Smith (2011)).

[29] Theoretical and empirical research on entrepreneurial overconfidence includes Cooper, Woo, and Dunkelberg (1988), Busenitz and Barney (1997), Camerer and Lovallo (1999), Bernardo and Welch (2001).

beliefs, the incentive rationality condition of the entrepreneur, (7), becomes

$$c^*(i,e) = \underset{c\in C:\pi_e^e(i,e,c)\geq V_e(e)}{\arg\max} \pi_i^i(i,e,c). \tag{31}$$

Note that even though the VC solves its optimization problem under its own beliefs, it has to provide the entrepreneur with at least its expected present value from continued search under the *entrepreneur's* beliefs. We compare parameter estimates of the main model with those of the modified model for $(p_i, p_e) = (0.75, 1)$. Panel B of Table A5 shows that even a rather substantial entrepreneurial overconfidence does not appear to affect the estimates.

F.2 Match-specific shocks

Two key results of the main model is that the set of counterparties a VC or entrepreneur matches with is fixed in equilibrium (however, within this set, the agents can match randomly), and that a given combination of agents always signs the same contract. One limitation of our model is that in reality, deal-specific information revealed during due diligence and contract negotiation may prevent a match between good-quality counterparties or allow a match between counterparties of vastly different qualities, or result in very different contracts between identical pairs of VCs and entrepreneurs by quality. Another limitation is that for many parameters, the model imposes a theoretical bound on the VC fraction of equity and firm value, which is estimated at 44.5% and 52.8%. However in practice, there are deals in which VCs sign deals with more VC-friendly terms.

To address both concerns, we extend the model to include match-specific shocks. Specifically, we change (4) as

$$\pi(i,e,c,z) = g(i,e)\cdot h(c,z), \tag{32}$$

where z is a match-specific shock drawn from $N(0,\sigma^2)$. An alternative specification, in which z affects g instead, gives similar results but does not address the second limitation of the main model, because the bound on VC-friendly contracts is entirely determined by h. $h(c,z)$ is parameterized as

$$h(c^*,z) = \exp\left\{\beta_1 c_1^* + (\beta_2 + z)c_1^{*2} + \beta'_{3:D+1}c_1^*(1-c_1^*)c_{2:D}^*\right\}. \tag{33}$$

The idea behind this particular parameterization is that deals between identical pairs of VCs and entrepreneurs by quality can still differ in terms of entrepreneurial risks and cost of effort, and agency conflicts between the parties, which tend to be more important as the VC owns a larger fraction of the firm. Alternative parameterizations, in which z impacts β_1 or all coefficients at once, give similar results.

Due to high computational complexity of adding an additional state variable, we discretize quality distributions on a 30 point grid and the distribution of match-specific shocks on a five point grid. The extended model's theoretical bound on the VC fraction of equity is 100% (for very low realizations of z) and thus encapsulates all observable deals. Panel C of Table A5 shows that the addition of a match-specific shock does not substantially affect the estimates.

F.3 Investment amount

In the main model, we do not treat capital raised by an entrepreneur as an endogenous contract term. This assumption is consistent with the view that the entrepreneur's idea requires a fixed amount of capital and constitutes a fraction of the entrepreneur's quality. An alternative polar case would be to treat capital raised as an entirely endogenous term. This assumption is consistent with the view that it is the entrepreneur's intrinsic quality, but not the startup's financing requirements, that determines the amount of capital a VC will give it. The reality is somewhere in between the two polar cases. Entrepreneurs may be unable to realize their idea at all if the amount of capital is below a certain threshold, while incremental improvements from the amount of capital above their initial estimate may be modest. Additionally, legal conventions in VC agreements produce a natural upper bound on capital invested in a single startup. In particular, VCs typically cannot have an investment in any startup exceed 10-15% of the total fund size.

