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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, which 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. Counterfactuals show that reducing 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 entrepreneurs' ability to promise outcome-independent payments to venture capitalists (VCs) is affected by their limited initial resources and the limited liability constraint, as well as severe information asymmetries and agency problems (Hall and Lerner, 2010). The resulting observed contracts between entrepreneurs and VCs are quite complex. The predominant explanation in the theoretical literature is that 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). A typical, but not necessary set of assumptions in deriving this result is that investors are homogeneous and competitive, do not actively impact the value of the start-up, and thus earn zero rents.

A contrasting view, considered by papers that primarily focus on the VC market, is that in the presence of limited liability and various market imperfections, investors negotiate certain contract terms, not to grow the size of the pie divided between the contracting parties, but to change the distribution of the pie in investors' favor. This outcome 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), when VCs can actively impact the startup value, a VC of lesser quality (a shorthand for its experience, network, and other value-added activities) is usually a poor substitute for a higher quality investor. Moreover, VCs are not perfectly competitive, as each investor faces a flow of entrepreneurs and can choose among them (e.g., Opp, 2019). Finally, as repeat players in the market for startup financing, VCs have a broader view of the market and the distribution of possible outcomes than entrepreneurs, as well as a better understanding of the implications of complicated contract terms. As a result, VCs have substantial bargaining power; furthermore, lawyers and regulators do not have strong incentives to correct this imbalance. The resulting contracts are favorable to the VC – even if VC-friendly contracts reduce the startup's value – but come at a cost to 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

[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).

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 counterparties meet, the investor can either offer a contract or resume its search in the hopes of meeting a better entrepreneur. 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). It also allows, as a special case, a world with perfectly competitive homogenous investors with no bargaining power. 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 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 give 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 even higher ownership stakes since they add more value to the firm, and it is costly for the entrepreneur to search for another high-quality 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 the lowered value is better 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 rights significantly lower 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. However, these effects 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. The effects of pay-to-play are also slightly weaker in magnitude than those of VC board seats.

We find that the equilibrium contract terms negotiated between VC and entrepreneur depend on their respective qualities. There are also 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 with a low VC equity share and without participation rights or VC board seats. As the same entrepreneur matches with a VC of increasingly 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 negotiate additionally for participation.

The model does not identify the mechanisms driving these results, but we offer the following observations. First, the increased VC cash flow rights of the participation term explain the increase in the fraction of firm value that goes to the VC. However, the channel through which participation rights reduce 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). Second, VC board seats can move a higher fraction of value to VCs through increased control rights. At the same time, board seats 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; Kaplan and Strömberg, 2004; Zhu, 2019). This value reduction may offset any value creation 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. Next, we observe that 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. In turn, pay-to-play may increase firm value due to increased incentives to exert effort on the part of the entrepreneur. Finally, the results on interactions among contact terms 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 quality VC match 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 goes to higher-quality VC due to a higher equity share, participation, and board representation. Also note that to preserve incentives and remain competitive, 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 hardly 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 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. A similar consequence of reducing search frictions is derived theoretically for OTC markets by Glode and Opp (2018). In the appendix we explore a different counterfactual that removes certain contractual features (implemented by contract terms) altogether. Generally, removing VC-friendly features could lead to modest firm value creation, but some VCs and entrepreneurs would be worse off. 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.

Our search-and-matching model is designed to be tractable and transparent, but this comes at the cost of making some judgement calls on model inputs and simplifying assumptions about certain features of the data generating process. We show that our results are robust to alternative measures of success (e.g. follow-on financings or IPOs), different discount rates, and sub-sample splits by industry, location, time, syndication characteristics, and proxies for startup capital intensity. Moreover, our results are qualitatively unaffected when the model incorporates directed search among agents for counterparties, additional bargaining power of the entrepreneur, variation in the startup value and contract for a given pair of agent qualities, entrepreneur overconfidence, endogenous startup capital requirements, or one-dimensional asymmetric information about entrepreneur quality.

Our paper is related to multiple strands of literature. First, we make a novel contribution to the emerging empirical literature on selection in venture capital. Our paper is most 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 because the dollar impact of various contract terms on the value of the startup and its split has to be estimated. Also, most entrepreneurs only match with a VC once. As a result, we estimate our 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 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 (their VCs are assumed to break even). Key to obtaining valuations in dollars, their complex option valuation model 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-and-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; as the meet rates increase, the model outcomes converge to those in the static model of Hatfield and Milgrom (2005). While our model is continuous-time, 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, in contrast to 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. A more fully developed extension of our two-sided search and matching model would also include two-sided adverse selection and information aggregation; however, we leave this extension for future work.

1 Identification Problem

To illustrate the identification problem and the source of variation the model exploits, 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 (an assumption we relax in an extension). 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. Suppose that 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 $1.2 \cdot \exp\{-1\}$.

