

Competition in the Venture Capital Market and the Success of Startup Companies: Theory and Evidence*

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March 11, 2019

Abstract

We examine the effect of a competitive supply of venture capital (VC) on the exits (IPO or M&A) of startups. We develop a matching model with double-sided moral hazard, and identify a novel differential effect of VC competition on the success of startups. Using VC data, we find evidence for this differential effect. For example, when the VC market becomes more competitive (HHI decreases by 10% from its mean of 0.08), the absolute likelihood of success increases by 3% for startups backed by less experienced VC firms, but it decreases by 4.5% for startups backed by the most experienced VC firms.

Keywords: entrepreneurship, venture capital, matching, double-sided moral hazard, exit, IPO and M&A.

JEL classifications: C78, D86, G24, L26, M13.

*We would like to thank Katie Moon, Georgios Petropoulos, Elvira Sojli, and seminar participants at the 2018 MaCCI Annual Conference, 2018 IIOC, 2018 Searle Center Annual Conference on Innovation Economics, 2018 CRETE, University of Cyprus and University of Crete for helpful comments.

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1 Introduction

Over the last three decades, venture capital (VC) has become an increasingly important source of startup funding for entrepreneurs with innovative products. For example, the number of VC firms has more than quadrupled in the US: while 408 VC firms actively invested in startup companies in 1991, this number rose to 1,639 in 2015 (Thomson One). At the same time a substantially larger number of startup companies received VC financing: 970 companies in 1991 versus 3,743 in 2015 (Thomson One). The list of successful and well-known companies that received VC at some point during their startup phase includes Google, Facebook, Airbnb, and Uber. Other companies, such as Pets.com, eToys, Jawbone (and many others), received VC funding but eventually failed.

Governments around the globe have implemented various policies to spur VC investments (e.g. capital gains holidays, R&D subsidies etc.), which has contributed significantly to the rise of venture capital (e.g. Gompers and Lerner (1998)). Clearly, startup companies that would have otherwise not received VC funding benefit from a more competitive VC supply. However, in this paper we pursue a more nuanced approach, and examine, both theoretically and empirically, whether a more competitive supply of VC has a differential impact on the funded companies, depending on the ‘quality’ of their investors. For this, we focus on the likelihood to experience a successful exit, which is critical for entrepreneurs, investors, and policy makers alike.

To analyze the relationship between the supply of VC and the rate of successful exits for startup companies, we first develop an equilibrium model of the VC market with two-sided heterogeneity, matching, and double-sided moral hazard.¹ In our model, entrepreneurs (ENs) and venture capital (VC) firms are vertically heterogenous with respect to the quality of their business ideas (ENs), and their experience or management expertise (VC firms). In equilibrium, entrepreneurs with high (low) quality projects match with high (low) quality VC firms (positive assortative matching). Each VC firm then provides capital in exchange for an equity stake, which in turn determines the valuation of the startup company. Moreover, for a given match, both the entrepreneur and the VC firm (as an active investor) need to exert private effort to bring the entrepreneurial project to fruition.² The joint effort then determines the probability for the venture to generate a positive payoff (double-sided moral hazard).

The main insight from our theory is that a more competitive supply of VC (through the entry of new VC firms in a market) has a differential effect on startup companies: it improves the success rate of lower quality entrepreneurial projects (backed by less experienced VC firms), while it diminishes the success rate of high quality projects (backed by more experienced VC firms).

The key mechanism behind this differential effect is as follows. For each EN-VC pair there exists a specific allocation of equity that harmonizes the effort incentives between the two sides, and therefore

¹There is ample empirical evidence that the VC market is characterized by both sorting (see, e.g., Sørensen (2007)) and double-sided moral hazard (see, e.g., Kaplan and Strömberg (2003) and Ewens, Gorbenko, and Korteweg (2018)).

²VC firms typically take an active role when investing in startup companies. Their so-called *value-adding services* include mentoring, conducting strategic analyses, and recruiting managers (e.g. Sahlman (1990), Gorman and Sahlman (1989), and Lerner (1995)). Moreover, Bottazzi, Da Rin, and Hellmann (2008) provide empirical evidence that an active involvement of the VC firm has a positive effect on the success rate of their portfolio companies.

maximizes the probability of generating a positive payoff. However, we show that in the matching equilibrium, an entrepreneur backed by a more experienced VC firm (i.e., an entrepreneur with a high quality project) has ‘too much’ equity, which is driven by the competition among VC firms for high quality projects. The VC firm then does not apply enough effort (or does not provide sufficient value adding services), and this deficiency cannot be compensated by the entrepreneur (despite being motivated to exert more effort). As a result the venture’s probability of experiencing a successful exit is inefficiently low. In contrast, an entrepreneur backed by a less experienced VC firm (i.e., with a low quality projects) retains ‘too little’ equity in equilibrium, because weak competition among VC firms for these lower quality startups allows investors to obtain higher equity stakes, driving down company valuation. The entrepreneur’s effort is then inefficiently low, and this cannot be fully compensated by the VC firm’s higher effort. Again we find that the likelihood of a successful exit is not maximized in equilibrium.

A more competitive supply of venture capital (i.e., when more VCs compete in a market) forces investors to provide funding in exchange for less equity. This implies a higher valuation of all startup companies, regardless of whether they have high or low quality projects. However, leaving entrepreneurs with high quality projects with more equity, exacerbates the inefficient equity allocation (which is tilted in favor of entrepreneurs), and therefore further diminishes the joint efficiency of effort incentives. As a result, ventures backed by more experienced VC firms (with high quality projects) are then less likely to generate a positive payoff (or to have a successful exit). We find the opposite for ventures backed by less experienced VC firms (with low quality projects): more equity for entrepreneurs partially offsets the initial inefficiency associated with unbalanced effort incentives, and therefore improves the likelihood of success.

We then test our theoretical predictions using VC investment data from Thomson One, covering all investments in the US from 1991 to 2010.³ We define VC markets based on the geographical locations of the portfolio companies (using the metropolitan statistical areas), and industries. To measure VC market concentration (or the degree of VC competition) we use (i) the Herfindahl-Hirschman index, and (ii) the inverse number of VC firms in a given market. Variations in market concentration occur either when VC firms make investments in a market for the first time (Hochberg, Ljungqvist, and Lu, 2007) or concentration measures change through changes in shares of investments (with a fixed number of VC firms). These variations in concentration may be caused by changes in fixed costs associated with making a first time investment in a market and/or variations of flows of capital into a VC market. VC experience is measured by the number of prior investments, as suggested by prior literature (see, e.g., Sørensen (2007) and Nahata (2008)). Finally, we use IPOs and mergers and acquisitions (M&A) to measure the success of startup companies.

Using our full sample, we first find that a more competitive supply of VC in a given market improves the success rate of the average portfolio company. As our theory suggests, we then split the sample into high and low experience VC firms. For VC firms below the 90th percentile experience level, the effect of

³This leaves us with at least six years to observe the exit results of portfolio companies, as the status of the companies in our sample is current as of December 2016.

competition on success remains positive. But for VC firms in the top 10 percentile of experience, stronger competition has a negative effect on success. We therefore find empirical support for the differential effect of VC competition, as identified by our theory model.

The significance of our findings can be summarized as follows. First, there is prior empirical evidence that the matching in the VC market is positive assortative (Sørensen (2007)): high (low) experience VC firms fund high (low) quality startups. Our data also support this finding. For example, companies funded by VC firms in the top 10 percent in terms of investment experience have, on average, a 24 percent likelihood of a successful exit. In contrast, only 17 percent of companies funded by VC firms below the top 10 percent, experience a successful exit; see Table 2. Second, and given positive assortative matching, we show that a more competitive supply of venture capital has a negative effect on the success rate of the highest quality startups, while it has a positive effect on the success of lower quality companies (differential effect). Specifically, we find that if the HHI decreases from its mean (0.08) by 10 percent (i.e., the market becomes more competitive), the likelihood of a successful exit (IPO or acquisition) decreases by 4.5 percent for companies backed by the most experienced VC firms (the ones in the top 10th percentile).⁴ In contrast, the success rate of companies receiving funding from less experienced VC firms (the ones below the 90th percentile), increases by 3 percent. An alternative measure of competition that we use is the number of VC firms in a market. Our estimates show that if the number of VC firms in a given market increases from the average (15) by one, the success rate of companies backed by the top VC firms decreases by 1.5 percent, At the same time, the success rate for companies backed by less experienced VC firms increases by 2.5 percent.

Overall we find that VC competition has a negative effect on the success rates of the most innovative startups, which tend to receive funding from the most experienced VC firms. Clearly, these ‘star companies’ are fewer in numbers to begin with but have much higher valuations than the companies funded by lower experience VC firms (see Table 2). Therefore, they are much more likely to generate innovation (Kortum and Lerner, 2000), and economic growth and employment (Samila and Sorenson, 2011) in a region. Our research therefore identifies a significant economic and societal cost of promoting VC investments (e.g. through capital gains holidays and tax credits), if this results in a more competitive VC market: it diminishes the number of such successful ‘star companies’, with all the implications for innovation and economic growth.

The literature on the structure of VC markets is small. Hochberg, Mazzeo, and McDevitt (2015) examine VC market competition by accounting for a particular type of product differentiation: the choice to be a specialist or a generalist investor. They find that in the VC industry – unlike in other industries – the incremental effect of additional same-type competitors increases with the number of these competitors. They attribute this finding to the presence of strong network effects within the VC industry. Gompers, Kovner, and Lerner (2009) look at the success of VC investments, and how it is affected by industry specialization. They show that investments made by more specialized VC firms are more likely to suc-

⁴If we assume that all the investing VC firms in a market have equal market shares, then this change in HHI indicates that the number of investing VC firms increases from 13 to 14.

ceed. Gompers and Lerner (2000) examine empirically the relationship between the supply of capital in the VC market (which is related to the degree of competition) and the success of startup companies. They do not differentiate between different types of VC firms, and they find no statistically significant relationship between supply of VC capital and success.

Our theory model is close in spirit to the search models of entrepreneurial finance, as devised by Inderst and Müller (2004), Hellmann and Thiele (2015), and Silveira and Wright (2016). Although these models assume frictions in the matching process, while we assume a frictionless environment, the main qualitative difference is our assumption of ex-ante heterogeneity. Inderst and Müller (2004) and Hellmann and Thiele (2015) consider homogenous VC firms and entrepreneurs, while Silveira and Wright (2016) introduce ex-post heterogeneity (i.e., the heterogeneity materializes after a VC firm is matched with an entrepreneur). In our model it is the heterogeneity of VC firms and entrepreneurial projects, in conjunction with double-sided moral hazard, that leads to the differential effect of VC competition on the likelihood of new ventures to succeed (for which we also find empirical support). Our paper is also related to Jovanovic and Szentes (2012), who consider random matching within a VC context with ex-post heterogeneity, to examine the link between excess returns and the scarcity of VC firms. Our paper is also related to Ewens, Gorbenko, and Korteweg (2018), who also look at the contractual matching outcome in the VC market accounting for double-sided moral hazard. They provide empirical evidence that most VC investors use their bargaining power to obtain more favorable contract terms, which in turn compromises the success probability of startups.

Sørensen (2007) investigates empirically how the experience of VC firms affects the likelihood of startup companies to go public. He distinguishes between the sorting effect (more experienced VC firms invest in better projects), and the treatment effect (more experienced VC firms provide better value-adding services). Estimating a structural two-sided matching model, he finds that the sorting effect is almost twice as important as the treatment effect in explaining observed differences in IPO rates across portfolio companies. Bengtsson and Hsu (2015) look at a different type of sorting in the VC industry, based on human and social characteristics of entrepreneurs and VC partners. They provide empirical evidence that belonging to the same ethnicity increases the likelihood of a match.

An important feature of our model is that both parties in a given match (the entrepreneur and the VC firm) need to apply private effort to bring the project to fruition. This leads to a typical double-sided moral hazard problem, which is a key driver for the differential effect of VC competition on the success rates of startup companies. Casamatta (2003), Schmidt (2003), Repullo and Suarez (2004), and Hellmann (2006), also consider double-sided moral hazard within the context of entrepreneurial finance. However, these papers focus on the optimal security design for a single entrepreneur-investor pair, while we consider simple equity contracts, similar to Keuschnigg and Nielsen (2004). Moreover, we consider endogenous matching in a market setting with multiple heterogenous entrepreneurs and VC firms.⁵

⁵The model in Hellmann (1998) also features two-sided efforts exerted by an entrepreneur and a VC. The allocation of control rights is used to mitigate the double-sided moral hazard problem in that model.

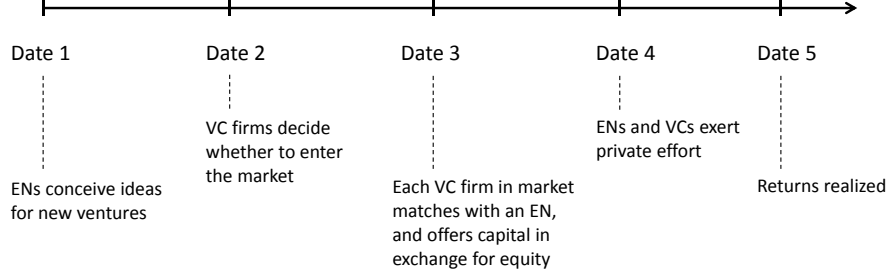


Figure 1: Timeline

The remainder of this paper is structured as follows. Section 2 introduces the theoretical model and discusses its main predictions. Section 3 describes the data and presents our empirical results. Section 4 summarizes our key insights and concludes. All proofs and additional regression tables are in Appendix A and B respectively.

2 Theoretical Model and Results

2.1 Main Assumptions

We consider a market consisting of a continuum of risk-neutral and wealth-constrained entrepreneurs (ENs) of mass one, and a continuum of risk-neutral venture capital firms (VC firms) of mass one. ENs differ in terms of the quality (or market potential) of their projects. We index ENs by $i \in E = [0, \bar{i}]$, with $H(i)$ as the distribution of i , and $h(i)$ as its density. A higher index i indicates a higher project quality. Likewise, VC firms differ in terms of their investment experience (and therefore management expertise). We index VC firms by $j \in V = [0, \bar{j}]$, with distribution $G(j)$ and density $g(j)$. A higher index j indicates a more experienced VC firm. The quality of entrepreneurial projects (i) and VC firm experience (j) are common knowledge.

There are five dates; see Figure 1 for a graphical overview. At date 1, EN i conceives an innovative business idea of quality i . To commercially exploit his idea, each entrepreneur requires capital K from a VC firm. At date 2, VC firms decide whether to incur the sunk cost $F > 0$ to enter the market. At date 3, each VC firm matches endogenously with one EN. VC firm j then offers its entrepreneur i capital K in exchange for an equity stake s_{ij} in the company. The EN retains the remaining equity share $(1 - s_{ij})$.⁶ The cost of capital faced by each VC firm is $r > 0$. The utility of an EN who remains unmatched is $\underline{u} \geq 0$.

At date 4, each EN and VC exert private efforts e_i and v_j respectively, to turn the idea into a marketable product. The non-contractibility of both efforts leads to a typical double-sided moral hazard problem between ENs and VCs. The combined effort levels determine the likelihood of whether the

⁶To ensure tractability of our matching model, we do not consider separate financing rounds. We thus interpret K as the cumulative venture capital invested in a startup company.

venture succeeds ($Y = 1$) or fails ($Y = 0$), where $\Pr[Y = 1|e_i, v_j] \equiv \rho = e_i^\phi v_j^{1-\phi}$. This implies that both efforts are complements, and that the startup can only succeed if both, the EN and the VC firm, apply effort. Moreover, the parameter $\phi \in (0, 1)$ measures the relative importance of the entrepreneur's effort e_i relative to the VC's effort v_j . Intuitively, the entrepreneur's effort e_i is at least as important as the VC's effort v_j , to bring the project to fruition, so that $\phi \geq 1/2$. The entrepreneur's disutility of effort is $e_i^2/2$, and the VC's disutility of effort is given by $v_j^2/2$.

If the venture succeeds it generates the payoff $\pi(i, j)$ at date 5, which we assume to be continuously differentiable. We can interpret $\pi(i, j)$ as the payoff from a successful IPO or acquisition. Intuitively, a higher project quality i or more VC experience j leads to a higher payoff. Formally we assume that $\pi_i, \pi_j > 0$, where π_k denotes the partial derivative of $\pi(i, j)$ with respect to $k = i, j$. Moreover, we assume that project quality and VC experience are (weak) strategic complements, i.e., $\pi_{ij} \geq 0$. In case of failure the venture generates a zero payoff.

The equity stake obtained by a VC firm, s_{ij} , in exchange for investing K , determines the valuation of the startup company. The so-called post-money valuation is defined by $\Omega_{post} \equiv K/s_{ij}$, while the pre-money valuation is given by $\Omega_{pre} \equiv \Omega_{post} - K$. We follow the convention in the empirical VC literature and use pre-money valuations throughout this paper (including our theory). Both valuation measures are obviously equivalent within our model.