In this section, we take an alternative polar view that capital raised is entirely endogenous. Specifically, we modify (11) as

$$h(c^*) = \exp\left\{\beta_0 \log c_0^* + \beta_1 c_1^* + \beta_2 c_1^{*2} + \beta'_{3:D+1}(1-c_1^*)c_{2:D}^*\right\}, \tag{34}$$

and modify (5) as

$$\pi_i(i,e,c^*) = \phi(c_0^*) \cdot \alpha(c^*) \cdot \pi(i,e,c^*), \tag{35}$$

keeping (6) unchanged. Equation (34) implies that the matching function in the presence of endogenous investment exhibits returns to scale with factor β_0. Equation (35) implies that the VC experiences costs of investment $1-\phi(c_0^*)$ per unit of profit. These include direct costs, such as loss of c_0^* at the time of financing, and indirect costs, such as time and effort spent monitoring and making decisions on the board of directors. We parameterize $\phi(c_0^*) = \exp\{\gamma_0 c_0^*\}$.[30]

The model with endogenous investment (an additional continuous contract term) is very computationally complex, therefore we do not attempt to estimate it. Instead, we examine its comparative statics with respect to β_0 and γ_0. For all reasonable parameter values, the model produces several unsatisfactory results. First, for a given entrepreneur, investments by the worst VCs it matches with are substantially higher than by the best VCs, as the worst VCs try to retain better entrepreneurs despite (as a practical concern) facing tighter upper bounds on capital invested in a single startup. Second, this pattern of investments results in a lower variance of the VC equity share, moving it farther away from that in the data. Finally, the dispersion of VC investments scaled by the industry-time average investment in the data is 144%, but the model underestimates it by a factor of 10 even for β_0 close to 1 (high returns to scale should result in a high dispersion). A fixed entrepreneur quality-related component in the VC investment would move the model output closer to the data, but this correction essentially amounts to assuming that investments are largely exogenously determined by agents' qualities. In any case, even if investment is indeed endogenous, it does not appear to affect moments of the model unrelated to investment for all reasonable parameter values.[31] In turn, it is unlikely that the impact of other contract terms on deal values and their split would be substantially affected.

G Calibration of the value of convertible preferred equity

To rationalize the 13.5% estimated valuation gap between common equity and (nonparticipating) convertible preferred in the value-maximizing contract of the search model, consider the following example. A startup raises $1 million using a preferred equity security that is convertible into

[30]It is easy to justify the positive relationship between total costs of investment and the VC share of the firm via a simple model. See, e.g., Grossman and Hart (1986).

[31]These results are available from the authors upon request.

14.7% of common equity (the estimated value-maximizing equity share). As is common for first rounds, the liquidation preference is 1X. The annual risk-free rate is 2% and the expected time until exit is 5 years (these are the average numbers over our sample period). The startup's value is $4 million, with return volatility of 50% per year. For simplicity, assume no future financing rounds are expected to be necessary.

Metrick and Yasuda (2010) derive the contingent claims valuation of convertible preferred equity. Under the above assumptions, the Black-Scholes value of the convertible preferred is $1.0 million, or 25.0% of firm value, which is close to the estimated 28.2% of firm value that the VC receives in our model. Relative to 14.7% of common equity, the Black-Scholes valuation implies that the convertible preferred feature is worth 10.3% of firm value.

The contingent claims example ignores other contractual features of the convertible preferred equity security, such as voting rights and protective provisions, which are nearly always present. These features increase the security's value and widen the valuation gap with common equity.

Note that the true $4 million valuation is different from the post-money valuation computed as $1 million / 0.147 = $6.8 million. The post-money valuation overstates the true value because its calculation assumes common equity (Gornall and Strebulaev, 2019).

Finally, note that the estimated valuation gap between convertible preferred and common equity is substantially smaller for the average observed contract $c^{*,Avg}$ and the unconstrained VC contract $c^{*,Unc}$.

H Identification

Section 1 describes the intuition behind the identification of β, the parameter vector that captures the impact of contract terms on firm value. In a nutshell, the outcomes and their correlations with contract terms are key in identifying these parameters. The γ parameters, which capture the impact of contract terms on the split of value between the VC and entrepreneur, are identified from the contract terms and their pairwise correlations. Intuitively, observed deals imply inequality constraints on agents' payoffs from their outside options to wait until the next encounter and contract offer, such that the deal is acceptable to both the entrepreneur and the investor. Across many deals, these inequalities identify the γ's.

The frequency of encounters parameters, λ_i and λ_e, have a first-order impact on the moments related to the time between investors' deals, as shown in the top row of graphs in Figure A1. An increase in λ_i decreases both the first moment (deals occur more frequently on average) and the second moment (high-quality VCs meet more entrepreneurs and hence stop matching with lower-quality entrepreneurs, who instead match with low-quality VCs, driving up their low incidence of matches and compressing the distribution of time between investors' deals). An increase in λ_e also decreases the first moment but increases the second moment (high-quality entrepreneurs meet more VCs and hence stop matching with lower-quality VCs, lowering their incidence of matches and widening the distribution of time between investors' deals). The impact of λ_i and λ_e on other moments (i.e., contract terms and correlations between time between deals and contract terms) is weaker.