Feasible matches are 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). In cells where a match is feasible, we report the value of the startup, π, and the 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

[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.

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, the researcher has very limited information about most entrepreneurs and infrequently observes VC 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 would lead the researcher to incorrectly conclude that a higher 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. In our data set, however, almost all entrepreneurs and some investors only participate in a single startup, leaving only a small and selected subset of repeat players to identify the model.[3]

An alternative approach 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 with value. This can be imprecise and is extremely computationally intensive. Instead of reverse-engineering individual i, e, and π for each match, we 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, when 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). Section 4.2.2 discusses parameter identification in our method-of-moments setting in more detail.[5]

[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.

[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.

[5]A different way of viewing our dynamic search and matching model is to interpret it as a selection model that captures the endogenonous selection of agents into deals. Like an instrument in a Heckman model, the randomness in agents' encounters serves as a source of exogenous match variation that helps to identify the model. 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 and 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 agents cannot observe potential counterparties subsamples other than their own. If subsamples are exogenously different, a given investor type exogenously matches with a different entrepreneur type (and vice versa) across subsamples, resolving the identification problem. The necessary randomness in encounters for a given agent's type arises naturally in our dynamic model, without any need for arbitrarily splitting the market. 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.

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, as well as across agents.[6] Search is costly because agents discount the value of potential future encounters at a constant rate r. Upon an encounter, counterparties' identities are instantly revealed to each other, and they may enter contract negotiations.[7]

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 in the market.[8] For reasons explained below, this set explicitly prohibits fixed cash transfers from the entrepreneur to the investor (transfers in the opposite direction can be allowed). 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,

[6] In Section 7, we present an extension that allows for directed search. The qualitative results do not change, and the random search assumption makes the driving forces of the model more transparent.

[7] Chemmanur, Krishnan, and Nandy (2011) and Kerr, Lerner, and Schoar (2011) provide evidence that counterparties acquire much information about each other before financing. Section 7 discusses a model extension with one-sided asymmetric information.

[8] 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. Casual conversations with first-time entrepreneurs confirm that at early stages of startup financings, there is little room for contract negotiation. Nevertheless, in Section 7 we present an extension that allows the entrepreneur to retain a fraction of the startup's surplus over and above her outside option. The qualitative results do not change.

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 expected value of

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

Importantly, π is the expected present value of all the startup's future uncertain cash flows, including the exit value, and is obtained over the course of several years. This uncertainty, coupled with very limited wealth on the part of the early-stage entrepreneur and her limited liability (startups financed by VCs typically incorporate), implies that the Coase Theorem (Coase, 1960) does not generally hold. That is, the agents cannot simply agree on a firm value-maximizing fixed cash transfer from the entrepreneur to the investor; instead, they have to sign an outcome-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 $h(c)$.[9] 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,

$$\begin{aligned} \pi_i(i,e,c) &= \alpha(c) \cdot \pi(i,e,c), & (5)\\ \pi_e(i,e,c) &= (1-\alpha(c)) \cdot \pi(i,e,c). & (6) \end{aligned}$$

For example, if the counterparties can only negotiate over the fraction of common equity that the investor receives, then $\alpha(c) = c$. In practice, they can negotiate over additional contract terms, so $\alpha(c)$ 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

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

are replaced by new unmatched agents in their populations.[10]

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

[10] 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.

The model includes, as a special case, perfectly competitive investors as typically assumed in the theoretical literature. Investors become more competitive when they increase in number (λ_e is higher), when they are more substitutable ($F_i(i)$ has lower dispersion), and when their impact on the startup value is small ($\pi(i, e, c) \approx \pi(e, c)$), 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.[11] 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 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 (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.[12] We

[11]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.

[12]California and Delaware are the preferred choices of states of incorporation. Of all startups in VentureSource,

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. The unfiltered sample has over 21,000 contracts, with some 8,500 associated with first round financings. 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 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 by the largest investor in the round if a flag is missing. 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 11% of first financing rounds, all of which involve either 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, defined below, is based on initial public offerings and high-value acquisitions. 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

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.

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 0.69 (0.28) years.[13] This variable helps 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.[14] While the post-money valuation is usually interpreted as the market value of the firm at the time of financing (π in the model), 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 choice of metric.[15] 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 (after 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. 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

[13] To give an unbiased view on deal frequency, this statistic does not impose the filter that the outcome variable and the main contract terms of interest are known for each deal.

[14] 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.

[15] 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.

contributes more deals and spans a longer time series than VC Experts.

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 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, after which the investor receives 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 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. Overall, there is a substantial variation in both cash flow and control terms across deals.