To keep our model as simple and transparent as possible, we focus in our main text on the allocation of equity as the only contracting tool between ENs and VC firms. In some cases, however, it may be Pareto improving if a VC firm makes a monetary transfer payment to its EN (in addition to providing K), in order to buy some additional equity. In Section A.6 in the Appendix, we show that allowing for additional transfer payments does not change our main results, as long as there is a cost (even if very small) to making such transfers (e.g. income taxes or financial intermediation costs).

2.2 Contracts in the Absence of Matching

We first consider the contractual relationship between an arbitrary EN-VC pair, ignoring for now any effects arising from the matching process. The analysis in this section therefore closely resembles those in Repullo and Suarez (2004), Inderst and Müller (2004), and Hellmann (2006), of the optimal sharing rule for a single EN-VC pair. We proceed in three steps: First, we derive the equilibrium effort levels for the EN and the VC firm for a given allocation of equity. Second, we characterize the utility-possibility frontier, and identify the feasible payoff allocations. For this we derive (i) the allocation of equity preferred by the VC firm, (ii) the equity allocation preferred by the EN, and (iii), the jointly optimal (i.e., Pareto efficient) allocation of equity. Third, we characterize the equilibrium allocation of equity as a function of the entrepreneur's outside option (which will be endogenous when allowing for matching). For parsimony we suppress subscripts whenever possible.

Let U^E and U^V denote the expected utility for the EN and the VC firm, respectively. For a given sharing rule s , the EN and VC firm choose, simultaneously and independently, efforts e and v to maximize their expected utilities:

$$\max_{\{e\}} U^E(e; s, v) = e^\phi v^{1-\phi} (1-s) \pi - \frac{e^2}{2} \quad (2.1)$$

and

$$\max_{\{v\}} U^V(v; s, e) = e^\phi v^{1-\phi} s \pi - \frac{v^2}{2}. \quad (2.2)$$

We show in Section A.1 in the Appendix that for a given sharing rule s , the EN and the VC firm choose the following effort levels:

$$e(s) = [(1-\phi)s]^{\frac{1-\phi}{2}} [\phi(1-s)]^{\frac{(1+\phi)}{2}} \pi, \quad v(s) = [\phi(1-s)]^{\frac{\phi}{2}} [(1-\phi)s]^{\frac{2-\phi}{2}} \pi.$$

Moreover, using $e(s)$ and $v(s)$ we show that the equilibrium success probability is given by

$$\rho(s) = [(1-\phi)s]^{1-\phi} [\phi(1-s)]^\phi \pi.$$

The next Lemma characterizes some important properties of the utility-possibility frontier, which is an important stepping stone towards establishing the matching outcome in Section 2.3.

Lemma 1 *Consider an arbitrary EN-VC pair in the absence of endogenous matching. The utility-possibility frontier has the following properties:*

- (i) *The VC firm's expected utility U^V is maximized for the sharing rule $s = s^V \equiv \frac{1}{2}(2 - \phi)$.*
- (ii) *The EN's expected utility U^E is maximized for the sharing rule $s = s^E \equiv \frac{1}{2}(1 - \phi)$.*
- (iii) *The efficient sharing rule, which maximizes the joint utility $U^V + U^E$, is $s = s^J \equiv 1 - \phi$. For $s = s^J$ the success probability $\rho(s)$ is also maximized.*

For any $s \in [s^E, s^V]$ the payoff allocation is feasible, with $s^E < s^J < s^V$.

Figure 2 illustrates the utility-possibility frontier (UPF) for all sharing rules $s \in [0, 1]$. Both the EN and the VC firm need to exert private effort to generate a positive expected payoff. If one party gets the entire equity ($s \in \{0, 1\}$), the other party will not exert any effort, so that the project fails and generates a zero payoff ($U^V = U^E = 0$). As a result the UPF is backward bending. We can see from Figure 2 that the joint utility, and likewise the success probability $\rho(s)$, is maximized for $s = s^J$. However, the EN and the VC firm each prefer more equity, which is optimal from an individual perspective, but inefficient from a joint perspective. Lemma 1 also implies that in equilibrium both parties will settle on any sharing

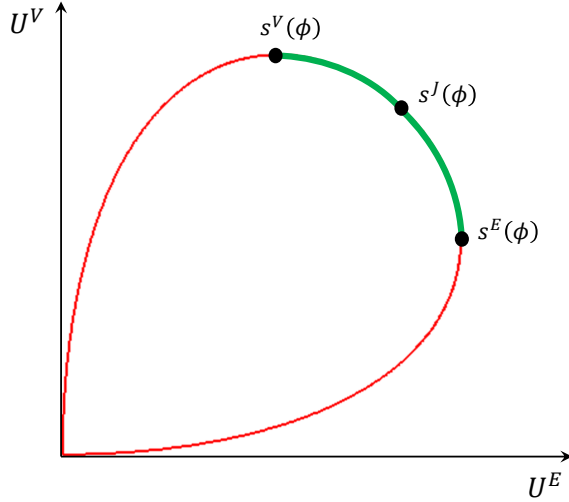


Figure 2: Utility-possibility frontier

rule $s \in [s^E, s^V]$, which is reflected by the green portion of the UPF in Figure 2 ($s \in [s^V, s^E]$).⁷ Along this green portion, a higher expected utility for the EN (U^E) implies a lower expected utility for the VC firm (U^V), which is attained by allocating less equity to the VC firm (i.e., both parties agree on a lower s). The feasible portion of the utility-possibility frontier for EN i and VC firm j , denoted $UPF(i, j)$, is then defined by

$$UPF(i, j) = \{ (U^E(s; i, j), U^V(s; i, j)) : s \in [s^E, s^V] \}.$$

We can now characterize the main properties of the equilibrium sharing rule s^* for a given EN-VC pair. For this we denote the EN's reservation utility by u . Specifically, the VC firm offers capital K in exchange for the equity stake $s^*(u)$, which maximizes its expected utility $U^V(s)$, subject to the EN's participation constraint $U^V(s) \geq u$. The next lemma identifies the main properties of $s^*(u)$.

Lemma 2 *There exists a threshold reservation utility u' for the EN, so that $s^*(u) = s^V$ for $u \leq u'$. For $u > u'$, the optimal sharing rule $s^*(u) \in [s^E, s^V]$ satisfies $U^E(s) = u$, and is decreasing in u (i.e., $ds^*(u)/du < 0$ for $u > u'$).*

If the EN has a sufficiently low outside option ($u \leq u'$), then the VC firm can implement its own preferred sharing rule s^V . This would still provide the EN with a (weakly) higher expected utility compared to his next best alternative ($U^E(s^V) \geq u$). However, the sharing rule s^V would violate the EN's participation constraint if his outside option is sufficiently attractive ($u > u'$). The VC firm is then forced to offer the EN more utility by taking less equity in the company, so that $s^*(u) < s^V$. And a more attractive outside option implies that the EN can retain more equity in his company in equilibrium ($ds^*(u)/du < 0$ for $u > u'$).

⁷Note that the shape of the UPF is determined by the relative productivity parameter ϕ . If $\phi = 1/2$ then the UPF is symmetric around the 45 degree line, with $s^E = 1/4$, $s^V = 3/4$, and $s^J = 1/2$.

2.3 Market Equilibrium

We now characterize the equilibrium outcome in a two-sided market with heterogeneous ENs and VC firms. We proceed in two steps. In Section 2.3.1 we derive the conditions that ensure a positive assortative matching equilibrium. We then examine in Section 2.3.2 the effect of competition in the VC market on (i) the equilibrium allocation of equity (or pre-money valuations of startup companies), and (ii) the equilibrium success rate of new ventures.

2.3.1 Positive Assortative Matching

We now define the equilibrium of the VC market when each VC firm matches endogenously with one entrepreneur (*one-to-one matching*).⁸ The reservation utility of each EN, u , is then *endogenously* determined by potential contract offers from alternative VC firms. Moreover, note that the VC firm's expected utility $U^V(s)$ depends on the sharing rule s , and according to Lemma 2, the equilibrium sharing rule $s^*(u)$ is a function of the EN's outside option u . We denote the expected utility of VC firm j , when matched with EN i with outside option $u(i)$, by $U^V(i, j, u(i))$.

We now state two important characteristics of the matching equilibrium.

Definition 1 (Matching Equilibrium) *An equilibrium of the VC market consists of a one-to-one matching function $m : E \rightarrow V$ and payoff allocations $U^{V*} : V \rightarrow \mathbb{R}_+$ and $U^{E*} : E \rightarrow \mathbb{R}_+$, that satisfy the following two conditions:*

- (i) *Feasibility of (U^{V*}, U^{E*}) with respect to m : For all $i \in E$, $\{U^{V*}(m(i)), U^{E*}(i)\}$ is on the feasible utility-possibility frontier $UPF(i, j)$.*
- (ii) *Stability of m with respect to $\{U^{V*}, U^{E*}\}$: There do not exist a pair $(i, j) \in E \times V$, where $m(i) \neq j$, and outside value $u(i) > U^{E*}(i)$, such that $U^V(i, j, u(i)) > U^{V*}(j)$.*

The *feasibility* condition requires that the payoffs for VC firms and ENs are attainable, which is guaranteed whenever the payoffs for any pair $(i, m(i))$ are on the feasible portion of the utility-possibility frontier. Moreover, the *stability* condition ensures that all matched VC firms and entrepreneurs cannot become strictly better off by breaking their current partnership, and matching with a new VC firm or entrepreneur.

We have a positive assortative matching equilibrium (PAM) whenever entrepreneurs with high quality projects match with high-experience VC firms. Applying the criterion derived by Legros and Newman (2007) for an imperfectly transferable utility (ITU) case, our matching equilibrium is positive assortative if and only if the *generalized increasing differences* condition holds (GID). The GID condition is equivalent to a single-crossing property (Chade, Eeckhout, and Smith, 2017). The idea is as follows.

⁸While often multiple VC firms invest in individual startup companies (syndication), one VC firm typically takes the lead when negotiating the contract terms with the founder(s); see e.g. Kaplan and Strömberg (2004). We could thus interpret a single VC firm in our model as a syndicate of multiple VC firms with the 'aggregate' experience j .

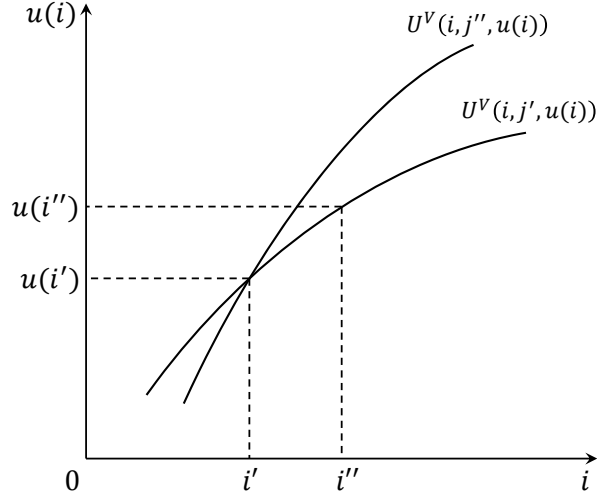


Figure 3: The single-crossing property

Consider two VC firms j'' and j' , with $j'' > j'$, and two ENs i'' and i' , with $i'' > i'$. Assume that VC j' is indifferent between $(i', u(i'))$ and $(i'', u(i''))$, so both of these points lie on VC j' 's indifference curve. Then, VC j'' is better off matching with i'' and offering the utility $u(i'')$, compared to matching with i' and offering the utility $u(i')$. More formally,

$$U^V(i', j', u(i')) = U^V(i'', j', u(i'')) \Rightarrow U^V(i'', j'', u(i'')) > U^V(i', j'', u(i')). \quad (\text{GID})$$

The single-crossing property is illustrated by Figure 3. Specifically, point $(i'', u(i''))$ lies on a higher indifference curve of VC j'' than point $(i', u(i'))$, while both points lie on the same indifference curve of VC j' , with $j'' > j'$. Consequently, if (GID) holds, the higher quality VC firm j'' can always outbid the lower quality VC firm j' for the higher quality EN i'' . Formally, (GID) holds as long as the slope of a VC firm's indifference curve is increasing in its own type. We show in Section A.4 in the Appendix that the slope of VC j' 's indifference curve in the (i, u) space is given by

$$\Psi(i, j) \equiv -\frac{U_i^V(i, j, u)}{U_u^V(i, j, u)} = 2\frac{\pi_i}{\pi} \frac{1}{2 - 2s(u) - \phi} u, \quad (2.3)$$

where U_k^V denotes the partial derivative of U^V with respect to $k = i, u$, and $s(u)$ is derived (implicitly) from the EN's participation constraint, see (A.6). We can see that $\Psi(i, j)$ is strictly positive for all $s^* \in [s^E, s^V)$. Moreover, in Section A.4 in the Appendix we show that $d\Psi(i, j)/dj > 0$. This implies that the stable matching outcome in our model is positive assortative (PAM).

2.3.2 The Effects of VC Competition

We now turn to the main objective of our theory, namely identifying the effects of competition among VC firms on the success rate of new ventures.

Positive assortative matching (PAM) implies that the matching function $m(i)$ is increasing in i . Note that the measure of ENs must be equal to the measure of VC firms for the one-to-one matching equilibrium. Thus, it must hold that $H(i) = G(m(i))$ in order to ensure measure consistency. This implies that $m(i) = G^{-1}(H(i))$. Using this consistency condition, we can derive the slope of the matching function $m(i)$:

$$\frac{dm(i)}{di} = G^{-1'}(H(i)) h(i) = \frac{h(i)}{G'(G^{-1}(H(i)))} = \frac{h(i)}{g(m(i))}. \quad (2.4)$$

This says that the slope of the matching function $m(i)$ is equal to the ratio of the densities of EN and VC types, $h(i)$ and $g(m(i))$.

The next lemma characterizes the equilibrium utility $U^{E*}(i)$ of entrepreneur i .

Lemma 3 *The equilibrium utility $U^{E*}(i)$ for EN i is characterized by the ordinary differential equation*

$$\frac{dU^E(i)}{di} = -\frac{U_i^V(i, m(i), U^E(i))}{U_u^V(i, m(i), U^E(i))} = \frac{2\pi_i(i, m(i))}{\pi(i, m(i))} \frac{U^E(i)}{(2 - 2s(U^E(i)) - \phi)} > 0 \quad (2.5)$$

with the initial condition $U^E(\underline{i}(F)) = \max\{U^E(s^V; \underline{i}, m(\underline{i})), \underline{u}\}$.

Equation (2.5) is derived from (2.3) by setting $j = m(i)$ and replacing u with U^E . It implies that as i increases, j also increases according to the equilibrium matching function. By construction, (2.5) guarantees that VC firm j maximizes its expected utility over all possible i 's, given $U^E(i)$, only when it matches with $i = m(j)$. From the stability requirements, it then follows that $U^{E*}(i)$ and $U^{V*}(i)$ are increasing in i .

We assume that $U^E(\underline{i}(F)) = \max\{U^E(s^V; \underline{i}, m(\underline{i})), \underline{u}\} = \underline{u}$. This implies that every unmatched EN has a reservation utility \underline{u} higher than the minimum expected utility he receives in the PAM equilibrium (so that $s^E \leq s^*(\underline{u}) < s^V$). The unique solution $U^{E*}(i)$ to (2.5) must then (implicitly) satisfy⁹

$$U^{E*}(i; F) = \underline{u} + \int_{\underline{i}(F)}^i \frac{dU^{E*}(s)}{ds} ds, \quad (2.6)$$

where $\underline{i}(F)$ is the EN that receives funding from the marginal VC firm \underline{j} in the matching equilibrium.

The marginal VC firm \underline{j} gets a zero expected utility from entry, i.e., $U^{V*}(m(i)) - rK - F = 0$. If the entry cost F decreases, then more VC firms enter the market and match with previously unmatched ENs, so that $\underline{i}(F)$ decreases (i.e., $d\underline{i}(F)/dF > 0$).

We can now examine how a more competitive supply of VC affects contracts and success rates in the matching equilibrium. For this we first note that a startup company is most likely to succeed when the efforts of both, the EN and the VC firm, are “balanced”, which is achieved when the equity stakes are balanced (see Lemma 1). This is the case whenever $s^* = s^J$; see Figure 2. However, the equilibrium sharing rule s^* depends on the actual match quality (i, j) , and the next best alternative for the entrepreneur

⁹A closed form solution for $U^{E*}(i)$ does not exist. Nevertheless, in Section A.5 in the Appendix we show that a unique (numerical) solution must exist.

(which in turn depends on VC competition). And we know from Lemma 2 that a more attractive outside option implies that the EN can retain more equity in his company ($ds^*(u)/du < 0$) (i.e., the EN-VC pair “moves down” on the green portion of the utility-possibility frontier in Figure 2).

Technically we can vary the entry cost F to change the equilibrium number of VC firms in the market, and therefore the degree of competition. Suppose the entry cost F decreases, so that more VC firms enter the market and match with previously unmatched ENs. Because of PAM, all the previous EN-VC matches remain the same; however, VC entry affects the equilibrium outside option of each EN, and therefore the equity allocation (or the pre-money valuation). By differentiating (2.6) we obtain

$$\frac{dU^{E^*}(i; F)}{dF} = -\frac{dU^{E^*}(i; F)}{di} \frac{di}{dF} < 0.$$

A lower cost of entry F , and therefore a larger number of competing VC firms, implies higher expected utility levels for all ENs in equilibrium. This is because each EN then retains a higher equity share in his company (i.e., s^* decreases), implying a higher pre-money valuation.¹⁰ For EN-VC pairs with $s^* > s^J$, whose projects are of lower quality, this implies a higher probability $\rho(s^*)$ for the venture to succeed.