The quality distribution parameters, a_i, b_i, a_e, and b_e, have the strongest impact on the correlations between time between deals and contract terms (while these parameters also impact moments of time between deals and contract terms, this impact is easily overshadowed by the frequency of encounters parameters). The middle row of graphs in Figure A1 shows that an increase in a_i (b_e) shifts a mass of VCs (entrepreneurs) from low quality to middle quality (from high quality to middle quality), increasing competition between VCs for high-quality entrepreneurs. This affects the correlations through a simultaneous shift in both the expected time between deals and contracts that is uniquely different from non-distribution parameters (the impact of a_i and b_e is often both qualitatively and quantitatively different). Conversely, an increase in a_e (b_i) shifts a mass of VCs (entrepreneurs) from high quality to middle quality (from low quality to middle quality), decreasing competition between VCs and generally affecting the correlations in the opposite direction.

A lower value of the complementarity parameter, ρ, makes the matching function $g(i, e)$ in (10) more complementary. As a result, high-quality (low-quality) VCs and entrepreneurs become more (less) competitive. This increases the dispersion of time between investors' deals (low-quality VCs become less attractive and wait longer between deals, widening the distribution of time between investors' deals) but decreases the dispersion of contract terms (with high complementarities, the market becomes more segmented in quality, so VCs of all qualities become unafraid to lose entrepreneurs and offer more VC-friendly contracts with lower variation across investors). The bottom row of graphs in Figure A1 illustrates this intuition.

Finally, the remaining two success outcome-related moments, the average success frequency and the correlation between time between investors' deals and success, naturally identify the parameters capturing the link between the firm value and success, κ_0 and κ_1.