Panel C of Table II summarizes exit outcomes, tracked until March 2018. Binary outcome variables have been the traditional measure of success in the empirical VC literature. 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 are financed by VCs who conclude first-round deals slightly faster (0.69 vs. 0.85 years since leading their previous first-round deal), raise more capital per deal ($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 usage of contract terms. 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 have 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 to date, 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, a hump-shaped relation with an internal optimal equity share is predicted by theory (for example, double moral hazard problems that require both agents to expend effort), which we discuss 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 changes only 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 above. We address these problems using the search model. To operationalize the model, we have to make a few 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 would not necessarily provide the same quality as an $e = 2$ entrepreneur, if the agents' roles shifted).[16]

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 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. In a computationally expensive extension of our main model, we find that cumulative dividends do not materially impact the firm value and its split.

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 the case of 100% ownership, and their impact is likely greatly diminished when the investor owns no equity.

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

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

[16] 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.

Without the exponential term, this equation represents a common equity contract (that is, $\alpha(c^*) = c_1^*$). The exponential term captures the effect of additional contract terms. The observed contract terms, $c_{2:D}^*$, are multiplied by $c_1^*(1-c_1^*)$ because, similar to the firm value function, their impact on the agents' payoffs vanishes when the investor owns a very large or very small fraction of the company.[17] The intercept, γ_1, captures the effect of any terms for which we do not have data or for terms that are always present. Of these terms, liquidation preference is probably 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 $1 - c_1^*$. The value split is bounded between zero and one at estimated parameters.[18]

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 includes all first and second moments of the equilibrium model outcomes (contract terms, success rates, and investors' time between financings), and their covariances. The only exception is that we exclude

[17] For both the value function (11), and the value split (12), all our quantitative 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., $\zeta_1 = 0$).

[18] To be precise, in the model solution we flip the sign of any term that is perceived as entrepreneur-friendly, 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 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.

4.2.2 Identification and estimated moments

Our empirical model has 24 parameters and uses 24 moments to estimate them. In general, each moment contains information about each parameter. However, economic forces in our model dictate that small subsets of moments contain much more information about certain subsets of parameters and hence can be said to economically "identify" these parameters. Here, we briefly discuss such first-order links between models and parameters. Outcomes and their correlations with contract terms are key in identifying the main parameters. The β parameters – which capture the impact of contract terms on the startup value – are identified from the contract terms and their correlations with the success variable. Intuitively, a change in β has a first-order effect on both the incidence of a term across deals and the likelihood of a success. The γ parameters – which capture the impact of contract terms on the split of value between the VC and entrepreneur – are identified from the the remaining information in contract terms. Intuitively, a change in γ only has an indirect effect on the likelihood of a success (via rebalancing of terms across deals and rematching) but a first-order effect on the incidence of a term across deals. The subset of β and γ parameters that captures interactions among simple contract terms is intuitively identified from pairwise correlations among terms.

The frequencies 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 2. An increase in λ_i decreases both the first moment (deals occur more frequently on average) and the second moment (an increase in investor frequency of meets, in the model, is equivalent to there being more entrepreneurs to match with, so VCs of all qualities make deals more frequently, compressing the distribution of time between deals). An increase in λ_e also decreases the first moment but increases the second moment (a decrease in investor frequency of meets is equivalent to there being more VCs, so VCs of lower qualities are rarely accepted as matches, widening the distribution of time between deals). The impact of λ_i and λ_e on other moments 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.[19] Intuitively, the change in quality distributions changes the bargaining power both within populations of VCs and entrepreneurs

[19] While these parameters also impact the moments of the time between deals and contract terms, this impact is easily overshadowed by the frequency of encounters parameters.

and across populations, jointly changing contracts and match rates. The middle row of graphs in Figure 2 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 among VCs for high-quality entrepreneurs. This affects the correlations through a simultaneous shift in both the expected time between deals and contracts, which is uniquely different from non-distribution parameters. Since the impact of a_i and b_e is often both qualitatively and quantitatively different, they are not interchangeable and can be separately estimated. 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 among VCs and generally affecting the correlations in the opposite direction.

Next, 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 2 illustrates this intuition (as we will see below, the estimated ρ turns out to be negative such that an increase along the horizontal axis means a more negative value of ρ). Hence, higher-order moments of the VC equity share (as well as the remaining information in moments capturing time between deals) intuitively identify ρ. 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.

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.

4.2.3 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).[20]

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.[21]

4.2.4 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 3 shows the contracts for all combinations of VC and entrepreneur qualities for which both parties are willing to match 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

[20] 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.

[21] 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.

sometimes attract higher quality entrepreneurs by offering more entrepreneur-friendly terms.[22] 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%. This equity share 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 4 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 but is otherwise the same as the representative contract. Firm value is 77.5% of its maximal value under this contract.