Moreover, entrepreneurs with higher quality projects obtain higher expected utilities in the matching equilibrium, because they can retain higher stakes in their companies (i.e., $dU^{E^*}(i)/di > 0$ because of $ds^*/di < 0$). And we know from Lemma 1 that the jointly optimal sharing rule $s^J = 1 - \phi$ is not a function of i . This implies that for a sufficiently high degree of heterogeneity among ENs, there exists a threshold EN-VC pair above which the equity stake given to the entrepreneur exceeds the jointly optimal level s^J . These pairs with $s^* < s^J$, which have the higher quality projects, therefore experience a lower success probability $\rho(s^*)$ when the number of competing VC firms in the market increases (because of a lower entry cost F).

We summarize these insights in the next proposition.

Proposition 1 *Suppose the fixed entry cost F decreases so that more VC firms enter the market. Then, there exists an $\hat{i} \in [\underline{i}, \bar{i}]$ such that:*

- (i) *For all $(i, m(i)) \ll (\hat{i}, m(\hat{i}))$, the probability of success $\rho(s^*)$ increases.*
- (ii) *For all $(i, m(i)) \gg (\hat{i}, m(\hat{i}))$, the probability of success $\rho(s^*)$ decreases.*
- (ii) *All VC-backed ENs retain more equity, which implies higher pre-money valuations.*

Another important insight from our model is that the quality of the VC firm matters for whether competition has a positive or a negative effect on the success probability for its portfolio company. In

¹⁰This insight is related to a known result from the endogenous matching literature (see, e.g., Terviö (2008)). Specifically, each VC firm offers its EN just enough utility to prevent being outbid by the marginally lower VC firm. More competition then forces VC firms to transfer more utility to their ENs. Within our context, this means that VC firms ask for less equity when investing in startup companies.

a positive assortative matching equilibrium, only high quality VC firms match with high quality ENs. The equity allocation in these relationships is already tilted in favor of ENs due to the strong competition among VCs for the high quality projects. Consequently, in equilibrium VC firms exert insufficient effort from a joint perspective (as $s^* < s^J$). Now with increased competition these high quality VC firms are forced to leave their ENs with even more equity (i.e., they need to offer higher valuations), so the equity allocation becomes even more tilted in favor of ENs. This provides yet more effort incentives to ENs, but further curbs effort incentives for the high quality VC firms. The net effect of this increased imbalance is that the startup becomes less likely to succeed (i.e., $\rho(s^*)$ decreases). By contrast, the equity allocation for low quality EN-VC pairs is inefficiently tilted in favor of VC firms. More competition then (partially) corrects this inefficiency by forcing a VC firm to leave its EN with more equity. This in turn makes low quality ventures, backed by lower quality VC firms, more likely to succeed.

Inderst and Müller (2004) also show that stronger competition in the VC market first increases and then decreases a company's probability of success (see Proposition 3). Nevertheless, because they consider homogenous entrepreneurs and VC firms, competition has the same effect on all companies. In contrast, we differentiate between high and low quality EN-VC pairs, and show that the non-monotonicity identified by Inderst and Müller (2004), can *co-exist* in the market and competition can have a *differential* effect on startups.

3 Empirical Analysis

We now empirically test the predictions from our endogenous matching model pertaining to the effect of VC competition on the success rates of startup companies. Specifically, we test the following hypotheses which follow directly from Proposition 1:

Hypotheses *Suppose the VC market becomes more competitive. Then,*

1. *the probability of a successful exit for ventures backed by more experienced VC firms decreases,*
2. *while the probability for ventures backed by less experienced VC firms increases.*

The model also predicts that competition has a positive effect on the valuation of all portfolio companies, despite the differential effect on success rates. Even though this is not the main focus of this paper, we test this prediction to verify the predictive power of our theory model – details can be found in Appendix B. The empirical results indicate that stronger competition among VC firms increases the company valuations.

3.1 Data

We use the VC investment data from the Thomson One database (formerly called VentureXpert). This comprehensive database has been extensively used in VC research (see, e.g., Kaplan and Schoar (2005),

Sørensen (2007), and Samila and Sorenson (2011)). Thomson One provides detailed information on VC-backed companies, which includes the dates and investment amounts for different financing rounds, the identities of investing VC firms, the development stages and industry groups of portfolio companies, and the dates and types of an exit (e.g. IPO, acquisition, or liquidation). We also extract information about fundraising by buyout funds and limited partners' VC investments, which are used for constructing our instrumental variable. Furthermore, we supplement information regarding IPO and M&A exits from the New Issues database and M&A database under SDC Platinum provided by Thomson Reuters.

It is well known that VC firms specialize in specific industries and tend to invest in local startup companies (e.g. Sørensen (2007) and Hochberg, Ljungqvist, and Lu (2010)). We therefore define VC markets as follows: First, we differentiate among the six main industry groups in the Thomson One database. These include "Communications and Media," "Computer Related," "Semiconductors and Other Electronics," "Biotechnology," "Medical, Health and Life Sciences," and "Non-High-Technology." Second, for each industry, we group all companies located in the same US Metropolitan Statistical Area (MSA). For example, "Computer Related" in the MSA of Philadelphia-Camden-Wilmington is a different market from "Biotechnology" located in Greater Boston. To improve the explanatory power of our regression analysis, we exclude all observations for inactive market periods. This concerns markets with either fewer than five deals in the current year, or fewer than 25 deals in the past five years. Moreover, we exclude funding rounds that are in the stage of buyouts and drop deals led by corporate venture capital (CVC) firms. Unlike independent VC firms that are primarily focused on the financial returns from their investments, CVCs also seek to achieve strategic objectives, such as gaining access to entrepreneurial innovations and exploring emerging business opportunities. As a result, compared to independent VC firms, CVCs usually provide higher investment amounts and show greater tolerance for failure; see Gompers and Lerner (2000), and Guo, Lou, and Perez-Castillo (2015). However, all of our results remain robust to including CVC-backed deals.

VC investments are typically made in stages. This allows investors to closely monitor the progress of the portfolio company before providing follow-on funding (see Gompers (1995) and Tian (2011)). Consequently, the financing terms at later rounds are largely affected by information previously obtained by VC firms. We therefore focus on the initial funding rounds to ensure that *ex ante* no VC firms have superior access to information that may affect the financing terms. The status of the companies is current as of December 2016, and we restrict the sample to initial rounds of investments made between 1991 and 2010, thereby allowing for at least six years to observe an exit. We focus on the investments made after 1990 due to the availability of the information of limited partners' investments which are used to construct the instrumental variable.¹¹ The final sample contains a total of 5,254 VC firms investing in 12,246 portfolio companies that received their initial funding in the US between 1991 and 2010.

¹¹In constructing the instrumental variable, we use the 10-year lag of the number of limited partners (LPs) investing in venture capital, and such information is available only after year 1980. Therefore, our sample starts from year 1991.

3.2 Variables

Market Level Measures

We use two alternative measures of market concentration: the Herfindahl-Hirschman Index (HHI) and the inverse number of VC firms in a given market. Our HHI accounts for the deal shares of VC firms in a given market and year.¹² When multiple VC firms participate in a financing round (syndication), we split the total investment amount equally (as Thomson One does not report individual investment amounts). Table 1 reports the summary statistics for our market concentration measures. The mean number of VC firms investing in a given market and year, is about 15.

To control for the number of entrepreneurs seeking VC funding, we use the number of VC deals financed in a given market-year, which is proportional to the total number of entrepreneurs seeking funding in a market. In controlling for the investment environment for each market, following Gompers and Lerner (2000), we construct the book-to-market ratios of a company's industry. We also control for the amounts of inflows into VC funds within the prior four quarters to capture any "money chasing deal" phenomena.

Portfolio Company Performance Measures

We use a portfolio company's successful exit status to measure success. Naturally it takes several years for a company to go through a successful exit after its initial investment. Thus, we restrict our sample to all the investments made between 1991 and 2010. This leaves us with at least a six-year time window to identify the exit status of a portfolio company. Our performance measure, *Success*, is binary and is equal to one if a company eventually goes public or goes through a merger & acquisition (M&A) deal (see, e.g., Nahata (2008), Hochberg et al. (2007)). In addition to using the information provided by Thomson One, we verify the successful exit status of a company using data extracted from the New Issues database and M&A data base under SDC Platinum.¹³

Other Portfolio Company Characteristics

Thomson One provides information about the development stage of a portfolio company at each financing round. We use this information to create four dummy variables that indicate four distinct development stages of a company: "Seed," "Early Stage," "Later Stage," and "Expansion." The age of a company is the number of years since it was founded, up to the date of a given financing round. To control for the unobservable quality of its business project, we use the investment amount raised by the

¹²Thomson One only reports overall investment amounts received by a portfolio company from a given VC firm, but does not disclose round-level amounts raised from individual VC firms. As a result, we are not able to compute the HHI based on the investment amounts for a given market-year. However, as a robustness check we attribute the total amounts invested by a given VC firm to all the rounds that this VC firm participated in, accounting for the size of the funding round. We then calculate the HHI based on the attributed investment amounts. For example, suppose a startup company received in total \$1 million from VC_i that participated in rounds 1 and 3. If the total amounts raised in rounds 1 and 3 are \$1 million and \$3 million dollars, respectively, then the investment in round 1 attributed to VC_i is $1/(1+3) = 0.25$ million, and in round 3 $3/(1+3) = 0.75$ million. The HHI based on the attributed investment amounts is highly correlated with the deal-based HHI, and the estimation results are qualitatively similar. For parsimony we only report results using the deal-based HHI.

¹³We also construct a short-term performance measure, "Survival", that captures whether a portfolio company survived and received subsequent financing (which requires the company to have reached certain business milestones). We use this measure as an interim signal of success, and find qualitatively similar results for our regressions (unreported).

portfolio company in the current round. Moreover, “Round number of investors” is the number of VC firms investing in the current round.

VC Firm Characteristics

We control for the characteristics of lead investors in a given financing round. For this we identify the VC firm that made the highest investment in the portfolio company across all rounds (see Tian (2011), Nahata (2008)). We use the fund size and the experience of a VC firm as control variables. If fund size information is missing, we use the average size of all other funds managed by the same VC firm. To measure the experience of a VC firm, we follow Sørensen (2007) and use the total number of its prior investments.¹⁴ Such experience measure captures firm-level expertise accumulated through participation in prior investment rounds.

3.3 Relationship between VC Experience and Success of the Venture

Using structural estimation, Sørensen (2007) provides empirical evidence that the matching between VC firms and entrepreneurs is positive assortative: more experienced VC firms invest in companies of better quality. Given that many dimensions of companies' quality are unobservable to researchers, we present descriptive evidence showing that more experienced VC firms tend to invest in better performing portfolio companies. Such evidence is robust to controlling for capital amounts received by the company. For a given market and year combination, we rank all investing VC based on their experience and divide VC firms into ten decile groups. We adopt the same VC experience measure as in Sørensen (2007): the number of prior investment rounds in which a VC firm participates. Figure 4 illustrates the fraction of companies backed by each decile group of VC firms that go through a successful exit. This evidence suggests a positive relationship between a VC firm's experience and investment outcomes. The most experienced VC firms (10th decile group) have a successful exit rate of 23.3 percent. In contrast, the least experienced VC firms (1st decile group) has a success rate of only 13.7 percent. The two groups' success rates are statistically different with a p-value of 0.000. However, the most experienced firms may also have access to more capital, and thus, invest larger amounts in portfolio companies. The stronger capital support can also lead to higher exit rates of companies backed by high-experience VC firms. We therefore control for the total investment amounts received by a portfolio company, and then compare the success rates across decile groups of VC firms. For each market and year combination, we consider companies receiving their initial funding rounds and rank their total capital received throughout all rounds. Moreover, for each quartile group of total investment, Figure 5 illustrates the success rates of companies backed by VC firms of different experience levels. We observe the same pattern across all quartile groups of investment amounts.¹⁵ We note that such a positive relationship between VC experience and success rates, may not only be rooted in positive assortative matching (sorting), but may

¹⁴Nahata (2008) proposes the following two measures of VC reputations that are related to VC investment outcomes: (i) the cumulative market capitalization of IPOs backed by a VC firm, (ii) a VC firm's share of the aggregate investment in the VC industry. Since we do not have round-level investment amounts for individual VC firms, we are not able to construct investment shares for each individual VC firm. However, we use another experience measure based on a VC firm's capitalization share of IPOs, and find that our main results remain robust.

¹⁵Despite the variations for companies backed by medium-level-experience VC firms, we note that across all the quartile groups of investment amounts, companies backed by the most experienced VC firms (10th decile) have the highest success rate, while companies backed by the least experienced VC firms (1st decile) have the lowest success rate.

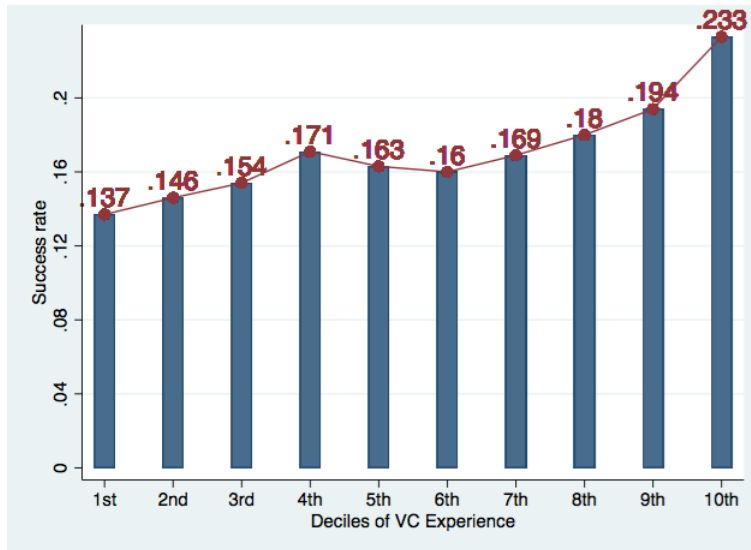


Figure 4: Success Rate in Groups of Different VC Experience

This figure illustrates the success rates of companies backed by VC of different experience. For each market and year combination, we rank VC firms according to their experience levels, and group all the portfolio companies into ten decile groups backed by VC firms of different experience. There are in total 1,672 distinct market and year combinations from the sample period from 1991 to 2010. The 10th decile group indicates companies backed by most experienced VC firms and the 1st decile group receive funding from the least experienced VC firms. A successful exit refers to either an IPO or an M&A deal for a given portfolio company.

also results from the higher added value from high-experience VC firms (treatment). However, Sørensen (2007) shows that the selection effect is twice as important than the treatment effect for explaining differences in IPO rates.

3.4 Variations in Market Concentration

The descriptive statistics reported in Table 1 suggest a relatively large degree of variation of market concentration in the sample: the HHI ranges from a minimum of 0.005 to a maximum of 0.68, with a mean of 0.08 and a standard deviation of 0.07. Our alternative measure of market concentration, “1/total vc number,” has a mean of 0.07 and a standard deviation of 0.07, ranging from 0.002 to 0.5. Figure 6 shows the histograms for the two alternative measures of market concentration.