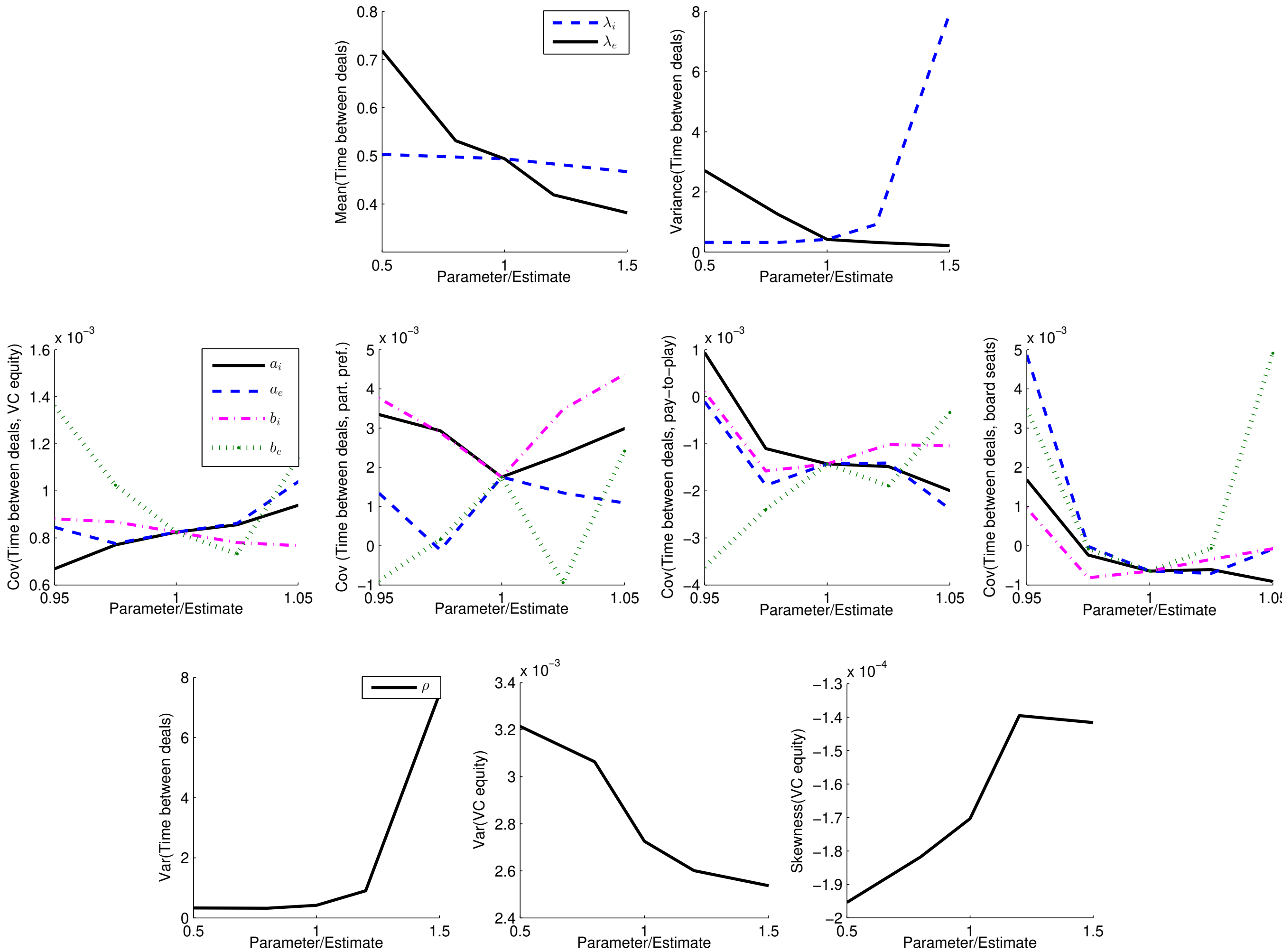

Figure A1: **Sensitivity of selected moments to model parameters.** The top row shows sensitivity of moments of the time between investors' deals to the change in frequency of encounters parameters, λ_i and λ_e. The middle row shows sensitivity of covariances between time between deals and contract terms to the change in quality distribution parameters, a_i, b_i, a_e, and b_e. The bottom row shows sensitivity of higher moments of time between deals and the VC equity share to the change in the complementarity parameter, ρ. The change in parameters on the horizontal axes is relative to their estimated values presented in Table V.

Table A1: Summary statistics: follow-on sample.

Descriptive statistics of startups and their first round equity financings for the samples described in section 3. The "Follow-on sample" includes financing rounds between 2002 and 2015 where the outcome variable is a dummy variable equal to one if the startup raised a new round of financing or had a successful exit within two years of their first financing. A financing is in this sample if the equity stake and contract terms are known. "All deals" are all the financings in 2002–2015 regardless of missing data. The variables are as defined in Table I. Only means are reported for indicator variables.

Panel A: Firm and financing characteristics

	Follow-on sample				All deals 2002–2015			
	Obs	Mean	Median	Std dev	Obs	Mean	Median	Std dev
Firm age at financing (yrs)	2,581	1.624	1.147	1.65	10,613	1.691	1.169	1.70
Information technology	2,581	0.462			10,613	0.476		
Healthcare	2,581	0.234			10,613	0.183		
Time since last VC financing (yrs)	2,343	0.707	0.255	1.27	8,938	0.793	0.304	1.34
Syndicate size	2,581	1.821	2	1.03	10,613	1.649	1	1.02
Capital raised in round (2012, $ mil.)	2,581	7.207	4.586	9.27	9,754	5.502	2.894	8.16
Post-money valuation (2012, $ mil.)	2,581	22.069	12.927	41.47	6,104	19.036	11.399	34.16
Financing year	2,581	2008.491	2008	3.59	10,613	2009.6	2010	3.92
Seed round	2,581	0.150			10,613	0.227		

Panel B: Contracts

	Follow-on sample		All deals 2002–2015	
	Obs	Mean	Obs	Mean
% equity sold to investors	2,581	0.367	6,104	0.351
Participating pref.	2,581	0.401	4,733	0.396
Cumulative dividends	2,577	0.168	4,559	0.186
Pay-to-play	2,581	0.101	3,071	0.099
Redemption rights	2,529	0.311	3,460	0.332
VC has board seat	2,581	0.872	10,613	0.624
Liquidation mult. > 1	2,558	0.032	4,682	0.031
Full ratchet anti-dilution	1,642	0.014	3,379	0.012
Common stock sold?	2,578	0.082	4,895	0.051

Table A2: Parameter estimates of model modifications: alternative success outcome and contract definitions.