4.2.5 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 4 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 a 14.7% VC equity share in the value-maximizing contract c^{Max} may appear low, this contract actually leaves the VC with 28.2% of the total value. In Appendix F, 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: It accounts for approximately 76% of the

[22] 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.

gap (10.3% of the 13.5% gap). The presence of participation and VC board seats further increases the VC's fraction of firm value. 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 firm value 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 instead use the fraction of the firm retained by the VC. 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. In deals with the representative contract, $c^{*,Avg}$, the difference in valuations is 19.3%. In large first-round financings, the dollar difference between the post-money and modified valuation can easily reach millions of dollars.

4.2.6 Equilibrium Effects of Matching

Figure 4 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, a higher quality VC offers more investor-friendly contracts to the same entrepreneur, compared to a lower quality VC. 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 5 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 goes to the VC through a higher equity share, as well as 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.

4.2.7 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 the theoretical VC contracting literature on which mechanisms are likely at work in practice and uncover new insights for consideration in future work. 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 effectiveness of the contract to deal with the above inefficiencies, compared to a regular convertible equity contract in equilibria without perfect competition.[23] 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 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

[23] 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.

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 worse outcomes (measured as the probability of an IPO). Caselli, Garcia-Appendini, and Ippolito (2013) find the same result in a sample of Italian private equity deals, using various outcome measures. Practitioners have also become concerned with the possibility that some VC-driven boards can negatively impact firm value.[24] 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 the 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.

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

4.2.8 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 3 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.

4.2.9 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%.

4.2.10 Persistence in Contracts

Without making any explicit assumptions about choice persistence, 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 vary little 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: Search Frictions

The introduction of online platforms where agents can easily find each other, such as 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 VII 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). They find 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.[25]

Appendix G explores a different counterfactual, in which we consider the removal of VC-friendly contractual features (such as the "double-dip" of receiving a liquidation payment and participating in the firm's upside) implemented by observed contract terms (such as participation). While the model predicts a modest increase in firm value creation, implementing a prohibition on contractual features is difficult to achieve in reality and may affect entry and exit into the VC market.

6 Robustness

In this section, we examine the robustness of our results to changes in various model inputs and in subsamples. First, we use IPOs or follow-on financings as alternative outcome variables. The IPO outcome variable is the most commonly used measure of a success in the venture capital literature, while the follow-on financing variable focuses on shorter-term success. The sample using IPOs is the same as the one in the main model (see Table II); 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 A3 in the appendix. Note that the link between firm value and follow-on financing becomes insignificant. However, this is not surprising because 73% of startups receive follow-on financing, and many are likely of low

[25] 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.

quality.

Second, we check robustness to missing data. Instead of requiring that all modeled contract terms be observed, we impute missing contract terms as zero for deals containing 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 A3 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 A4 in the appendix show that the parties encounter each other more frequently in IT, compared to Healthcare. Agent 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 A4 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 reliable 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 A5 in the appendix show that the frequency of encounters rises after 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.[26] Panels C and D of Table A5 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 ends by 2010, we are unable to examine the post-crisis period.

Finally, in unreported results, we have also estimated our model in subsamples of only seed rounds or only series A rounds; syndicated or non-syndicated deals; high or low capital intensity startups; and narrower industry definitions, 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). Our results are quantitatively unaffected.

[26]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.

7 Extensions

Our search-and-matching model is designed to be tractable and transparent, but this comes at the cost of making simplifying assumptions about certain features of the data generating process. We examine the robustness of our results to various assumptions through model extensions.

First and perhaps most importantly, it may be the case that higher-quality VCs and entrepreneurs are more likely to encounter counterparties more frequently or to encounter counterparties from a more favorable distribution of qualities, as a result of a directed rather than random search. While a full-blown model of an optimally conducted directed search is beyond the scope of this paper, we examine two reduced-form versions. In the first version, encounter frequencies are $\lambda_i + \Lambda_i i$ and $\lambda_e + \Lambda_e e$, so different agent qualities encounter counterparties with different frequencies. In the second version, counterparties encountered by investor i (entrepreneur e) are drawn from distributions $F_e(e, i)$ ($F_i(i, e)$), so different agent qualities encounter counterparties from different quality pools. Since both model extensions are fundamentally similar to the main model but more notationally tedious, we make them available upon request. Panels A and B of Table A6 in the appendix show that while there is some evidence of directed search in both extensions (agents of higher quality encounter counterparties of higher quality and faster), our main results are robust.

Second, the main model assumes that investors make take-it-or-leave-it offers to worthy entrepreneurs they encounter. Note that this assumption does not imply that the entrepreneur never shares in the startup's surplus, $\pi(i, e, c^*) - V_i(i) - V_e(e)$: as long as the entrepreneur's input into the startup is sufficient, it is often in the interest of the investor to motivate the entrepreneur with a fraction of the surplus. In fact, under estimated parameters, entrepreneurs in our model are further motivated in every deal in which the investor offers the unconstrained contract $c^{*,Unc}$. Still, it is possible that entrepreneurs have additional bargaining power during contract negotiations and can therefore secure a higher fraction of the surplus. In an extension (available upon request), we add an "entrepreneur bargaining power" parameter, which impacts negotiations (by acting similarly to a "Nash Bargaining Solution" parameter). In estimation, we fix this parameter at 20%, which is generous and likely overstates the extent of the entrepreneur's influence on the contract. Panel C of Table A6 in the appendix shows that qualitative results do not change.