We relate our market concentration measures to the number of entrant VC firms in a market. For a given market and year we define entrants as VC firms that invest in the market for the first time (see, e.g., Hochberg, Ljungqvist, and Lu, (2007)). In a median market-year in our sample, there are 6 entrants and 12 incumbent VC firms making investments. Furthermore, the entrant VC firms have a significantly lower investment experience than incumbents. A median entrant VC has financed 11 rounds (in other markets) prior to entering a new market, while an incumbent VC firm has a median experience of 147

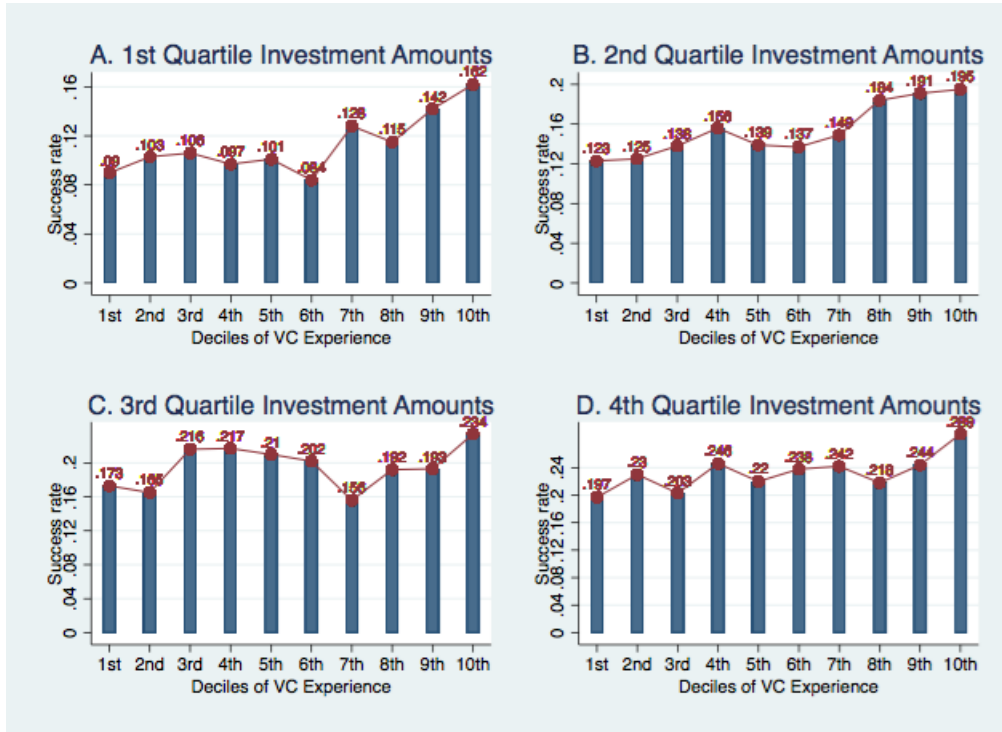


Figure 5: Success Rate in Groups of Different Investment Amounts and of Different VC Experience

This figure illustrates the success rates of companies backed by VC firms of different experience levels, conditional on the total investment amount received throughout all rounds. For each market and year combination, we rank VC firms according to their experience, and group all the portfolio companies into four quartile groups backed by VC firms of different experience. The 10th decile indicates the highest ranked group and the 1st decile group represents the lowest ranked group. We also rank total investment amounts received by portfolio companies in a given market and year, and divide the sample in quartile groups of investment amounts. The 4th quartile indicates the highest ranked group and the 1st quartile group represents the lowest ranked group. There are in total 1,672 distinct market and year combinations from the sample period from 1991 to 2010. A successful exit refers to either an IPO or an M&A deal for a given portfolio company.

funding rounds. This observed pattern is consistent with our theoretical model, where entrants have the lowest expertise relative to all incumbents.

Figure 7 shows how market concentration is related to the entry of VC firms. As more VC firms enter a given market, our two alternative market concentration measures decrease, implying a more competitive market structure. The correlation coefficients between the number of entrants and our two alternative concentration measures are -0.4 for the HHI, and -0.38 for $1/(\text{total VC number})$, respectively. Both coefficients have a p-value of 0.000.

One plausible reason for market entry of VC firms is a lower cost of entry, as also considered by our theory. Additionally, we show in Section 3.5.1 that an increased inflow of capital into VC funds can also lead to more market entry. In fact, according to our sample entry of VC firms is very common – there is no entry for only 45 out of the 1,672 market-year combinations.

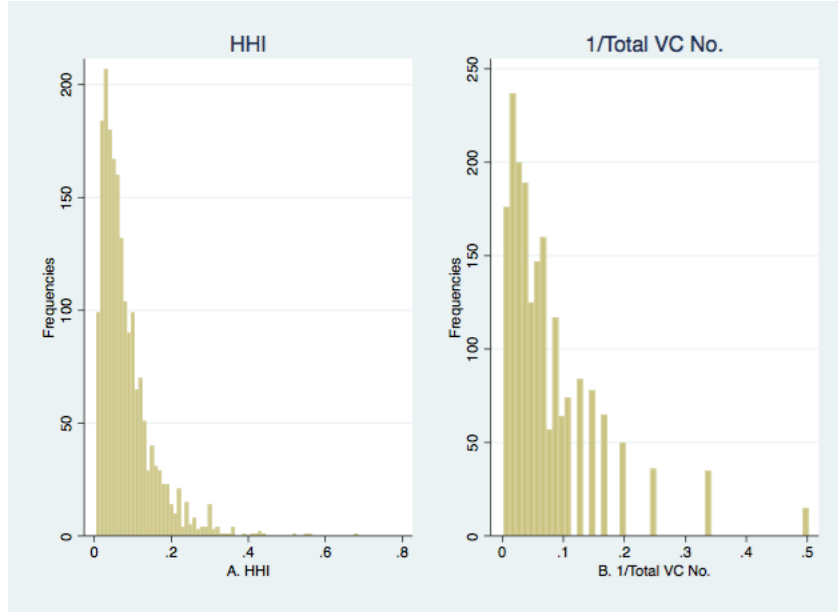


Figure 6: Histograms for Market Concentration Measures

This figure displays the histograms for the two alternative market concentration measures: HHI and the reciprocal of number of investing VC firms. There are in total 1,672 distinct market and year combinations from the sample period from 1991 to 2010. For each market and year, we construct the HHI based on the shares of the number of deals financed by VC firms.

3.5 The Effects of Concentration on Portfolio Company Performance

We estimate the effect of concentration on the performance of portfolio companies using the following specification:

$$\begin{aligned}
 Success_{ijmt} = & \alpha + \beta_1 Concentration_{mt} + \beta_2 C_{imt} + \beta_3 X_{jmt} + \beta_4 M_{mt} \\
 & + \phi_m + \tau_t + \epsilon_{ijmt},
 \end{aligned} \tag{3.1}$$

where i , j , m , and t index the portfolio company, VC firm, market, and year, respectively. The dependent variable, $Success_{ijmt}$, is binary, and indicates if a company had a successful exit through IPO or M&A.

We use two alternative measures of market concentration: (i) the Herfindahl-Hirschman Index (HHI) based on the number of VC firms investing in a given market and year, and (ii) the inverse number of investing VC firms in a given market and year. Moreover, C_{imt} represents a set of control variables for the characteristics of portfolio companies, including (i) the logged value of the age of a portfolio company, (ii) company development stage dummies (i.e., seed, early stage, later stage, expansion), (iii), the logged number of participating investors in the current round, (iv) and the logged investment amounts received in the current funding rounds. In addition, X_{jmt} refers to a set of controls for the characteristics of the lead investor in the current round, which includes the logged number of prior funding rounds, and the logged value of its fund size. Finally, M_{mt} is a set of market characteristics, including (i) the logged

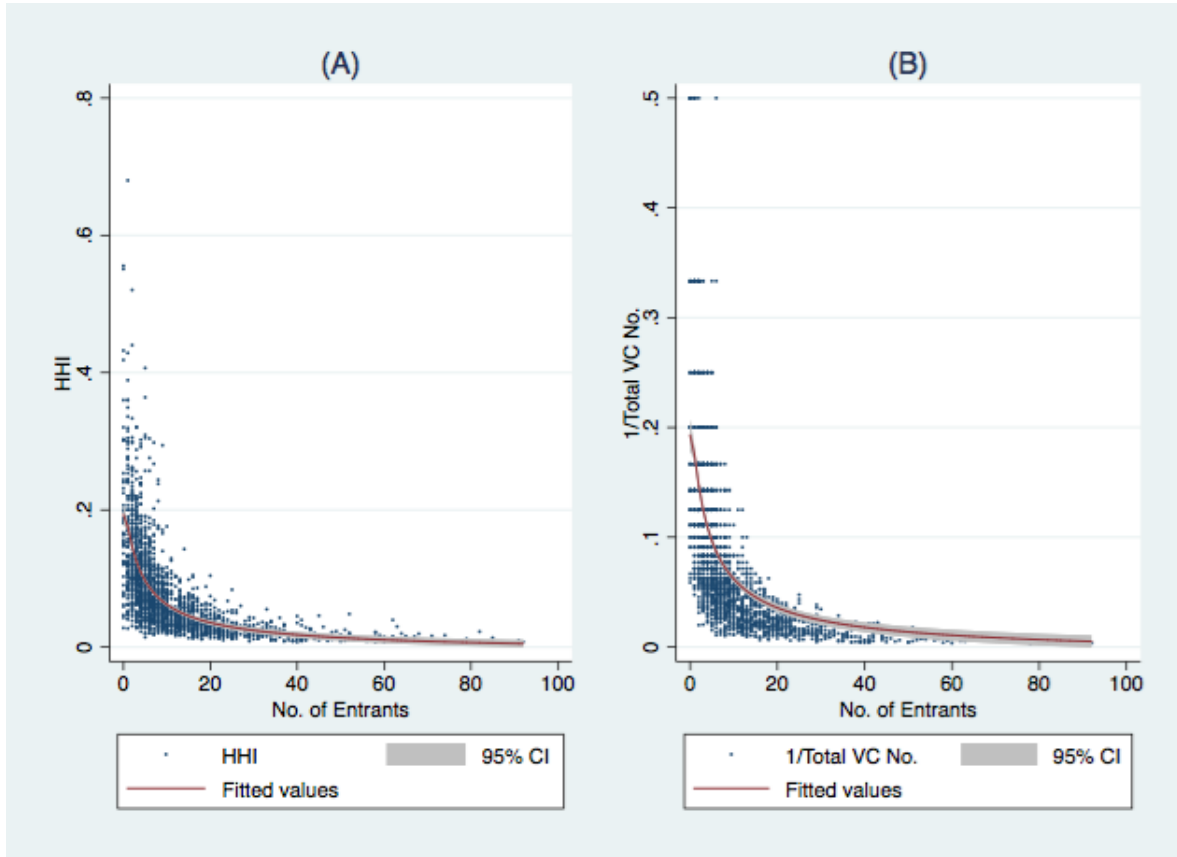


Figure 7: Market Concentration versus Number of Entrants

This figure illustrates how market concentration (i.e. HHI and the reciprocal number of investing VC firms) is related to the entry of VC firms. There are in total 1,672 distinct market and year combinations for the sample period from 1991 to 2010. For each market and year, we construct the HHI based on the shares of the number of deals financed by VC firms. Panels A and B plot the market concentration measures against the number of entrants in a market. We identify entrants as VC firms that invest in a given market for the first time.

value of capital raised by all VC funds in the previous four quarters, *(ii)* the logged number of funding rounds in a market-year, and *(iii)* the book-to-market ratio of the public companies in the same industry as the portfolio companies. We use a linear probability model (LPM) to fit the data, and include both market and year fixed effects.

3.5.1 Identification Strategy

Our theory predicts differential effects of market concentration on the performance of portfolio companies. Specifically, a lower market concentration (i.e., more competition) improves the success rate of startup companies backed by less experienced VC firms, while it reduces the success rate of startups backed by more experienced VC firms.

However, the impact of market concentration is subject to endogeneity concerns. Unobservables about portfolio companies may correlate with market concentration and, at the same time, affect their performances, leading to omitted variable bias. The direction of such bias, however, is ambiguous. First, the high productivity or growth potential of startups in a given market is associated with higher likelihoods of a successful exit, and at the same time, leads to more VC firms entering the market to take advantage of the opportunities, resulting in a lower market concentration. If this was the main force driving our results, our OLS estimates would be biased downward. The second source of endogeneity stems from competition among VC firms being correlated with the risk profiles of portfolio companies. Previous literature suggests that in times the market is ‘hot’, VC firms invest in riskier and more novel startups that would have a lower chance of going through a successful exit (Nanda and Rhodes-Kropf, 2013). This can cause an upward bias in the OLS estimate of the coefficient on concentration. A third possible source of endogeneity concerns barriers to entry in local markets. In a market with high barriers to entry, only a small number of VC firms invest in startups that present sufficiently high quality (as also suggested by our theory model). This indicates an upward bias of the effect of market concentration.

We estimate the effects using an instrumental variable to control for the endogeneity of market concentration. For our IV approach we follow Gompers and Lerner (2000), and Nanda and Rhodes-Kropf (2013), and utilize the influx of capital into buyout funds. This IV approach captures two salient features of the VC industry. First, institutional investors constantly adjust their investment portfolios, which affects the supply of venture capital. As institutional investors realize a higher return, fund managers invest more capital in private equity assets, including venture capital and buyout funds. As a result, capital inflows into venture capital and buyout funds are likely correlated.¹⁶ An increase in the supply of capital, in turn, affects the competition landscape in the VC industry. Second, buyout and venture capital funds pursue significantly different investment opportunities. Buyout funds tend to invest in mature companies, traditionally in manufacturing, while venture capital funds invest in startup companies with high risk and high growth potential. The distribution of returns from venture capital investments are therefore much more skewed to the right (Kerr et al., 2014). All this suggests that past fund raising activities of buyout funds should have little correlation with the riskiness or growth potential of VC-backed companies.

We also exploit the regional and industry heterogeneity of VC activities to identify market-level variations. First, we utilize the fact that institutional investors tend to invest in local VC firms (Hochberg and Rauh, 2013). When limited partners (LPs) allocate capital to VC funds, a higher level of capital would flow into to VC funds in regions where a large cluster of LPs are located than to VC funds in regions where only a small number of LPs are present. In our data, an LP is about four-times more likely to invest in VC funds located in the same MSA than in VC funds in another MSA region. Second,

¹⁶Using annual data between 1990 and 2010, we find that the correlation coefficient between capital inflows to buyout and VC funds is 0.65 (with a p-value of 0.000).

there is consistency over time with regards to the composition of the VC industry in a given geographic location.¹⁷ Therefore, we augment the IV by utilizing the regional and industry level variations.

We build our instrumental variable (IV) in three steps. First we use the nationwide inflow of capital into buyout funds.¹⁸ Next, for each MSA region we count the number of LPs that invested in venture capital at least 10 years prior to the year of interest. Given this time lag the investment pattern of LPs should be unaffected by the local investment conditions. To account for the tendency of LPs to invest in local VC funds, we weight the instrumental variable by the distance between an MSA region and the market of interest. Lastly, we include the share of VC investments made in the focal industry and MSA region, considering all deals that took place at least 10 years before the year of interest. By using a 10-year lag we ensure that variations are not caused by recent changes in investment opportunities within a particular industry.

We denote by IV_{ist} the instrument for the competitive supply of venture capital in MSA s , industry i , and year t , which is defined by

$$IV_{ist} = Indshare_{ist} \sum_j \sum_{h=t-1}^{t-3} \frac{\ln(\text{Buyout Inflows}_h) \ln(1 + LP_{jh})}{1 + dist_{sj}}, \quad (3.2)$$

where Buyout Inflows_h is the nationwide total amount of capital inflow into buyout funds in year h , and LP_{jh} is a counter of the distinct LPs in MSA j that invested in VC funds at least 10 years prior to year h . Moreover, $dist_{sj}$ represents the distance between the centroid of MSA s and the centroid of MSA j , and $Indshare_{ist}$ is the ratio of the number of VC investments at least 10 years prior to time t in industry i and MSA s , and the number of all VC investments in MSA s . Because it takes time for LPs to allocate capital across different asset classes, the measure is cumulated for three years of lagged buyout funds inflows. And the distance weight takes into account that LPs tend to invest in VC funds located nearby.

The relevance of the instrumental variable depends in general on how the buyout fund inflows affect competition in the VC market. Previous work shows a strong correlation between inflows into buyout and venture funds. However, it remains unclear how the additional capital is allocated among VC firms, which further determines how market concentration changes. If only a small number of VC firms benefit from the additional capital from LPs, then each has more resources to fund companies, leading to a more concentrated market structure. On the other hand, if a large number of VC firms obtain additional capital from LPs, then competition in local VC markets intensifies.

Our analysis shows that higher inflows into buyout funds are related to less concentrated markets. In the first stage of all models, our instrument variable strongly predicts market concentration (see the

¹⁷We compute the percentages of funding rounds for companies in each industry group, relative to all funding rounds in a given location in each year. The coefficients of variation for the industry distributions of VC deals ranges from 0.118 and 1.039, with a median of 0.464.

¹⁸Alternatively, we could use regional capital inflows for each MSA. However, regional inflows are potentially influenced by local economic conditions, and this would likely violate the exclusion restriction. For completeness we also estimate our models using the inflows into buyout funds on a regional level (MSA). The results are qualitatively similar to those reported in the Appendix, and are available from the authors upon request.

first-stage results in Table 6). The F-statistics for the instrument in all first stage estimations are sufficiently higher than the classic rule-of-thumb value of 10. We also report the partial R-squared for the instrumental variable.

Table 3 shows how the inflow of capital into buyout funds affects market concentration. We first examine how buyout fund inflows affect the number of deals and the number of investing VC firms in a given market. We also control for the average book-to-market ratio of the public companies in the given industry and the extent of VC networks in a given market.¹⁹ We utilize dynamic panel estimations, following the methods proposed by Arellano and Bond (1991), to address the concern that the dependent variables in a given year likely depend on their past realizations. We therefore include the lagged dependent variables as explanatory variables, and use the lags of regressors as instruments for the first-difference models. The results are presented in Columns 1 and 2 of Table 3. Column 1 shows that following higher inflows into buyout funds, more deals are financed. Moreover, Column 2 of Table 3 indicates that more VC firms invest in a given market, when more capital flows into buyout funds.