The table describes parameter estimates of model modifications described in Section 6. Panel A describes the estimates of the model where success outcomes are captured by IPO. Panel B describes the estimates of the model where success outcomes are captured by follow-on financing. Panel C describes estimates of the main model (success outcomes are captured by IPO+Acq.$> 2X$ variable) where missing contract terms are imputed as zeros, provided the VC equity fraction and at least one additional term is non-missing in the data. Significance: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

	A. IPO		B. Follow-on financing		C. Imputed terms	
Parameter	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Distribution of qualities, a_i	1.876***	0.579	2.191***	0.398	1.921***	0.251
Distribution of qualities, b_i	3.512***	1.166	2.369***	0.580	3.653***	1.400
Distribution of qualities, a_e	3.182**	1.571	4.612***	0.667	3.106***	0.710
Distribution of qualities, b_e	4.233***	0.924	3.711***	1.362	4.062***	0.789
Frequency of encounters, λ_i	13.417***	4.568	12.936**	5.444	13.475***	3.656
Frequency of encounters, λ_e	10.311	7.363	9.076**	4.099	10.954***	4.127
Substitutability of qualities, ρ	-1.334***	0.261	-1.307***	0.121	-1.343***	0.152
Probability of success, intercept, κ_0	-4.072***	1.157	-6.661	7.328	-4.091***	1.235
Probability of success, total value, κ_1	0.075***	0.029	0.458	0.488	0.113***	0.043
Total value, share of VC equity, β_1	0.682*	0.367	0.754***	0.108	0.650**	0.312
Total value, share of VC equity squared, β_2	-2.347***	0.639	-2.692***	0.326	-2.375***	0.322
Total value, participation, β_3	-0.163***	0.032	-0.168**	0.083	-0.163***	0.043
Total value, pay-to-play, β_4	0.024	0.066	0.031	0.047	0.023	0.027
Total value, VC board seat, β_5	-0.026***	0.010	-0.028*	0.016	-0.026***	0.007
Total value, participation × pay-to-play, β_6	0.016	0.091	0.013	0.035	0.017	0.026
Total value, participation × VC board seat, β_7	0.033	0.032	0.039	0.083	0.032	0.043
Total value, pay-to-play × VC board seat, β_8	0.019	0.020	0.013	0.038	0.019	0.058
Split of value, intercept, γ_1	-0.211*	0.116	-0.215***	0.058	-0.211***	0.032
Split of value, participation, γ_2	-0.175***	0.054	-0.157*	0.089	-0.171***	0.055
Split of value, pay-to-play, γ_3	0.056	0.057	0.053	0.051	0.057***	0.008
Split of value, VC board seat, γ_4	-0.040***	0.006	-0.041***	0.015	-0.040***	0.002
Split of value, participation × pay-to-play, γ_5	0.016	0.114	0.011	0.035	0.016	0.026
Split of value, participation × VC board seat, γ_6	0.029	0.054	0.028	0.089	0.029	0.055
Split of value, pay-to-play × VC board seat, γ_7	0.012	0.094	0.011	0.036	0.013	0.068
Number of observations	1,695		2,581		2,439	

Table A3: Parameter estimates of model modifications: industry and geography subsamples.

The table describes parameter estimates of model modifications described in Section 6. Panel A describes the estimates of the model using a subsample of deals in the IT industry. Panel B describes the estimates of the model using a subsample of deals in the Healthcare industry. Panel C describes the estimates of the model using a subsample of deals with startups located in California. Significance: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