In a third set of extensions, 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. Because the last two model extensions are less trivial, Appendix H describes them in detail. Table A7 in the appendix shows that in all cases, our results remain robust.

Fourth, Appendix H 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.

Fifth, to account for omitted, ex-ante less important contract terms such as redemption rights or cumulative dividends, we have estimated models in which the least important included term, pay-to-play, is substituted with each omitted term. We also estimate (at great computational cost) models in which each omitted term is added in turn to the set of three included terms. Neither of the newly included terms' impacts is statistically or economically significant in any specification.

Sixth, we estimate alternative specifications of the impact of contract terms on the firm value and its split. For example, the incremental impact of VC board representation may be uniformly stronger when the VC owns more of the firm's equity, and therefore is better captured by $(1-c_1^*)c_4$ and not $c_1^*(1-c_1^*)c_4$ in (11) and (12). The results (unreported) remain quantitatively unchanged.

Two more extensions are of potential interest. First, a VC firm can manage multiple investments at the same time. To our knowledge there are no dynamic search-and-matching papers that allow agents to form multiple matches. A way of interpreting our assumption that a matched VC exits the market and is replaced by a same-quality VC is that the same VC (perhaps, a different partner in the VC firm) starts to search for the next deal. However, this interpretation does not allow for a VC to pursue multiple deals simultaneously, and ignores any dynamic considerations that can make the VC fund's first deal different from, say, its tenth deal. We leave this extension for future research. A second extension is to allow for counterparties to not completely observe each other's type even after an encounter, giving rise to adverse selection concerns. To our knowledge there are no papers that model adverse selection in VC contracting specifically (though it is used in some other topics in VC, for example, Winegar, 2018). Even the case of one-dimensional asymmetric information (e.g., about entrepreneurs' quality) is difficult to estimate, as it expands the state space of the model into an additional dimension (true versus perceived entrepreneur quality). 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 (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. We leave estimation of the precise form and impact of asymmetric information for future research.[27]

[27]We expect results from a more general adverse selection to be qualitatively similar to the main model (i.e., negative impact of participation and weak or negative impact of board seats) as long as the VCs retain the power to make take-it-or-leave-it offers to entrepreneurs (or as long as VC bargaining power dominates in negotiations).

Finally, in equation (4), agent qualities and contracts have separate impacts on firm value. This setup implies that the same contract maximizes firm value for any combination of agent types. In theory, our model can easily accommodate interactions between contract terms and agent qualities. However, estimation of this model is not as straightforward. Adding such interactions is akin to interacting agent type fixed effects in OLS regressions with all other regressors. Due to the large increase in dimensionality, it is not standard to introduce such interactions in structural work (for example, in estimating total factor productivity at the industry level, or the distribution of valuations across auctions net of the effect of observed covariates). Some reassurance that our model assumptions are reasonable can be found in the fact that our results are virtually unaffected in various subsample analyses of deals that are more homogeneous (see Section 6).

8 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. 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 could in theory. 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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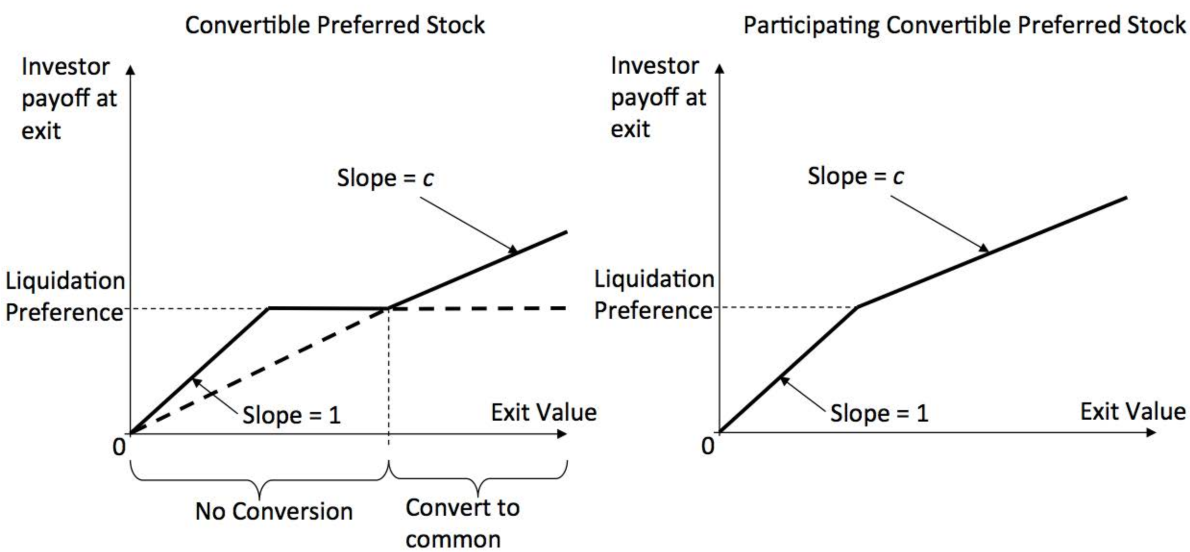