We further examine the investment activities of entrant VC firms, to provide an explanation for the rise in the number of deals and investors. Columns 3 through 5 of Table 3 present the results from our OLS estimation that includes both market and year fixed effects. We control for the average book-to-market ratio for public companies in the given industry, and for the market VC network level. As shown in Column 3, the number of entrant VC firms investing in a given market increases, following a higher inflow into buyout funds. Furthermore, those entrant VC firms finance more deals, as shown in Column 4. Column 5 implies that following a higher inflow into buyouts, entrants are able to raise more funds. The estimation results reported in Column 5 also control for the experience of entrant VC firms in other markets, and their total capital raised prior to year t . The standard errors reported in Table 3 are clustered at the market level. All this suggests that buyout fund inflows are positively related to entry of VC firms into a given market and the number of new funds raised by entrants. And this can potentially lead to less market concentration. We expect such patterns to be more pronounced in market with low barriers to entry, as the decrease in market concentration stems from entry.

Overall our instrumental variable estimation captures the variations in the performance of VC-backed startups due to changed market conditions, and these changes in market conditions are unrelated to the investment opportunities at the time of VC investments. This presumes that the inflow of capital into buyout funds is uncorrelated with the risk and growth potentials of startup companies seeking VC funding.

¹⁹We measure the connectedness of VC firms at the market level, following Hochberg, Ljungqvist, and Lu (2010). For each market and year combination, we consider syndication relationships among all the investing VC firms over a five-year time window ending in $t - 1$. With n investors, there are at most $\frac{1}{2}n(n - 1)$ possible ties formed through syndication. We then track the actual syndication relationships in all markets within the five-year window. The market level network measure is then defined as the ratio between the actual number of ties and the highest possible number ties.

3.5.2 Main Results

We first estimate equation (3.1) using the full sample of initial funding rounds with VC firms of all experience levels. We then examine whether competition has a differential effect on the performance of portfolio companies. For this we compute the experience of VC firms in each market and year, as measured by the number of previous funding rounds a VC firm participated in. We then divide the sample into two groups: VC firms with experience higher than the 90th percentile level in a given market-year, and VC firms with experience below the 90th percentile.²⁰ In our sample, the most experience VC firms (above the 90th percentile) participate in about 16 percent of the funding rounds, and their investments represent 23.6 percent of the total investments in portfolio companies. Moreover, companies backed by the most experienced VC firms receive more venture capital, and have higher exit rates, compared to companies backed by less experienced VC firms (below the 90th percentile); see Table 2. For these two groups of startups we estimate the effect of market concentration on their performance, using equation (3.1).

Table 4 reports the OLS estimation results. Columns 1 and 2 present the results for the initial funding rounds backed by VC firms with experience below the 90th percentile, suggesting a negative effect of market concentration on the likelihood of a successful exit. Columns 3 and 4 show the estimation results for startups backed by VC firms with an experience level above the 90th percentile. For these startups more market concentration makes a successful exit more likely. Columns 5 and 6 present the results using the entire sample. Since startups backed by less experienced VC firms (below the 90th percentile) represent the majority in the data (85 percent), the negative effect of market concentration on exits dominate for the full sample.

The first stage regression results are shown in Table 6, and the second stage results in Table 5. As explained in Section 3.5.1, a higher inflow of capital into buyout funds leads to less concentrated markets in the first stage. Moreover, the coefficients for our market concentration measures from the second stage results are all statistically significant and share the same signs with the OLS estimates. Specifically, more market concentration (less competition) implies a lower exit rate of startups backed by less experienced VC firms (below the 90th percentile); see columns 1 and 2 of Table 5. On the other hand, ventures backed by the most experienced VC firm (top 10 percentile) are more likely to go through a successful exit when the market becomes more concentrated; see Columns 3 and 4 of Table 5. We can see from Column 2 that the likelihood of a successful exit for a startup backed by a less experienced VC firm, increases by 2.5 percent when the total number of VC firms increases from 15, the number of VC firms

²⁰In Appendix B we provide the estimation results when using two additional sub-sample groups: VC firms with experience between the median level and the 90th percentile, and VC firms with experience below the median level. For these two sub-sample groups we continue to find a negative relationship between concentration of the probability of a successful exit. Only ventures backed by the most experienced VC firms (higher than the 90th percentile) have higher success rates when market concentration increases; see Table B.3. These estimates reinforce our theory: it is only for the top experience VC firms, who compete for the most promising startups, that competition has a negative effect on success. These VC firms, due to the intense competition, retain relatively low equity stakes in those companies and therefore have weak incentives to provide value-adding services. An increase in competition weakens these incentives even further resulting in a decrease in the likelihood of a successful exit.

in the average market, to 16. In contrast, the likelihood of a successful exit decreases by 1.5 percent for startups backed by the most experienced VC firms; see Column 4. Alternatively, we can examine changes in competition through changes in the HHI. Specifically we find that if the HHI decreases from its mean (0.08) by 10 percent (i.e., the market becomes more competitive), the likelihood of a successful exit decreases by 4.5 percent for companies backed by the most experienced VC firms (the ones in the top 10th percentile). In contrast, the success rate of companies receiving funding from less experienced VC firms (the ones below the 90th percentile), increases by 3 percent. Finally we note that the estimated effects from 2SLS are of larger magnitudes than those from OLS. This implies that endogeneity biases the OLS results upwards, as discussed in Section 3.5.1.

4 Conclusion

We examine how competition in the market for venture capital affects the likelihood of funded companies to experience a successful exit (IPO or M&A). We first develop and analyze a matching model of the VC market with two-sided heterogeneity and double-sided moral hazard. The model shows that VC competition has a differential effect, which depends on the actual quality of entrepreneurial projects and the experience of investors: ventures backed by less experienced VC firms (with lower quality projects) experience higher success rates, while ventures backed by more experienced VC firms (with higher quality projects) experience lower success rates, in more competitive VC markets. We then provide empirical support for our predictions using VC investment data from Thomson One. In particular, we find that, as the VC market becomes more competitive, companies that are funded by VC firms that have experience below the 90th percentile, have a higher likelihood of a successful exit. And companies funded by VC firms in the top 10 percentile of experience have a lower likelihood of a successful exit.

We believe that our key insights are important for the following main reasons. First, they help us to better understand the link between competition in the market for venture capital, and the success of innovative startups. Prior research, e.g., Gompers and Lerner (2000), had indicated that this link is absent. Second, our insights can have important policy ramifications: Any policy that enhances the supply of venture capital (such as investor tax credits), will lead to more innovative projects to be funded. This, however, can come at a cost: it deteriorates the likelihood for the most innovative ventures (typically backed by more experienced VC firms) to experience a successful exit, while it improves the funding and survival rates of new ventures with lower quality projects. Given that high quality startups are more likely to promote innovation, growth and employment in a region, policies that result in a more competitive VC market structure ought to take this differential effect of competition on success into account. Finally, the insights from our model and results can be applicable to other markets that are characterized by double-sided moral hazard, such as partnerships, joint ventures and more broadly settings where bilateral unverifiable investments are important.

We note, however, that our research focuses on the effects on valuations and exits, but there are clearly other important aspects to consider for policy makers when designing policies to foster startup funding. Overall, we believe that this provides an interesting and important avenue for future research.

Table 1: Summary Statistics

Notes: This table presents the descriptive statistics for the data. The sample contains a total of 12,246 portfolio companies in the US receiving their initial rounds of funding between 1991 and 2010 from 5,254 VC firms. Markets are defined based on MSA regions, and industry classifications from Thomson One. There are in total 1,672 market and year combinations in the sample.

	count	mean	median	max	min	sd
Later-stage dummy	12246	0.04	0.00	1.00	0.00	0.20
Early-stage dummy	12246	0.49	0.00	1.00	0.00	0.50
Seed stage dummy	12246	0.27	0.00	1.00	0.00	0.44
Expansion stage dummy	12246	0.20	0.00	1.00	0.00	0.40
Age (years)	12246	2.31	1.00	63.00	0.00	5.50
Round number of investors	12246	2.22	2.00	15.00	1.00	1.50
Fund size (\$ mil)	12246	228.76	120.00	8234.00	0.10	441.74
VC experience	12246	217.46	79.00	2784.00	0.00	344.75
Success exit	12246	0.17	0.00	1.00	0.00	0.38
Round amount(\$ mil)	12246	5.87	3.20	311.77	0.01	9.93
hhi	1672	0.08	0.06	0.68	0.005	0.07
1/total vc number	1672	0.07	0.05	0.50	0.002	0.07
VC prior 4 Qt. inflow (\$mil)	1672	30380.63	23061.20	106449.60	1803.30	25993.85
Value-weighted industry avg. B/M ratio	1672	0.28	0.26	1.34	0.08	0.15

Table 2: Descriptive Statistics for Companies Backed by VCs of Different Experiences

Notes: This table presents the descriptive statistics for 12,246 companies that received initial funding between 1991 and 2010. Markets are defined based on MSA regions, and industry classifications from Thomson One. There are in total 1,672 market and year combinations in the sample. In each market and year, we rank VC firms' experience based on prior number of investment rounds that they participated in. We then divide companies into two groups: companies backed by VC firms with experience below 90th percentile and companies backed by VC firms with experience above 90th percentile. p-Values pertaining to a t-test for equality of means and Wilcoxon test for equality of medians are reported.

	VC Experience<90th PCTL			VC Experience>90th PCTL			Tests of Equality(p-values)	
	Count	Mean	Median	Count	Mean	Median	Mean	Median
Success exit	10706	0.17	0.00	1540	0.24	0.00	0.00	0.00
Round amount(\$ mil)	10706	5.49	3.00	1540	8.30	5.11	0.00	0.00
Age (year)	10706	2.36	1.00	1540	1.52	1.00	0.00	0.00
Round Number of Investors	10706	2.23	2.00	1540	2.50	2.0	0.00	0.00
Pre-money Valuations (\$mil)	2871	13.06	6.10	496	19.41	8.70	0.00	0.00

Table 3: Relevance of the Instrumental Variable

Notes: This table presents the effects of the instrumental variable *IV* on the fundraising and financing activities in a local market. Entrants are defined as VC firms that invest in a given market for the first time. The instrumental variable *IV* measures the variation of buyout fund inflows; see the text for more details on the variable construction. Other controls include the market network measure, logged number of deals financed in the market in previous year, industry book-to-market ratio, logged total fund amount raised by incumbents/entrants up to year t-1, and logged average experience of entrants (measured by number of prior rounds). Column 1 and 2 report dynamic panel estimation using the methods proposed by Arellano and Bond (1991). Column 3 through 5 reports results from OLS estimations that include market as well as year fixed effects. All standard errors are clustered at the market level.

	(1)	(2)	(3)	(4)	(5)
	Log(Deal No.)	Log(No. of Investing VCs)	Log(1+No. of Entrants)	Log(1+No. of Entrants' Deal)	Log(1+No. of New Funds by Entrants)
	Arellano-Bond Estimation	Arellano-Bond Estimation	FE OLS	FE OLS	FE OLS
IV	0.0163** (0.00657)	0.0231** (0.00920)	0.0127** (0.00608)	0.0117** (0.00525)	0.00647** (0.00277)
Log(Deal No.,t-1)	0.454*** (0.115)		0.787*** (0.0297)	0.812*** (0.0273)	0.327*** (0.0258)
Log(No. of Investing VCs, t-1)		0.345** (0.148)			
Network measure	-3.521*** (0.975)	-4.481** (1.960)	-0.720 (0.661)	-0.844 (0.564)	
Value-weighted industry avg. B/M ratio	-0.766*** (0.259)	-0.743*** (0.204)	-0.520*** (0.102)	-0.440*** (0.105)	-0.387*** (0.0931)
Log(Avg. Experience of Entrants)					-0.0162 (0.0143)
Log(Total amt raised by entrants prior to t)					0.150*** (0.00380)
Observations	1479	1479	1670	1670	1670
AR(2) (p-value)	0.63	0.32			
Adjusted R ²			0.601	0.665	0.801

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Table 4: Effect of Market Concentration on the Likelihoods of Success of Companies (OLS)

Notes: This table presents the effect of market concentration on the likelihoods of a successful exit for portfolio companies. A successful exit indicates a company goes through an IPO or an M&A transaction. The sample includes all US portfolio companies that received their first round of funding between 1991 and 2010. Markets are defined based on MSA regions, and industry classifications from Thomson One. The dependent variable is binary, and indicates if a portfolio company experienced a successful exit either through IPO or an M&A deal. Market concentration is measured by (i) the Herfindahl-Hirschman Index (HHI) based on deal shares, and (ii) the inverse number of VC firms in a given market. All specifications control for the characteristics of portfolio companies at the current funding round (logged company age, dummies for development stages, logged funding amount received, logged number of investors), the characteristics of the lead VC firm (logged number of participating rounds, logged fund size), characteristics of the market (logged number of deals financed in the market, logged capital inflow into VC funds in the prior four quarters, industry book-to-market ratio), as well as include market fixed effects and year fixed effects. To investigate the differential effects of market concentration, we compute the experience of VC firms in each market and year, as measured by the number of previous funding rounds a VC firm participated in. We then divide the sample into two groups: initial funding rounds backed by VC firms with experience higher than the 90th percentile level in a given market-year, and initial funding rounds backed by VC firms with experience less than the 90th percentile level. Column 1 and 2 report results using observations of funding rounds backed by VC firms with experience below 90th percentile level in a given market year; Column 3 and 4 report estimation results for funding rounds backed by VC firms with experience above 90th percentile level in a given market year. Column 5 and 6 report the estimation results for the full sample. All standard errors are clustered at the market level.

	(1) Success VC Exp<90th PCTL	(2) Success VC Exp<90th PCTL	(3) Success VC Exp>90th PCTL	(4) Success VC Exp>90th PCTL	(5) Success Full Sample	(6) Success Full Sample
hhi	-0.288* (0.166)		0.261 (1.185)		-0.318** (0.147)	
1/total vc number		-0.663*** (0.172)		4.100** (1.802)		-0.632*** (0.167)
Log(Lead VC's Experience+1)	0.00264 (0.00309)	0.00245 (0.00307)	0.0572** (0.0236)	0.0592** (0.0237)	0.00492* (0.00255)	0.00475* (0.00253)
Log(Round investment amounts)	0.0216*** (0.00275)	0.0216*** (0.00271)	0.0247* (0.0128)	0.0259** (0.0126)	0.0220*** (0.00240)	0.0221*** (0.00237)
log(VC Prior 4 Qt. Inflow)	-0.0304 (0.0213)	-0.0306 (0.0212)	-0.107 (0.0736)	-0.109 (0.0728)	-0.0295 (0.0221)	-0.0296 (0.0220)
Log(Fund size)	0.0108*** (0.00393)	0.0111*** (0.00391)	0.0160 (0.0125)	0.0157 (0.0121)	0.0111*** (0.00353)	0.0114*** (0.00351)
Log(age of company)	0.0253*** (0.00504)	0.0251*** (0.00505)	0.0353* (0.0206)	0.0342* (0.0204)	0.0263*** (0.00515)	0.0261*** (0.00516)
Value-weighted industry avg. B/M ratio	-0.125** (0.0549)	-0.121** (0.0535)	0.179 (0.119)	0.161 (0.120)	-0.133** (0.0513)	-0.129** (0.0501)
Log(round number of investors)	0.0576*** (0.00862)	0.0570*** (0.00859)	0.0488 (0.0407)	0.0495 (0.0407)	0.0598*** (0.00800)	0.0592*** (0.00798)
Log(deal no)	-0.0542*** (0.0135)	-0.0656*** (0.0132)	-0.0561 (0.0478)	-0.00802 (0.0483)	-0.0522*** (0.0123)	-0.0617*** (0.0124)
Observations	10706	10706	1540	1540	12246	12246
Adjusted R^2	0.122	0.123	0.098	0.100	0.127	0.127

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Table 5: Effect of Market Concentration on the Likelihoods of Success of Companies (2SLS)

Notes: This table presents the instrumented estimation for the effect of market concentration on the likelihoods of a successful exit for portfolio companies. A successful exit indicates a company goes through an IPO or an M&A transaction. The sample includes all US portfolio companies that received their first round of funding between 1991 and 2010. Markets are defined based on MSA regions, and industry classifications from Thomson One. The dependent variable is binary, and indicates if a portfolio company experienced a successful exit either through IPO or an M&A deal. Market concentration is measured by (i) the Herfindahl-Hirschman Index (HHI) based on deal shares, and (ii) the inverse number of VC firms in a given market. All specifications control for the characteristics of portfolio companies at the current funding round (logged company age, dummies for development stages, logged funding amount received, logged number of investors), the characteristics of the lead VC firm (logged number of participating rounds, logged fund size), characteristics of the market (logged number of deals financed in the market, logged capital inflow into VC funds in the prior four quarters, industry book-to-market ratio), as well as include market fixed effects and year fixed effects. To investigate the differential effects of market concentration, we compute the experience of VC firms in each market and year, as measured by the number of previous funding rounds a VC firm participated in. We then divide the sample into two groups: initial funding rounds backed by VC firms with experience higher than the 90th percentile level in a given market-year, and initial funding rounds backed by VC firms with experience less than the 90th percentile level. Column 1 and 2 report results using observations of funding rounds backed by VC firms with experience below 90th percentile level in a given market year; Column 3 and 4 report estimation results for funding rounds backed by VC firms with experience above 90th percentile level in a given market year. Column 5 and 6 report the estimation results for the full sample. The instrumental variable measures the variation of inflows into buyout funds; see the text for more details on the variable construction. All standard errors are clustered at the market level.