	A. IT		**B. Healthcare**		**C. California**	
Parameter	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Distribution of qualities, a_i	1.681***	0.259	2.075***	0.408	1.920**	0.775
Distribution of qualities, b_i	3.407***	0.912	3.756**	1.653	3.559***	0.924
Distribution of qualities, a_e	3.131***	1.057	2.709*	1.516	3.132***	0.728
Distribution of qualities, b_e	4.272***	0.897	4.333**	2.066	4.161***	1.449
Frequency of encounters, λ_i	13.785***	4.077	10.901**	4.957	16.494***	5.241
Frequency of encounters, λ_e	11.736**	5.138	8.571*	4.488	12.952***	4.099
Substitutability of qualities, ρ	-1.155***	0.094	-1.597***	0.175	-1.367***	0.306
Probability of success, intercept, κ_0	-4.113*	2.296	-4.308*	2.476	-3.967**	2.000
Probability of success, total value, κ_1	0.112*	0.060	0.115*	0.059	0.108*	0.062
Total value, share of VC equity, β_1	0.701**	0.290	0.738***	0.233	0.680	0.569
Total value, share of VC equity squared, β_2	-2.452***	0.204	-2.113***	0.376	-2.373***	0.547
Total value, participation, β_3	-0.170*	0.099	-0.147***	0.022	-0.163***	0.059
Total value, pay-to-play, β_4	0.029	0.131	0.022	0.050	0.023	0.152
Total value, VC board seat, β_5	-0.026***	0.009	-0.025***	0.008	-0.026***	0.010
Total value, participation × pay-to-play, β_6	0.016	0.097	0.014	0.042	0.016	0.032
Total value, participation × VC board seat, β_7	0.033	0.099	0.034*	0.020	0.032	0.059
Total value, pay-to-play × VC board seat, β_8	0.016	0.035	0.018	0.089	0.019	0.024
Split of value, intercept, γ_1	-0.206***	0.070	-0.174***	0.054	-0.211***	0.076
Split of value, participation, γ_2	-0.177*	0.096	-0.179***	0.031	-0.174**	0.070
Split of value, pay-to-play, γ_3	0.058	0.172	0.058*	0.034	0.056	0.173
Split of value, VC board seat, γ_4	-0.041***	0.006	-0.043***	0.005	-0.041***	0.007
Split of value, participation × pay-to-play, γ_5	0.018	0.121	0.016	0.079	0.016	0.095
Split of value, participation × VC board seat, γ_6	0.028	0.096	0.030	0.031	0.029	0.070
Split of value, pay-to-play × VC board seat, γ_7	0.012	0.025	0.012	0.074	0.013	0.101
Number of observations	788		444		934	

Table A4: Parameter estimates of model modifications: time subsamples.

The table describes parameter estimates of model modifications described in Section 6. Panel A describes the estimates of the model using a subsample of deals before the release of Amazon's AWS cloud in 2007. Panel B describes the estimates of the model using a subsample of deals after the release of Amazon's AWS cloud. Panel C describes the estimates of the model using a subsample of deals before the Lehman bankruptcy (09/15/2008). Panel D describes the estimates of the model using a subsample of deals after the Lehman bankruptcy. Significance: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

	A. Before AWS		**B. After AWS**		**C. Before Lehman**		**D. After Lehman**	
Parameter	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Distribution of qualities, a_i	1.972***	0.542	2.017***	0.669	1.924***	0.421	2.092***	0.735
Distribution of qualities, b_i	3.686***	0.952	3.415***	1.230	3.748***	1.015	3.485*	1.778
Distribution of qualities, a_e	3.014***	1.381	3.103***	1.078	3.154**	1.574	3.110**	1.272
Distribution of qualities, b_e	4.057***	1.353	3.743***	1.375	4.157***	1.347	3.599	2.412
Frequency of encounters, λ_i	12.117**	3.002	13.409***	5.048	13.434***	2.965	13.518**	5.304
Frequency of encounters, λ_e	8.301**	3.358	17.037***	5.342	10.431**	4.166	17.699***	6.316
Substitutability of qualities, ρ	-1.594***	0.218	-1.213***	0.521	-1.400***	0.162	-1.301***	0.375
Probability of success, intercept, κ_0	-4.058**	1.951	-4.236	3.287	-3.997*	2.252	-4.300	4.203
Probability of success, total value, κ_1	0.103**	0.058	0.108*	0.062	0.105*	0.059	0.102	0.808
Total value, share of VC equity, β_1	0.673*	0.395	0.656*	0.394	0.682***	0.209	0.556	0.667
Total value, share of VC equity squared, β_2	-2.176***	0.228	-2.550***	0.542	-2.333***	0.201	-2.497***	0.837
Total value, participation, β_3	-0.146***	0.015	-0.177***	0.045	-0.159***	0.022	-0.177**	0.077
Total value, pay-to-play, β_4	0.024*	0.014	0.026	0.055	0.027	0.018	0.027	0.073
Total value, VC board seat, β_5	-0.026***	0.004	-0.027***	0.011	-0.026***	0.004	-0.027*	0.015
Total value, participation × pay-to-play, β_6	0.014	0.043	0.017	0.303	0.016	0.063	0.016	0.257
Total value, participation × VC board seat, β_7	0.027***	0.002	0.033	0.045	0.032***	0.0082	0.033	0.077
Total value, pay-to-play × VC board seat, β_8	0.018	0.043	0.016	0.113	0.017	0.047	0.017	0.090
Split of value, intercept, γ_1	-0.216***	0.035	-0.232***	0.040	-0.196***	0.037	-0.230***	0.085
Split of value, participation, γ_2	-0.182***	0.018	-0.175***	0.034	-0.174***	0.0183	-0.172***	0.064
Split of value, pay-to-play, γ_3	0.056**	0.027	0.056	0.138	0.057	0.036	0.057	0.105
Split of value, VC board seat, γ_4	-0.045***	0.004	-0.043***	0.011	-0.041***	0.003	-0.040***	0.010
Split of value, participation × pay-to-play, γ_5	0.015	0.171	0.016	0.416	0.015	0.174	0.017	0.458
Split of value, participation × VC board seat, γ_6	0.033***	0.008	0.029	0.034	0.029***	0.008	0.029	0.064
Split of value, pay-to-play × VC board seat, γ_7	0.016	0.081	0.012	0.070	0.012	0.056	0.012	0.104
Number of observations	885		810		1,360		335	