Figure 1: **Exit payoff diagrams.** The left graph shows the final payoff to convertible preferred stock (vertical axis) as a function of the startup's exit value (horizontal axis). The investor has the right to receive a liquidation preference (equal to a multiple of the invested amount, typically 1X 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.

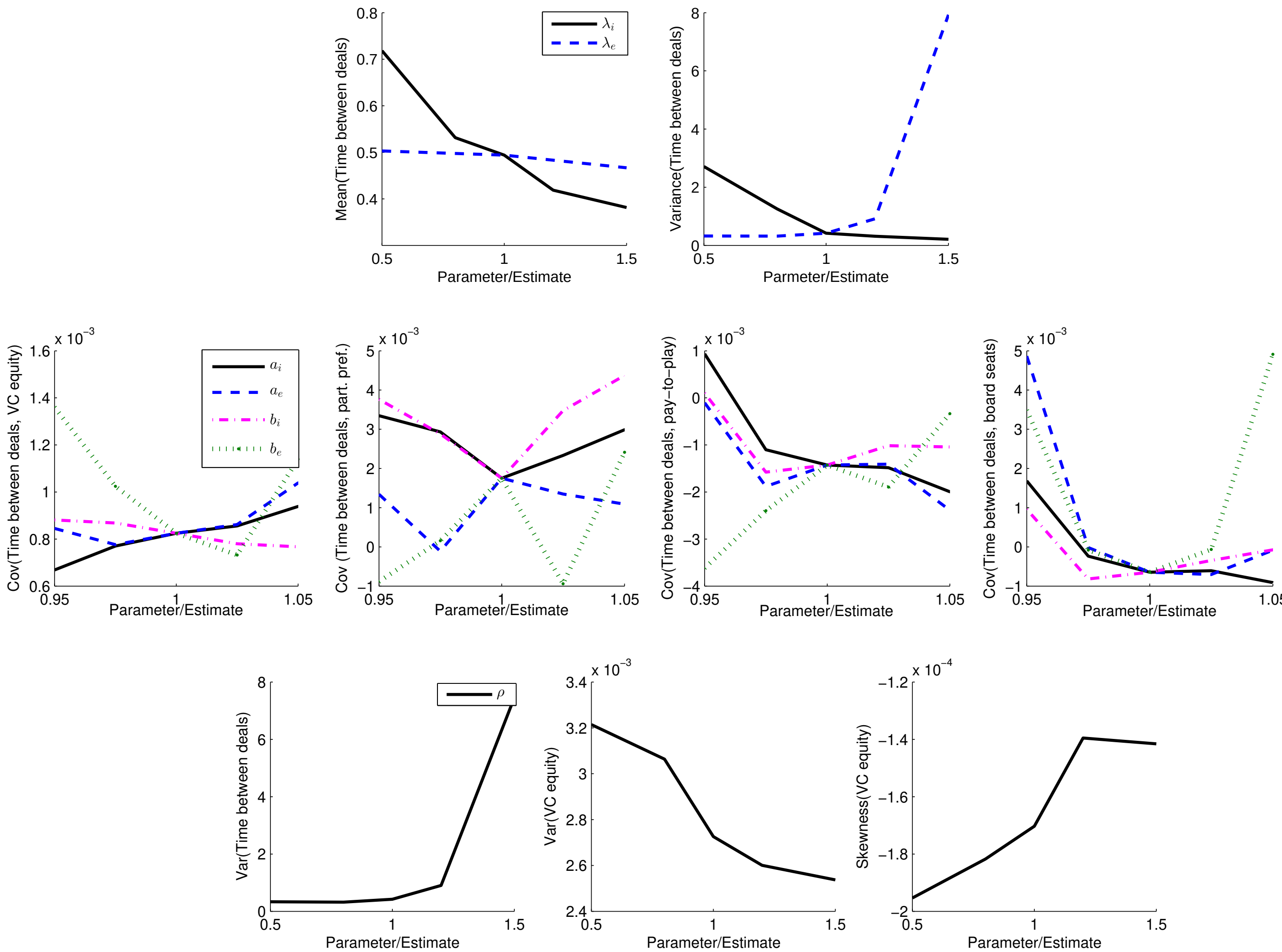

Figure 2: **Sensitivity of selected moments to model parameters.** The top row shows sensitivity of moments of the time between investors' deals to the change in frequency of encounters parameters, λ_i and λ_e. The middle row shows sensitivity of covariances between time between deals and contract terms 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. The estimated ρ is negative, such that a higher parameter value relative to the estimate means a more negative ρ. All other parameters estimates are positive.