	(1) Success VC Exp<90th PCTL	(2) Success VC Exp<90th PCTL	(3) Success VC Exp>90th PCTL	(4) Success VC Exp>90th PCTL	(5) Success Full Sample	(6) Success Full Sample
hhi	-3.843*** (1.395)		5.601** (2.698)		-3.067** (1.344)	
1/total vc number		-3.710*** (1.309)		5.976** (2.683)		-3.003** (1.342)
Log(Lead VC's Experience+1)	0.00369 (0.00346)	0.00194 (0.00302)	0.0690** (0.0276)	0.0941*** (0.0329)	0.00568** (0.00274)	0.00442* (0.00246)
Log(Round investment amounts)	0.0172*** (0.00358)	0.0199*** (0.00278)	0.0214* (0.0120)	0.0307*** (0.0111)	0.0188*** (0.00295)	0.0209*** (0.00240)
log(VC Prior 4 Qt. Inflow)	-0.0311 (0.0209)	-0.0319 (0.0208)	-0.105 (0.0728)	-0.134* (0.0720)	-0.0299 (0.0217)	-0.0301 (0.0216)
Log(Fund size)	0.0102** (0.00402)	0.0126*** (0.00393)	0.0211** (0.0106)	0.0229** (0.0112)	0.0105*** (0.00362)	0.0122*** (0.00348)
Log(age of company)	0.0233*** (0.00536)	0.0231*** (0.00519)	0.0265 (0.0182)	0.0297 (0.0188)	0.0247*** (0.00533)	0.0247*** (0.00527)
Value-weighted industry avg. B/M ratio	-0.118** (0.0506)	-0.0958* (0.0497)	0.213 (0.135)	0.225* (0.133)	-0.127*** (0.0481)	-0.111** (0.0472)
Log(round number of investors)	0.0528*** (0.00918)	0.0521*** (0.00924)	0.0662* (0.0364)	0.0723** (0.0362)	0.0564*** (0.00848)	0.0553*** (0.00870)
Log(deal no)	-0.126*** (0.0307)	-0.145*** (0.0371)	0.0468 (0.0678)	0.0984 (0.0892)	-0.106*** (0.0296)	-0.120*** (0.0375)
Observations	10706	10706	1540	1540	12246	12246
Adjusted R ²	0.053	0.081	0.100	0.089	0.087	0.102

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Table 6: First Stage Results for IV Estimation

Notes: This table presents the first stage results for the instrumented estimation of the effect of market concentration on the likelihood of success of a venture. The instrumental variable *IV* measures the variation of inflows into buyout funds; see the text for more details on the variable construction. The endogenous variables are (i) the Herfindahl-Hirschman Index (HHI) based on deal shares, and (ii) the inverse number of VC firms in a given market. We compute the experience of VC firms in each market and year measured by the number of previous funding rounds a VC firm participated in. We then divide the sample into two groups: initial funding rounds backed by VC firms with experience higher than the 90th percentile level in a given market-year, and initial funding rounds backed by VC firms with experience less than the 90th percentile level. Column 1 and 2 report results using observations of funding rounds backed by VC firms with experience below 90th percentile level in a given market year; Column 3 and 4 report estimation results for funding rounds backed by VC firms with experience above 90th percentile level in a given market year. Column 5 and 6 report the estimation results for the full sample. Market and year fixed effects are included and all standard errors are clustered at the market level.

	(1)	(2)	(3)	(4)	(5)	(6)
	hhi	1/total vc number	hhi	1/total vc number	hhi	1/total vc number
	VC Exp<90th PCTL	VC Exp<90th PCTL	VC Exp>90th PCTL	VC Exp>90th PCTL	Full Sample	Full Sample
IV	-0.000902*** (0.000204)	-0.000935*** (0.000207)	-0.00104*** (0.000267)	-0.000979*** (0.000290)	-0.000895*** (0.000200)	-0.000913*** (0.000207)
Log(Lead VC's Experience+1)	0.000286 (0.000311)	-0.000176 (0.000150)	-0.00547* (0.00294)	-0.00933*** (0.00342)	0.000268 (0.000251)	-0.000146 (0.000130)
Log(Round investment amounts)	-0.00121** (0.000528)	-0.000534** (0.000243)	0.00118 (0.00116)	-0.000459 (0.000498)	-0.00114** (0.000511)	-0.000473** (0.000222)
log(VC Prior 4 Qt. Inflow)	-0.000372 (0.00138)	-0.000594 (0.00149)	-0.00479 (0.00405)	0.000312 (0.00494)	-0.000226 (0.00120)	-0.000294 (0.00133)
Log(Fund size)	-0.000267 (0.000286)	0.000379 (0.000273)	-0.000350 (0.000563)	-0.000640 (0.000554)	-0.000344 (0.000265)	0.000245 (0.000245)
Log(age of company)	-0.000618 (0.000431)	-0.000688** (0.000304)	-0.00124 (0.000823)	-0.00170* (0.000976)	-0.000602 (0.000392)	-0.000638** (0.000291)
Value-weighted industry avg. B/M ratio	0.00330 (0.00632)	0.00928 (0.00752)	0.00350 (0.00803)	0.00121 (0.0106)	0.00325 (0.00630)	0.00890 (0.00738)
Log(round number of investors)	-0.00142** (0.000669)	-0.00166*** (0.000587)	-0.00332 (0.00256)	-0.00413** (0.00164)	-0.00132** (0.000592)	-0.00172*** (0.000503)
Log(deal no)	-0.0210*** (0.00265)	-0.0268*** (0.00357)	-0.0197*** (0.00409)	-0.0271*** (0.00615)	-0.0203*** (0.00269)	-0.0256*** (0.00350)
F-stats for instrument	19.533	20.38	22.25	22.23	19.907	19.539
Partial R^2 for the IV	0.020	0.027	0.025	0.021	0.024	0.028
Observations	10706	10706	1540	1540	12246	12246

Standard errors in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

A Appendix

A.1 Effort Levels and Success Probability

Consider the entrepreneur's expected utility U^E . We get the following first-order condition which defines EN's effort level e : $e = \phi e^{\phi-1} v^{1-\phi} (1-s) \pi$. Solving for e we get

$$e = v^{\frac{1-\phi}{2-\phi}} [\phi (1-s) \pi]^{\frac{1}{2-\phi}}. \quad (\text{A.1})$$

Now consider the VC firm's expected utility U^V . The first-order condition, which defines the VC firm's effort level, is given by $v = (1-\phi) e^\phi v^{-\phi} s \pi$. Solving for v ,

$$v = e^{\frac{\phi}{1+\phi}} [(1-\phi) s \pi]^{\frac{1}{1+\phi}}. \quad (\text{A.2})$$

Substituting (A.2) in (A.1) we get

$$e = e^{\frac{\phi(1-\phi)}{(1+\phi)(2-\phi)}} [(1-\phi) s \pi]^{\frac{1-\phi}{(1+\phi)(2-\phi)}} [\phi (1-s) \pi]^{\frac{1}{2-\phi}}.$$

Solving for e and simplifying,

$$\begin{aligned} e^{1-\frac{\phi(1-\phi)}{(1+\phi)(2-\phi)}} &= [(1-\phi) s \pi]^{\frac{1-\phi}{(1+\phi)(2-\phi)}} [\phi (1-s) \pi]^{\frac{1}{2-\phi}} \\ \Leftrightarrow e^{\frac{2}{(1+\phi)(2-\phi)}} &= [(1-\phi) s \pi]^{\frac{1-\phi}{(1+\phi)(2-\phi)}} [\phi (1-s) \pi]^{\frac{1}{2-\phi}} \\ \Leftrightarrow e &= \left[[(1-\phi) s \pi]^{\frac{1-\phi}{(1+\phi)(2-\phi)}} [\phi (1-s) \pi]^{\frac{1}{2-\phi}} \right]^{\frac{(1+\phi)(2-\phi)}{2}}. \end{aligned}$$

Consequently,

$$e(s) = [(1-\phi) s]^{\frac{1-\phi}{2}} [\phi (1-s)]^{\frac{(1+\phi)}{2}} \pi. \quad (\text{A.3})$$

Likewise, substituting (A.1) in (A.2) we get

$$\begin{aligned} v &= \left[v^{\frac{1-\phi}{2-\phi}} [\phi (1-s) \pi]^{\frac{1}{2-\phi}} \right]^{\frac{\phi}{1+\phi}} [(1-\phi) s \pi]^{\frac{1}{1+\phi}} \\ \Leftrightarrow v^{1-\frac{(1-\phi)\phi}{(2-\phi)(1+\phi)}} &= [\phi (1-s)]^{\frac{1}{2-\phi} \frac{\phi}{1+\phi}} [(1-\phi) s]^{\frac{1}{1+\phi}} \pi^{\frac{1}{2-\phi} \frac{\phi}{1+\phi} + \frac{1}{1+\phi}} \\ \Leftrightarrow v^{\frac{2}{(2-\phi)(1+\phi)}} &= [\phi (1-s)]^{\frac{1}{2-\phi} \frac{\phi}{1+\phi}} [(1-\phi) s]^{\frac{1}{1+\phi}} \pi^{\frac{2}{(2-\phi)(1+\phi)}}. \end{aligned}$$

Therefore,

$$v(s) = [\phi (1-s)]^{\frac{\phi}{2}} [(1-\phi) s]^{\frac{2-\phi}{2}} \pi. \quad (\text{A.4})$$

Finally, substituting (A.3) and (A.4) in the success probability $\rho = e_i^\phi v_j^{1-\phi}$ we get

$$\begin{aligned}\rho(s) &= \left[[(1-\phi)s]^{\frac{1-\phi}{2}} [\phi(1-s)]^{\frac{(1+\phi)}{2}} \pi \right]^\phi \left[[\phi(1-s)]^{\frac{\phi}{2}} [(1-\phi)s]^{\frac{2-\phi}{2}} \pi \right]^{1-\phi} \\ &= [(1-\phi)s]^{\frac{(1-\phi)\phi}{2} + \frac{(2-\phi)(1-\phi)}{2}} [\phi(1-s)]^{\frac{(1+\phi)\phi}{2} + \frac{(1-\phi)\phi}{2}} \pi \\ &= [(1-\phi)s]^{1-\phi} [\phi(1-s)]^\phi \pi.\end{aligned}$$

A.2 Proof of Lemma 1

Substituting $e(s)$, $v(s)$, and $\rho(s)$ in the EN's expected utility U^E we get

$$\begin{aligned}U^E(s) &= [(1-\phi)s]^{1-\phi} [\phi(1-s)]^\phi \pi (1-s) \pi - \frac{1}{2} [(1-\phi)s]^{1-\phi} [\phi(1-s)]^{(1+\phi)} \pi^2 \\ &= \left[\phi^\phi (1-s)^{1+\phi} - \frac{1}{2} \phi \phi^\phi (1-s)^{1+\phi} \right] [(1-\phi)s]^{1-\phi} \pi^2 \\ &= \left[\frac{2-\phi}{2\phi} \right] [\phi(1-s)]^{1+\phi} [(1-\phi)s]^{1-\phi} \pi^2.\end{aligned}$$

The EN's preferred sharing rule, denoted s^E , is defined by the first-order condition:

$$\left[\frac{2-\phi}{2\phi} \right] \pi^2 \left[-\phi(1+\phi) [\phi(1-s)]^\phi [(1-\phi)s]^{1-\phi} + (1-\phi)^2 [\phi(1-s)]^{1+\phi} [(1-\phi)s]^{-\phi} \right] = 0.$$

Solving for s ,

$$(1-\phi)^2 \phi(1-s) = \phi(1+\phi) [(1-\phi)s] \quad \Leftrightarrow \quad s^E = \frac{1}{2} (1-\phi).$$

Likewise, using $e(s)$, $v(s)$, and $\rho(s)$, we can write the VC firm's expected utility U^V as

$$\begin{aligned}U^V(s) &= [(1-\phi)s]^{1-\phi} [\phi(1-s)]^\phi \pi s \pi - \frac{1}{2} [\phi(1-s)]^\phi [(1-\phi)s]^{2-\phi} \pi^2 \\ &= \left[(1-\phi)^{-1} - \frac{1}{2} \right] [(1-\phi)s]^{2-\phi} [\phi(1-s)]^\phi \pi^2 \\ &= \frac{1+\phi}{2(1-\phi)} [(1-\phi)s]^{2-\phi} [\phi(1-s)]^\phi \pi^2.\end{aligned}\tag{A.5}$$

Let s^V denote the sharing rule preferred by the VC firms, which is defined by the first-order condition:

$$\frac{1+\phi}{2(1-\phi)} \pi^2 \left[(2-\phi)(1-\phi) [(1-\phi)s]^{1-\phi} [\phi(1-s)]^\phi - \phi^2 [(1-\phi)s]^{2-\phi} [\phi(1-s)]^{\phi-1} \right] = 0.$$

Solving for s ,

$$(2 - \phi)(1 - \phi)\phi(1 - s) = \phi^2(1 - \phi)s \quad \Leftrightarrow \quad s^V = \frac{1}{2}(2 - \phi).$$

Next, note that the joint utility is given by $U^E(s) + U^V(s) = \rho(s)\pi - [e(s)]^2/2 - [v(s)]^2/2$. Using the expressions for $\rho(s)$, $e(s)$, and $v(s)$, we get

$$\begin{aligned} U^E(s) + U^V(s) &= [(1 - \phi)s]^{1-\phi} [\phi(1 - s)]^\phi \pi^2 \\ &\quad - \frac{1}{2} \left[[(1 - \phi)s]^{1-\phi} [\phi(1 - s)]^{(1+\phi)} \pi^2 - [\phi(1 - s)]^\phi [(1 - \phi)s]^{2-\phi} \pi^2 \right] \\ &= [(1 - \phi)s]^{1-\phi} [\phi(1 - s)]^\phi \pi^2 - \frac{1}{2} [(1 - \phi)s]^{1-\phi} [\phi(1 - s)]^\phi \pi^2 [\phi - \phi s - 1 + \phi s] \\ &= \frac{1}{2} [3 - \phi] [(1 - \phi)s]^{1-\phi} [\phi(1 - s)]^\phi \pi^2. \end{aligned}$$

The Pareto efficient sharing rule, denoted by s^J , is defined the first-order condition:

$$\frac{1}{2} [3 - \phi] \pi^2 \left[(1 - \phi)^2 [(1 - \phi)s]^{-\phi} [\phi(1 - s)]^\phi - \phi^2 [(1 - \phi)s]^{1-\phi} [\phi(1 - s)]^{\phi-1} \right] = 0.$$

Solving for s :

$$(1 - \phi)^2 [\phi(1 - s)] = \phi^2 [(1 - \phi)s] \quad \Leftrightarrow \quad s^J = 1 - \phi.$$

Likewise, the sharing rule which maximizes the success probability $\rho(s)$, is given by the corresponding first-order condition:

$$(1 - \phi)^2 [(1 - \phi)s]^{-\phi} [\phi(1 - s)]^\phi - \phi^2 [(1 - \phi)s]^{1-\phi} [\phi(1 - s)]^{\phi-1} = 0.$$

Solving for s ,

$$(1 - \phi)^2 \phi(1 - s) = \phi^2(1 - \phi)s \quad \Leftrightarrow \quad s = 1 - \phi.$$

Thus, $\rho(s)$ is maximized for $s = s^J = 1 - \phi$.