Table A5: Parameter estimates of model modifications: alternative theoretical assumptions.

The table describes parameter estimates of model modifications described in Section 6. Panel A describes the estimates of the model where the annual discount rate for the agents is 20%. Panel B describes the estimates of the model where entrepreneurs are overconfident (the overconfidence parameter is 25%). Panel C describes estimates of the model where firm values are affected by a match-specific shock. Significance: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

	A. High discount rate		**B. Ent. overconfidence**		**C. Match-specific shocks**	
Parameter	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Distribution of qualities, a_i	2.030***	0.257	2.537***	0.305	1.925***	0.470
Distribution of qualities, b_i	3.560***	0.847	4.078**	1.693	3.495***	0.821
Distribution of qualities, a_e	3.423***	0.274	2.976***	0.905	3.300***	0.749
Distribution of qualities, b_e	4.372***	0.951	4.176**	1.745	3.930***	1.317
Frequency of encounters, λ_i	8.199***	0.815	13.732***	2.666	12.525***	4.650
Frequency of encounters, λ_e	7.458**	3.002	10.742***	3.055	11.940**	5.765
Substitutability of qualities, ρ	-1.391***	0.198	-1.343***	0.290	-1.506***	0.156
Probability of success, intercept, κ_0	-3.984***	0.752	-4.122*	2.188	-4.449**	2.098
Probability of success, total value, κ_1	0.105***	0.024	0.107*	0.056	0.110*	0.058
Total value, share of VC equity, β_1	0.680***	0.198	0.682	0.408	0.507	0.317
Total value, share of VC equity squared, β_2	-2.338***	0.750	-2.375***	0.273	-2.215***	0.297
Total value, participation, β_3	-0.161***	0.053	-0.165*	0.091	-0.143***	0.006
Total value, pay-to-play, β_4	0.022	0.015	0.023	0.032	0.019**	0.009
Total value, VC board seat, β_5	-0.026***	0.008	-0.026***	0.009	-0.021***	0.004
Total value, participation × pay-to-play, β_6	0.016	0.048	0.018	0.053	0.015	0.213
Total value, participation × VC board seat, β_7	0.033	0.053	0.032	0.091	0.032	0.042
Total value, pay-to-play × VC board seat, β_8	0.019	0.092	0.019	0.085	0.019	0.016
Split of value, intercept, γ_1	-0.205***	0.053	-0.204**	0.102	-0.271***	0.058
Split of value, participation, γ_2	-0.172***	0.015	-0.176*	0.093	-0.176***	0.024
Split of value, pay-to-play, γ_3	0.060***	0.017	0.056	0.040	0.062***	0.018
Split of value, VC board seat, γ_4	-0.041***	0.005	-0.041***	0.013	-0.044***	0.014
Split of value, participation × pay-to-play, γ_5	0.015	0.055	0.016	0.048	0.016	0.136
Split of value, participation × VC board seat, γ_6	0.029*	0.015	0.029	0.093	0.031	0.024
Split of value, pay-to-play × VC board seat, γ_7	0.012	0.152	0.011	0.269	0.013	0.071
Entrepreneur overconfidence (fixed)	–	–	25%	–	–	–
St.dev. of match-specific shock, σ	–	–	–	–	0.323*	0.171
Number of observations	1,695		1,695		1,695	