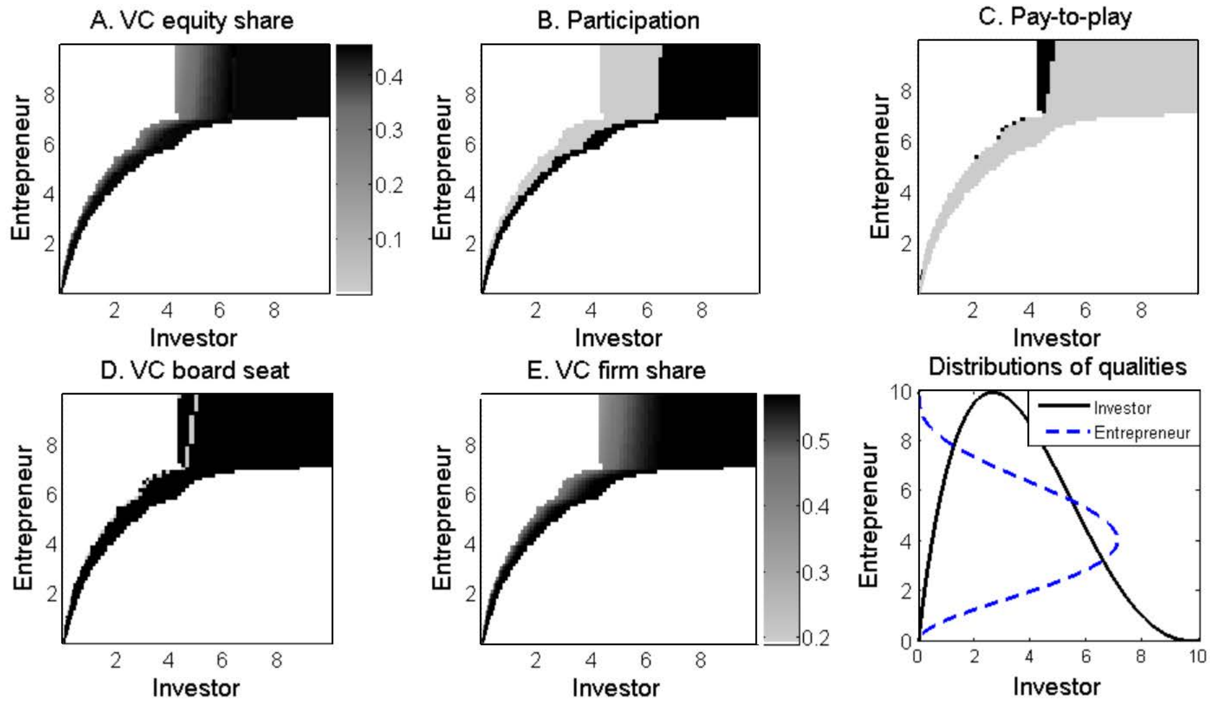

Figure 3: **Equilibrium contract terms at estimated model parameters.** Panel A shows the VC equity share, Panel B shows participation, Panel C shows pay-to-play, Panel D shows the VC board seat, and Panel E shows the resulting VC share of the firm for each combination of investor (VC) and entrepreneur 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.