Finally, it is easy to see that $s^E < s^J < s^V$. □

A.3 Proof of Lemma 2

Using the expressions for $U^V(s)$ and $U^E(s)$ we get the following maximization problem for the VC firm:

$$\max_{s \in [s^E, s^V]} U^V(s) = \frac{1 + \phi}{2(1 - \phi)} [(1 - \phi)s]^{2-\phi} [\phi(1 - s)]^\phi \pi^2$$

s.t.

$$U^E(s) = \left[\frac{2-\phi}{2\phi} \right] [\phi(1-s)]^{1+\phi} [(1-\phi)s]^{1-\phi} \pi^2 \geq u. \quad (\text{A.6})$$

Note that $U^E(s = s^V) > 0$. Thus, the EN's participation constraint (A.6) with $s = s^V$ is satisfied (and non-binding) for a sufficiently low u . Let u' denote the reservation utility so that (A.6) is binding for $s = s^V$, i.e., $U^E(s = s^V) = u'$. Thus, for $u \leq u'$ the equilibrium sharing rule is $s^*(u) = s^V$. For $u > u'$ the sharing rule $s = s^V$ would violate (A.6). Consequently, the VC firm chooses the sharing rule $s^*(u)$ which satisfies the binding participation constraint $U^E(s) = u$. Using the binding participation constraint $U^E(s) = u$ we can implicitly differentiate $s^*(u)$ w.r.t. u :

$$\frac{ds^*(u)}{du} = - \frac{1}{\left[\frac{2-\phi}{2\phi} \right] \pi^2 \left[\phi(1+\phi) [\phi(1-s)]^\phi [(1-\phi)s]^{1-\phi} + \phi(1-\phi) [\phi(1-s)]^{1+\phi} [(1-\phi)s]^{-\phi} \right]} < 0.$$

□

A.4 Indifference Curve of a VC Firm

The slope of VC firm j 's indifference curve, when being matched with EN i , is given by

$$\Psi(i, j) = - \frac{\frac{dU^V(i, j, u)}{di}}{\frac{dU^V(i, j, u)}{du}} = - \frac{U_s^V \frac{ds^*}{di} + U_i^V}{U_s^V \frac{ds^*}{du}}.$$

Using EN i 's binding participation constraint (A.6) (see Proof of Lemma 2), we get

$$\begin{aligned} \frac{ds^*}{di} &= - \frac{2\pi\pi_i \left[\frac{2-\phi}{2\phi} \right] [\phi(1-s)]^{1+\phi} [(1-\phi)s]^{1-\phi}}{\left[\frac{2-\phi}{2\phi} \right] \pi^2 \left[-\phi(1+\phi) [\phi(1-s)]^\phi [(1-\phi)s]^{1-\phi} + (1-\phi)^2 [\phi(1-s)]^{1+\phi} [(1-\phi)s]^{-\phi} \right]} \\ &= - \frac{2\pi_i}{\pi \left[-\phi(1+\phi) [\phi(1-s)]^{-1} + (1-\phi)^2 [(1-\phi)s]^{-1} \right]} = -2 \frac{\pi_i}{\pi} \frac{s(1-s)}{1-2s-\phi}. \end{aligned}$$

Likewise,

$$\begin{aligned} \frac{ds^*}{du} &= \frac{1}{\left[\frac{2-\phi}{2\phi} \right] \pi^2 \left[-\phi(1+\phi) [\phi(1-s)]^\phi [(1-\phi)s]^{1-\phi} + (1-\phi)^2 [\phi(1-s)]^{1+\phi} [(1-\phi)s]^{-\phi} \right]} \\ &= \frac{s(1-s)}{\left[\frac{2-\phi}{2\phi} \right] \pi^2 [\phi(1-s)]^{1+\phi} [(1-\phi)s]^{1-\phi} [1-2s-\phi]}. \end{aligned} \quad (\text{A.7})$$

Moreover, using (A.5), we get

$$\begin{aligned}
U_s^V &= \frac{1+\phi}{2(1-\phi)} \pi^2 \left[(1-\phi)(2-\phi) [(1-\phi)s]^{1-\phi} [\phi(1-s)]^\phi - \phi^2 [(1-\phi)s]^{2-\phi} [\phi(1-s)]^{\phi-1} \right] \\
&= \frac{1+\phi}{2(1-\phi)} \pi^2 [(1-\phi)s]^{2-\phi} [\phi(1-s)]^\phi \left[\frac{2-2s-\phi}{s(1-s)} \right] \\
U_i^V &= 2\pi\pi_i \frac{1+\phi}{2(1-\phi)} [(1-\phi)s]^{2-\phi} [\phi(1-s)]^\phi.
\end{aligned}$$

Thus, the slope of VC firm j 's indifference curve is given by

$$\begin{aligned}
\Psi(i, j) &= -\frac{\pi \left[\frac{2-2s-\phi}{s(1-s)} \right] \frac{ds^*}{di} + 2\pi_i}{\pi \left[\frac{2-2s-\phi}{s(1-s)} \right] \frac{ds^*}{du}} \\
&= -\frac{2\pi_i \left[1 - \left[\frac{2-2s-\phi}{1-2s-\phi} \right] \right] \left[\frac{2-\phi}{2\phi} \right] \pi^2 [\phi(1-s)]^{1+\phi} [(1-\phi)s]^{1-\phi} [1-2s-\phi]}{\pi [2-2s-\phi]} \\
&= 2 \frac{\pi_i}{\pi} \frac{1}{2-2s-\phi} \underbrace{\left[\frac{2-\phi}{2\phi} \right] [\phi(1-s)]^{1+\phi} [(1-\phi)s]^{1-\phi} \pi^2}_{=U^E(s,i,j)}.
\end{aligned}$$

According to EN i 's binding participation constraint (A.6), $U^E(s, i, j) = u(i)$. Thus,

$$\Psi(i, j) = 2 \frac{\pi_i}{\pi} \frac{1}{2-2s-\phi} u.$$

Next we need to show that $\Psi(i, j)$ is increasing in j . For this we first note that $u(i)$ is constant in j . Moreover, using EN i 's binding participation constraint (A.6) we get

$$\begin{aligned}
\frac{ds^*}{dj} &= -\frac{2 \left[\frac{2-\phi}{2\phi} \right] \pi \pi_j [\phi(1-s)]^{1+\phi} [(1-\phi)s]^{1-\phi}}{\left[\frac{2-\phi}{2\phi} \right] \pi^2 \left[-\phi(1+\phi) [\phi(1-s)]^\phi [(1-\phi)s]^{1-\phi} + (1-\phi)^2 [\phi(1-s)]^{1+\phi} [(1-\phi)s]^{-\phi} \right]} \\
&= -2 \frac{\pi_j}{\pi} \frac{1}{\left[-\phi(1+\phi) [\phi(1-s)]^{-1} + (1-\phi)^2 [(1-\phi)s]^{-1} \right]} = 2 \frac{\pi_j}{\pi} \frac{s(1-s)}{2s+\phi-1},
\end{aligned}$$

which is strictly positive for $s^* > s^E = \frac{1}{2}(1 - \phi)$. Consequently,

$$\begin{aligned} \frac{d\Psi(i, j)}{dj} &= 2u \frac{\pi_{ij}\pi(2 - 2s - \phi) - \pi_i \left[\pi_j(2 - 2s - \phi) - 2\pi \frac{ds^*}{dj} \right]}{[\pi(2 - 2s - \phi)]^2} \\ &= 2u \frac{\pi_{ij}\pi(2 - 2s - \phi) + \overbrace{\pi_i \pi_j \left[4 \frac{s(1-s)}{2s + \phi - 1} - (2 - 2s - \phi) \right]}{\equiv Z}}{[\pi(2 - 2s - \phi)]^2}. \end{aligned}$$

This is positive if $Z > 0$ (which is a sufficient condition, as by assumption $\pi_{ij} \geq 0$). Recall from Lemma 1 that $s^* \in (s^E, s^V) = (\frac{1}{2}(1 - \phi), \frac{1}{2}(2 - \phi))$. We can thus write $s^*(\eta) = \frac{1}{2}(1 + \eta - \phi)$, with $\eta \in (0, 1)$. It is then sufficient to show that $Z > 0$ for all $\eta \in (0, 1)$. Using $s^*(\eta)$ we can write $T > 0$ as

$$\begin{aligned} \frac{2(1 + \eta - \phi) \left(1 - \frac{1}{2}(1 + \eta - \phi)\right)}{(1 + \eta - \phi) + \phi - 1} &> 2 - (1 + \eta - \phi) - \phi \\ \Leftrightarrow (1 + \eta - \phi)(1 - \eta + \phi) &> (1 - \eta)\eta \\ \Leftrightarrow 1 - \phi^2 + 2\eta \left(\phi - \frac{1}{2}\right) &> 0, \end{aligned}$$

which is clearly satisfied for $\phi \in [\frac{1}{2}, 1)$. Consequently, $d\Psi(i, j)/dj > 0$.

A.5 Existence of a Unique Solution to the ODE (2.5)

We assume that the Picard-Lindelöf Theorem holds, and therefore a unique solution to (2.5) exists, at least in the neighborhood of the initial condition. We need $dU^E(i)/di$ to be Lipschitz continuous in U^E and continuous in i , see Birkoff and Rota (1989). Our assumptions ensure that $dU^E(i)/di$ is continuous in i (note that i enters through π , which we assume is continuously differentiable in its arguments). If a differentiable function has a derivative that is bounded everywhere by a real number, then the function is Lipschitz continuous. The derivative of (2.5) with respect to U^E , or u , is

$$\frac{\pi_i}{\pi} \left(\frac{2}{2 - 2s - \phi} + \frac{4u \frac{ds}{du}}{(2 - 2s - \phi)^2} \right).$$

The above is bounded by a real number provided that $s < s^V = \frac{1}{2}(2 - \phi)$ and $\frac{ds}{du}$ is bounded. The former holds since we have assumed that the initial condition \underline{u} is higher than the utility the EN would get when $s = s^V$ and $s < s^V$. And the latter holds as long as $s > s^E \equiv \frac{1-\phi}{2}$ (see (A.7)), which we assume to be the case. In other words, the highest quality VC in the market offers less equity than the one that maximizes the EN's utility.

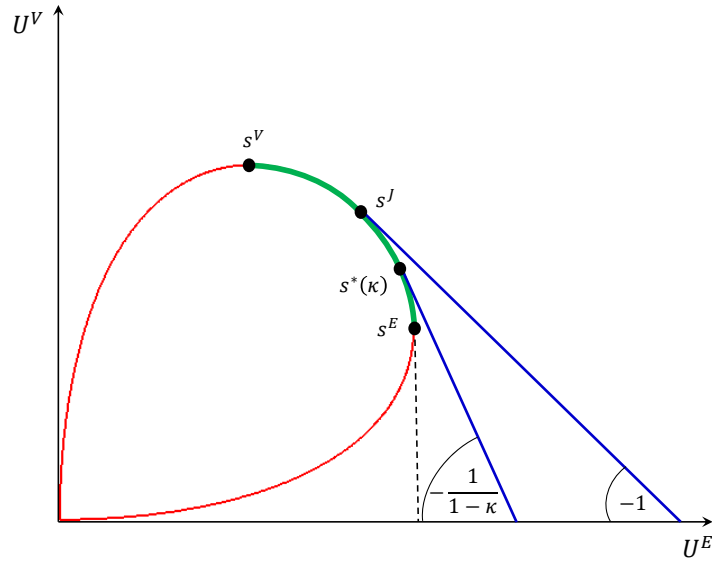


Figure A.1: Utility-possibility frontier with transfer payments

A.6 Model with Transfer Payments

In our main text we focus on simple equity sharing contracts between ENs and VC firms to keep the model as simple and transparent as possible. We therefore implicitly assumed that no party can make a monetary transfer payment to buy additional equity from the other party. This is intuitive for entrepreneurs who are typically wealth constrained (which is a reason why they need VC in the first place). However, VC firms may have some cash beyond the required investment amount K which they could use to buy some additional equity from their entrepreneurs (see, e.g., Hellmann (2006) and Jovanovic and Szentes (2012), and within the context of partnerships with double-sided moral hazard, Hellmann and Thiele (2017)). We now briefly show that allowing VC firms to make such transfer payments does not change the qualitative nature of our main results, as long as transfers are costly.

We first note that it can only be optimal for the VC firm to make a transfer payment, and for the EN to accept this payment, when it leads to a Pareto improvement. This is clearly the case when the VC firm gets too little equity from a joint perspective, i.e., $s^* \in [s^E, s^J]$; see Figure A.1. And we know from our analysis that this requires the EN's outside option u to be sufficiently high, which applies when the entrepreneur has a high quality project and receives funding from a high experience VC firm. For the remainder of this section we focus on this case.

Suppose the VC firm can transfer the amount T to the entrepreneur at a cost κT , with $\kappa \in [0, 1]$, to buy some additional equity. We can see from Figure A.1 how costly transfer payments affect the utility-possibility frontier (UPF) between the VC firm and the entrepreneur. Specifically, the VC firm can get a higher expected utility by increasing its equity share to some $s^*(\kappa) \in (s^E, s^J]$, where the marginal rate of substitution satisfies $dU^V/dU^E = -1/(1-\kappa)$. Buying even more equity would be inefficient for the VC firm, as the additionally required transfer would exceed the extra utility from getting a higher equity stake.

When $\kappa = 1$ we are back to our base model, where utility can only be transferred through the sharing rule s . With $\kappa = 0$ we have perfectly transferable utility up to the point s^J on the UPF, as reflected by the blue line at point s^J with a slope of negative one; see Figure A.1. In this case it would always be efficient for the VC firm to buy enough additional equity from the EN so that $s^* = s^J$. Consequently, VC competition would then not change the outcome (i.e., the valuation and probability of success) for high quality projects backed by high experience VC firms.

The most important insight is that for any $\kappa \in (0, 1)$, the maximum equity share that the VC firm can get, is somewhere between s^E and s^J . In Figure A.1 this is reflected by the point $s^*(\kappa)$ on the UPF (which has the slope $-1/(1 - \kappa)$). This implies that even monetary transfer payments cannot achieve the Pareto efficient outcome (s^J), as long as there is some cost $\kappa > 0$ to making such transfers. It would then still be true that stronger VC competition leads to lower valuations and success probabilities of high quality projects funded by high experience VC firms.

Finally, we note that our empirical results indicate that transaction costs may play a role in VC contracting (otherwise competition would not affect the valuation and success rate of high quality projects). Overall this suggests that the Pareto efficient outcome is often not achieved, so that the likelihood of startup companies to succeed is inefficiently low.

A.7 The Effects of Concentration on Pre-money Valuations

Our theory suggests a negative relationship between the level of market concentration and the equity retained by entrepreneurs. We test the following hypothesis which follow directly from Proposition 1:

Hypothesis: *Suppose the VC market becomes more competitive (i.e., concentration decreases). Then, the pre-money valuations of all VC-backed companies increase.*

We use the following specification to test for the effect of market concentration on pre-money valuations of startup companies:

$$\begin{aligned} \text{Log}(\text{Pre-money Valuation}_{s_{ijmt}}) = & \alpha + \beta_1 \text{Concentration}_{mt} + \beta_2 C_{imt} + \beta_3 X_{jmt} \\ & + \beta_4 M_{mt} + \phi_m + \tau_t + \epsilon_{ijmt}, \end{aligned} \quad (\text{A.8})$$

where i, j, m , and t index the portfolio company, VC firm, market, and year, respectively. The dependent variable, $\text{Log}(\text{Pre-money Valuations})$, is the logged pre-money valuation of a portfolio company in the first funding round.

We relate a company's pre-money valuations to the following variables: the characteristics of the lead investor (including fund size and experience), the characteristics of portfolio companies (such as age and development stage), the book-to-market ratio of the public companies in the same industry as the portfolio companies, the total inflow of capital into VC funds in the prior four quarters, the total number of deals financed in the market, the market network measures, the number of investors in the first funding round, and our measures of market concentration. We also include market and year fixed effects.

The effect of market concentration is subject to endogeneity concerns. For example, an unobservable shock to barriers to entry is correlated with not only the concentration of VC firms in local markets, but also the quality of entrepreneurial projects seeking funding in the market. Therefore, we rely on instrumented estimation to analyze the effect of market concentration on valuations received by startups. We use the same instrument as discussed in Section 3.5.1: the inflows into buyout funds. Such instrument is associated with capital supply but is not directly related to the changes of projects available for financing in the market. The first stage results are reported in Table B.2. Table B.1 shows the regression results concerning the effect of market concentration on pre-money valuations. Columns 1 and 3 report the OLS results for our two alternative concentration measures. Columns 2 and 4 present the 2SLS results. When comparing the estimation results using OLS and 2SLS, we can infer that failing to control for omitted variables results in an upward bias in the estimate of the effect of market concentration. This suggests that the omitted variables simultaneously make markets more concentrated and lead to higher valuations of portfolio companies. One plausible example of such an omitted variable is entry costs in the local market. On the one hand, in a market with high entry costs, only a small number of VC firms invest in entrepreneurial projects that are of sufficiently high quality, suggesting high valuations of those ventures at the time of funding. On the other hand, in a market with low entry costs, market concentration is low and many low quality projects are able to receive funding from VC firms. Furthermore, the valuations of those low quality ventures are likely to be low²¹. This suggests an upward bias in the OLS estimate of the effect of concentration on valuations.

The IV results indicate that market concentration is negatively related to company valuations, and this effect is statistically significant. Holding all other things constant, pre-money valuations decrease by 6.4 percent when the number of investing VC firms in a given market decreases from 10 to 9, as suggested by Column 4. Furthermore, in case all investing VC firms split the total investment amount in a given round equally, the same change in the number of investing VC firms causes the HHI to increase by 0.011, and this leads to a 8.2 percent lower valuation of startup companies.

It is important to note that the Thomson One valuation data is subject to a selection bias. More specifically, the sample contains only information on pre-money valuations for about one-fifth of all deals. And previous literature suggests that companies may strategically disclose information about valuation (see, e.g., Hochberg, Ljungqvist, and Lu (2007), and Hwang, Quigley, and Woodward (2005)). We correct for the potential bias from both sample selection and endogenous variables as follows (see Wooldridge (2010)): We first use a selection equation to estimate the inverse Mills ratios. We then estimate the structural model using 2SLS, and include the estimated inverse Mills ratios as an independent variable. We also correct for the generated regressors problem by using bootstrap standard errors.