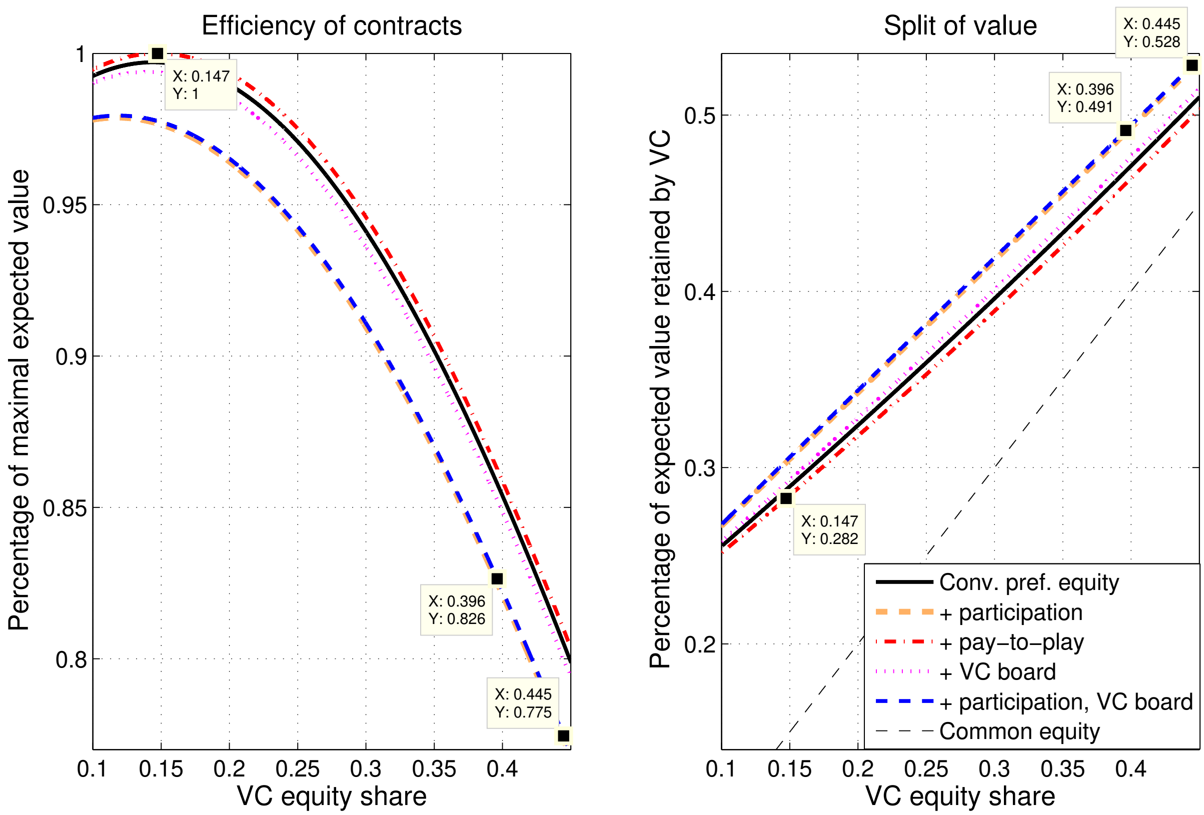

Figure 4: **Impact of contract terms on the startup value and its distribution.** The figure in the left panel shows the ratio of the total startup value to the maximal value, and right side panel shows the fraction of value acquired by the VC, as a function of VC equity share. Qualities of the VC and 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.

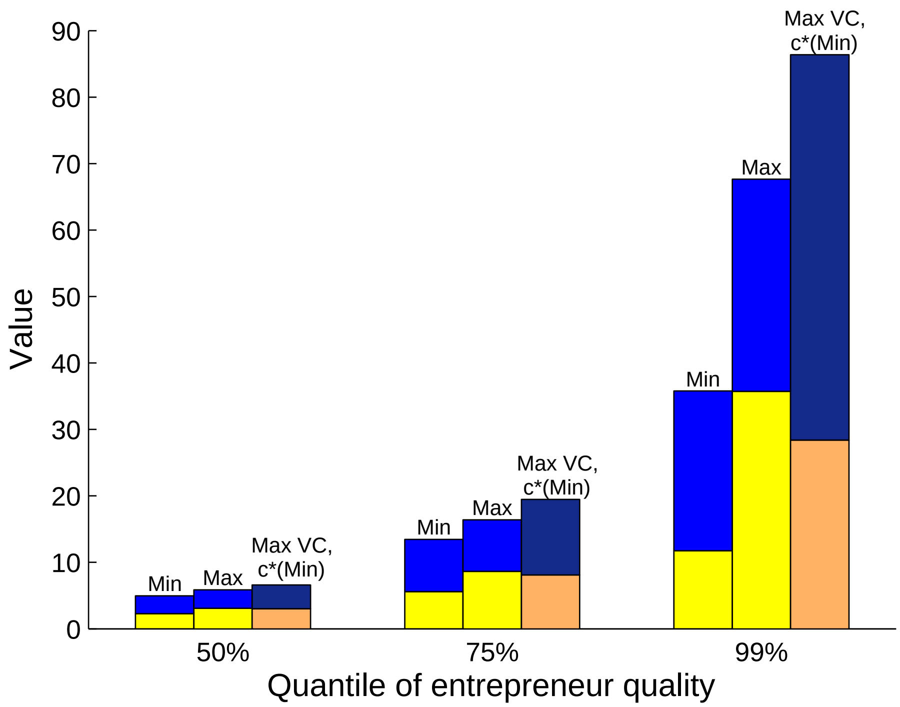

Figure 5: **VC and entrepreneur value creation.** Each bar shows the expected value to the VC (light yellow color) and entrepreneur (dark blue color) for a given combination of their qualities in the estimated equilibrium. These values add up to the expected value of the startup. The sets of bars refer 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: 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