To estimate the inverse Mills ratios we use a selection equation as proposed by Hwang, Quigley, and Woodward (2005); we provide more details in Section A.8 in the Appendix. We estimate an ordered

²¹In the regression, we include imperfect controls for quality of entrepreneurial ventures such as company age and book-to-market ratio of public companies in the focal industry. We also control for the degree of networks among VC firms in a market which reflect costs of entry. However, there are still likely to be unobservables regarding barriers to entry that are correlated with market concentration as well as the quality of entrepreneurial projects.

probit model that examines seven possible investment outcomes for a VC-backed company in each quarter. The seven possible outcomes are ordered from the least desirable to the most desirable outcome: (i) shutdown, (ii) acquisition without disclosure of company valuation, (iii) no funding at all, (iv) funding without disclosure of company valuation, (v) funding with disclosure of company valuation, (vi) acquisition with disclosure of company valuation, and (vii) IPO. The explanatory variables include company development status at the most recent financing round, its industry and geographic location, the stock market capitalization at the time, year effects, the number of days since the most recent financing round, and the type of the previous financing round (i.e., seed, early-stage, later stage, and so on). We then include the inverse Mills ratios when estimating (A.8) using 2SLS.

Columns 5 and 6 in Table B.1 report the regression results. After controlling for sample selection and endogeneity, we continue to observe a negative and statistically significant effect of market concentration on pre-money valuations. The magnitudes of the estimated coefficients for the concentration measures are slightly higher compared to those generated by 2SLS. Moreover, the inverse Mills ratios have a significant effect on pre-money valuations, indicating the presence of a sample selection bias if one does not correct for it.

A.8 Sample Selection with Endogenous Explanatory Variables

We now establish the sample selection model when one of the explanatory variables is endogenous (see Hwang, Quigley, and Woodward (2005)). The structural equation takes the following form:

$$y_{1it} = z_{1it}\delta_1 + y_{2it}\alpha_1 + u_{1it},$$

where y_{2it} is subject to endogeneity concerns. Moreover, we can identify y_{2it} using $y_{2it} = z_{2it}\delta_2 + v_{2it}$.

The selection equation is built around the following latent regression: $I_{it}^* = z_{3it}\delta_3 + v_{3it}$. Using the seven possible events as described in Section A.7, we define I_{it} as follows:

$$I_{it} = \begin{cases} \text{Event 1 if } I_{it}^* \leq \tau_1 \\ \text{Event } j \text{ if } \tau_{j-1} < I_{it}^* \leq \tau_j \text{ for } 2 \leq j \leq 6 \\ \text{Event 7 if } I_{it}^* > \tau_6. \end{cases}$$

Furthermore, we make the following assumptions: (i) (z_{3it}, I_{it}) is always observed, and the observation of y_{1it} is dependent on I_{it} , (ii) $v_{3it} \sim N(0, 1)$, (iii) $E(u_{1it}|v_{3it}) = \gamma_1 v_{3it}$, and (iv) $E(z'_{2it}v_{2it}) = 0$. Given these assumptions we can write y_{1it} as $y_{1it} = z_{1it}\delta_1 + y_{2it}\alpha_1 + E(u_{1it}|z_{3it}, I_{it}) + e_{1it}$, with $e_{1it} \equiv u_{1it} - E(u_{1it}|z_{3it}, I_{it})$. By definition, $E(e_{1it}|z_{3it}, I_{it}) = 0$. Moreover, $z_{2it}\delta_2 = z_{1it}\delta_{21} + z_{21it}\delta_{22}$, $\delta_{22} \neq 0$. For parsimony we suppress the subscript it whenever possible.

Given the selection equation we need to consider the following three cases.

Case 1: y_1 is observed only when $I_{it}^* > a$, so that

$$\begin{aligned} E(y_1 | \mathbf{z}_1, \mathbf{z}_3, I_{it}^* > a) &= \mathbf{z}_1 \delta_1 + \alpha_1 y_2 + E(u_1 | \mathbf{z}_3, I_{it}^* > a) \\ &= \mathbf{z}_1 \delta_1 + \alpha_1 y_2 + \gamma_3 \frac{\phi(a - \mathbf{z}_3 \delta_3)}{\Phi(-(a - \mathbf{z}_3 \delta_3))}. \end{aligned}$$

The Mills ratio is then given by $\frac{\phi(a - \mathbf{z}_3 \delta_3)}{\Phi(-(a - \mathbf{z}_3 \delta_3))}$.

Case 2: y_1 is observed only when $I_{it}^* \leq a$, so that

$$E(y_1 | \mathbf{z}_1, \mathbf{z}_3, I_{it}^* \leq a) = \mathbf{z}_1 \delta_1 + \alpha_1 y_2 + E(u_1 | \mathbf{z}_3, I_{it}^* \leq a) = \mathbf{z}_1 \delta_1 + \alpha_1 y_2 - \gamma_3 \frac{\phi(a - \mathbf{z}_3 \delta_3)}{\Phi(a - \mathbf{z}_3 \delta_3)}.$$

The Mills ratio is then $-\frac{\phi(a - \mathbf{z}_3 \delta_3)}{\Phi(a - \mathbf{z}_3 \delta_3)}$.

Case 3: y_1 is observed only when $a < I_{it}^* \leq b$, so that

$$\begin{aligned} E(y_1 | \mathbf{z}_1, \mathbf{z}_3, a < I_{it}^* < b) &= \mathbf{z}_1 \delta_1 + \alpha_1 y_2 + E(u_1 | \mathbf{z}_3, a < I_{it}^* \leq b) \\ &= \mathbf{z}_1 \delta_1 + \alpha_1 y_2 + \gamma_3 \frac{\phi(a - \mathbf{z}_3 \delta_3) - \phi(b - \mathbf{z}_3 \delta_3)}{\Phi(b - \mathbf{z}_3 \delta_3) - \Phi(a - \mathbf{z}_3 \delta_3)}. \end{aligned}$$

The Mills ratio is then given by $\frac{\phi(a - \mathbf{z}_3 \delta_3) - \phi(b - \mathbf{z}_3 \delta_3)}{\Phi(b - \mathbf{z}_3 \delta_3) - \Phi(a - \mathbf{z}_3 \delta_3)}$.

According to Theorem 19.1 in Wooldridge (2010, p. 794), given \mathbf{z}_3 and I_{it} we can use 2SLS to generate consistent estimates for δ_1 and α_1 by including the Mills ratio as one of the exogenous variables.

B Appendix: Additional Tables

Table B.1: Effect of Market Concentration on Valuations

Notes: This table presents the effect of market concentration on the pre-money valuations of portfolio companies. The sample includes all US portfolio companies that received their first round of funding between 1991 and 2010. Markets are defined based on MSA regions, and industry classifications from Thomson One. The dependent variable is the logged value of the pre-money valuations of portfolio companies. Market concentration is measured by (i) the Herfindahl-Hirschman Index (HHI) based on deal shares, and (ii) the inverse number of VC firms in a given market. All specifications control for the characteristics of portfolio companies at the current funding round (logged company age, dummies for development stages, logged number of investors), the characteristics of the lead VC firm (logged fund size, logged number of experience as measured by prior participating rounds), characteristics of the market (logged number of deals financed in the market, logged capital inflow into VC funds in the prior four quarters, industry book-to-market ratio, market network measure), as well as include market fixed effects and year fixed effects. The instrumental variable *IV* measures the variation of inflows into buyout funds; see the text for more details on the variable construction. Column 1 and 3 report the OLS estimation. Columns 2 and 4 report the results from the 2SLS estimation. Columns 5 and 6 present the results from the 2SLS estimation that corrects for a sample selection bias as described in Section A.7. Bootstrap standard errors are reported in Column 5 and 6. In all other columns, standard errors are clustered at the market level.

	(1)	(2)	(3)	(4)	(5)	(6)
	logpremoney OLS	logpremoney 2SLS	logpremoney OLS	logpremoney 2SLS	logpremoney 2SLS(selection corrected)	logpremoney 2SLS(selection corrected)
hhi	-4.351** (2.072)	-7.391* (4.265)			-10.13* (5.934)	
1/total vc number			-3.65** (1.682)	-5.780* (3.378)		-8.419* (4.936)
Log(deal no)	0.000964 (0.0647)	-0.111 (0.0901)	-0.00151 (0.0704)	-0.123 (0.0969)	-0.137 (0.101)	-0.144 (0.0943)
log(VC Prior 4 Qt. Inflow)	0.0842 (0.0993)	0.0767 (0.0991)	0.0843 (0.0993)	0.0837 (0.0991)	-0.0777 (0.111)	-0.0608 (0.102)
Log(Experience of lead VC)	0.00442 (0.0131)	0.00178 (0.0138)	0.00443 (0.0131)	0.00297 (0.0135)	0.00393 (0.0132)	0.00534 (0.0131)
Log(Fund size)	0.204*** (0.0238)	0.205*** (0.0242)	0.204*** (0.0238)	0.204*** (0.0241)	0.197*** (0.0211)	0.199*** (0.0214)
Log(age of company)	0.245*** (0.0303)	0.244*** (0.0303)	0.245*** (0.0303)	0.245*** (0.0302)	0.251*** (0.0337)	0.252*** (0.0331)
Value-weighted industry avg. B/M ratio	0.575 (0.376)	0.563 (0.371)	0.577 (0.376)	0.633* (0.374)	0.572 (0.402)	0.616 (0.411)
Log(round number of investors)	0.424*** (0.0431)	0.401*** (0.0413)	0.424*** (0.0428)	0.410*** (0.0419)	0.405*** (0.0398)	0.421*** (0.0411)
Market Network Measure	-0.556 (0.743)	0.340 (1.083)	-0.586 (0.696)	-0.809 (0.722)	1.606 (1.454)	-0.00506 (0.778)
Inverse Mills ratio					-3.426*** (0.853)	-3.349*** (0.852)
Observations	3350	3350	3350	3350	3350	3350
Adjusted R^2	0.269	0.225	0.269	0.235	0.258	0.268

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Table B.2: Effect of Market Concentration on Valuations (First Stage Results)

Notes: This table presents the first stage results for the instrumented estimation for the effect of market concentration on the pre-money valuations of portfolio companies. The sample includes all US portfolio companies that received their first round of funding between 1991 and 2010. Markets are defined based on MSA regions, and industry classifications from Thomson One. The endogenous variables are (i) the Herfindahl-Hirschman Index (HHI) based on deal shares, and (ii) the inverse number of VC firms in a given market. The instrumental variable IV measures the variation of inflows into buyout funds; see the text for more details on the variable construction. Column 1 and 2 report the first stage results from the 2SLS estimation. In Column 3 and 4, first stage results are present for the estimation procedure described in Section A.7 and A.8 that correct for a sample selection bias. All specifications control for the characteristics of portfolio companies at the current funding round (logged company age, dummies for development stages, logged number of investors), the characteristics of the lead VC firm (logged fund size, logged number of experience as measured by prior participating rounds), characteristics of the market (logged number of deals financed in the market, logged capital inflow into VC funds in the prior four quarters, industry book-to-market ratio, market network measure), as well as include market fixed effects and year fixed effects. Standard errors are clustered at the market level in Column 1 and 2, and bootstrap standard errors are reported in Column 3 and 4.

	(1) hhi	(2) 1/total vc number	(3) hhi (Selection corrected)	(4) 1/total vc number (Selection corrected)
IV	-0.00104*** (0.000246)	-0.00133*** (0.000310)	-0.00104*** (0.000311)	-0.00132*** (0.000392)
Log(deal no)	-0.0174*** (0.00356)	-0.0243*** (0.00394)	-0.0172*** (0.00346)	-0.0240*** (0.00421)
log(VC Prior 4 Qt. Inflow)	-0.00133 (0.00150)	-0.000491 (0.00194)	-0.00267 (0.00230)	-0.000971 (0.00188)
Log(Experience of lead VC)	-0.000395 (0.000271)	-0.000299 (0.000201)	-0.000383 (0.000292)	-0.000305 (0.000201)
Log(Fund size)	0.000104 (0.000415)	-0.000123 (0.000393)	0.0000581 (0.000448)	-0.000101 (0.000425)
Log(age of company)	-0.000413 (0.000606)	-0.000302 (0.000480)	-0.000369 (0.000626)	-0.000236 (0.000446)
Value-weighted industry avg. B/M ratio	-0.00695 (0.00834)	0.00328 (0.0101)	-0.00768 (0.00965)	0.00274 (0.0103)
Log(round number of investors)	-0.00334*** (0.000925)	-0.00274*** (0.000824)	-0.00349*** (0.000851)	-0.00274*** (0.000790)
Network measure	0.110 (0.0728)	-0.0584 (0.0565)	0.111 (0.0709)	-0.0534 (0.0544)
Inverse Mills ratio			-0.0307 (0.0266)	-0.00880 (0.0202)
F-stats for instrument	17.77	18.36		
Partial R^2	0.027	0.06		
Observations	3349	3349	3349	3349
Adjusted R^2	0.321	0.347	0.293	0.320

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Table B.3: Effects of Competition on Success

Notes: This table presents the estimation for the effect of market concentration on the likelihoods of a successful exit for portfolio companies. A successful exit indicates a company goes through an IPO or an M&A transaction. The sample includes all US portfolio companies that received their first round of funding between 1991 and 2010. Markets are defined based on MSA regions, and industry classifications from Thomson One. The dependent variable is binary, and indicates if a portfolio company experienced a successful exit either through IPO or an M&A deal. Market concentration is measured by (i) the Herfindahl-Hirschman Index (HHI) based on deal shares, and (ii) the inverse number of VC firms in a given market. All specifications control for the characteristics of portfolio companies at the current funding round (logged company age, dummies for development stages, logged funding amount received, logged number of investors), the characteristics of the lead VC firm (logged number of participating rounds, logged fund size), characteristics of the market (logged number of deals financed in the market, logged capital inflow into VC funds in the prior four quarters, industry book-to-market ratio), as well as include market fixed effects and year fixed effects. To investigate the differential effects of market concentration, we compute the experience of VC firms in each market and year, as measured by the number of previous funding rounds a VC firm participated in. We then divide the sample into two groups: initial funding rounds backed by VC firms with experience lower than the 50th percentile level in a given market-year, and initial funding rounds backed by VC firms with experience between 50th and 90th percentile level. For each group, we estimate both OLS and 2SLS for the effects of two alternative market concentration measures. The instrumental variable measures the variation of inflows into buyout funds; see the text for more details on the variable construction. All standard errors are clustered at the market level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Success OLS <50th PCTL	Success 2SLS <50th PCTL	Success OLS <50th PCTL	Success 2SLS <50th PCTL	Success OLS 50-90th PCTL	Success 2SLS 50-90th PCTL	Success OLS 50-90th PCTL	Success 2SLS 50-90th PCTL
hhi	-0.586** (0.229)	-4.382*** (1.497)			-0.459** (0.214)	-4.264** (2.138)		
1/total vc number			-0.542** (0.217)	-4.455*** (1.561)			-0.782*** (0.238)	-4.798* (2.596)
Log(Lead VC's Experience+1)	0.000990 (0.00530)	0.00493 (0.00442)	0.00250 (0.00395)	0.00352 (0.00423)	0.00231 (0.00722)	-0.00418 (0.00918)	0.00106 (0.00728)	-0.00922 (0.0116)
Log(Round investment amounts)	0.0158*** (0.00534)	0.0113** (0.00479)	0.0170*** (0.00393)	0.0144*** (0.00425)	0.0293*** (0.00399)	0.0273*** (0.00515)	0.0291*** (0.00397)	0.0273*** (0.00458)
log(VC Prior 4 Qt. Inflow)	-0.0536* (0.0319)	0.00448 (0.0290)	0.00688 (0.0290)	0.00316 (0.0295)	-0.0773** (0.0308)	-0.0814** (0.0331)	-0.0766** (0.0306)	-0.0746** (0.0320)
Log(Fund size)	0.0189*** (0.00565)	0.0118** (0.00534)	0.0101* (0.00522)	0.0125** (0.00549)	0.0106** (0.00477)	0.00896* (0.00524)	0.0114** (0.00473)	0.0148*** (0.00516)
Log(age of company)	0.0263*** (0.00790)	0.0277*** (0.00670)	0.0289*** (0.00608)	0.0263*** (0.00655)	0.0191** (0.00757)	0.0137* (0.00834)	0.0190** (0.00760)	0.0149* (0.00820)
Value-weighted industry avg. B/M ratio	0.0337 (0.0937)	-0.0982** (0.0435)	-0.112*** (0.0377)	-0.0671 (0.0462)	-0.121 (0.0919)	-0.106 (0.0847)	-0.117 (0.0905)	-0.0902 (0.0827)
Log(round number of investors)	0.0670*** (0.0147)	0.0613*** (0.0143)	0.0641*** (0.0135)	0.0609*** (0.0141)	0.0515*** (0.0125)	0.0411*** (0.0130)	0.0508*** (0.0125)	0.0407*** (0.0129)
Log(deal no)	-0.0555*** (0.0189)	-0.147*** (0.0388)	-0.0642*** (0.0157)	-0.172*** (0.0500)	-0.0425** (0.0180)	-0.114*** (0.0438)	-0.0537*** (0.0178)	-0.155** (0.0660)
1st Stage Results								
IV		-0.001*** (0.0002)		-0.00096*** (0.0002)		-0.0009*** (0.0002)		-0.0009** (0.0002)
F-stats for instrument		22.49		21.48		18.68		19.43
Partial R^2 for the IV		0.020		0.028		0.026		0.026
Observations	5427	5427	5427	5427	5548	5548	5548	5548
Adjusted R^2	0.105	0.06	0.113	0.058	0.138	0.052	0.139	0.062

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

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