Inter-Company Matching and the Supply of Informed Capital*

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Abstract

We model an economy where it is beneficial for high-type organizations to collaborate with other high types (assortative matching), and where the assortative-matching pattern allows informed financiers to provide inexpensive funds to partner companies of their high-type ventures. The funding benefit associated with finding a high-type partner provides an additional incentive for search, and we show how a critical mass of informed capital sometimes becomes a necessary condition for an efficient equilibrium to obtain. We also conduct a brief empirical analysis—combining data on alliances and venture-capital deals—that yields results consistent with the mechanisms proposed in the model.

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1 Introduction

Economists often use single-firm models for tractability, but most real-world organizations interact in important ways. For example, all ten top-selling biotechnology drugs in 2001 were developed by specialized biotech companies; but only five of the drugs were marketed by biotech companies, and only four were marketed by its developer (Powell, Koput, White, and Owen-Smith, 2005). If some important projects in the economy are a collaborative endeavor, it seems reasonable to conjecture that getting the "right" organizations to match plays an important role in achieving success. However, efficient matching may be challenging in fast-paced high-tech sectors that are naturally plagued by high uncertainty and informational asymmetries.

Our paper develops a model where a minimum supply of informed capital—for example, the number of venture capitalists catering to a particular technology cluster—is instrumental in enabling efficient matches on a large scale, where many high-quality organizations associate with one another to produce. We also present empirical evidence—combining data on alliances and VC deals—that suggests the key mechanisms operating in the model are present in the data.

In light of our main result, the normative takeaway of the paper is that fostering the supply of informed capital (e.g., by promoting the VC industry) might yield a high return, if this policy pushes the supply of informed capital beyond a critical threshold. The more positive implication of the model is that jumps or acceleration in economic output can sometimes be observed when certain levels in the supply of informed capital are exceeded.

The model we propose builds on a labor economics paper on job search and social connections (Montgomery, 1991). In this paper, employees exogenously display (positive) *as-*

sortative matching, that is, the tendency for high types to associate with other high types. As employers learn which current employees are high-type, they are able to make informed, above-market wage offers to their employees' social connections. In our model, the social connection is replaced by a business association between two organizations that want to collaborate on a project. As the employees in Montgomery (1991), the organizations in our model also differ with respect to type. The model assumes at the outset that assortative matching is desirable from a technological perspective.[1]

We consider two types of financiers: an exogenous number of VC-like agents (informed capital) and a competitive uninformed financial market, which operates as long as adverse selection is not too severe. The model then adds two key frictions. The first is that companies need to incur an exogenous certification cost to be matched with a high-quality partner. The second is that companies (or entrepreneurs) are financially constrained. With these ingredients, the model predicts that the economy is in one of two mutually exclusive equilibria: (1) only informed finance is available, and thus the level of aggregate output is dictated by the supply of informed capital; or (2) uninformed financial markets are feasible and many more projects are financed (large-scale regime). Our model generates two main results: (1) for the large-scale regime to be an equilibrium, a critical threshold for the supply of informed capital must be exceeded; and (2) if the critical threshold is positive, then the large-scale regime is more efficient than the informed-finance-only equilibrium when the supply of informed capital is *at the threshold*.

The mechanics of the result is as follows. Whereas an informed-finance-only economy

[1]A similar assumption is made in Rhodes-Kropf and Robinson (2008) in a context of mergers. Many other papers on search and matching start with the assumption that match synergies exist; for a review of this literature, see Smith (2011). With assortative matching, financiers are able to infer the quality of their current ventures' business associations, and in this way pursue profitable investment opportunities. For a discussion of assortative matching and efficiency, see Durlauf and Seshadri (2003).

can weed out many low types, the opening of the uninformed financial market attracts these types as well. However, the main problem with the presence of low types is not that they have negative net present value projects, but the fact that they may disrupt assortative matching, without which the large-scale regime is unfeasible. In the model, low-type organizations do not have an incentive to incur the certification cost required to find a high-quality partner, and not incurring in certification costs relaxes their financial constraints. In turn, the relaxed financial constraints allow low-type companies to make large transfers to their partners, who are picked from a residual matching market at random. Given high prices in the residual matching market, high-quality companies might not receive offers from prospective high-quality partners that are good enough, in which case assortative matching is no longer sustainable. The financial sector, then, plays an important role in offsetting the negative indirect effect of certification costs. A minimum supply of informed capital guarantees that, even with the financial slack of low types present, the difference in the costs of financing across high and low types is still large enough that high types want to engage in assortative matching (i.e., to incur certification costs). A higher supply of informed capital increases the probability that high types can obtain low-cost informed financing and worsens the adverse selection in the uninformed capital market, which in turn increases the cost of financing for low types.

The role of informed financial intermediaries in this model is thus different from its role in standard models, in the sense that they operate as enablers of the uninformed financial market. This situation is counter-intuitive because we expect adverse selection generated by informed intermediaries to simply crowd out uninformed financiers.

For a minimum supply of informed capital to be instrumental in sustaining the large-scale regime, internal funds must be at an intermediate level. On the one hand, they cannot be too high. This necessity is intuitive, as we would expect financially unconstrained agents to more easily implement the efficient outcome in equilibrium. However, on the other hand, internal funds also cannot be too low. With too few internal funds, high-quality companies participating in the certified matching market tend to overbid for potential partners, and these high bids come at the expense of uninformed financiers. Investors anticipate this behavior, and because uninformed finance is no longer available, the large-scale regime collapses. In other words, internal funds need to be high enough to align the interests of insiders and outsiders.

Another necessary condition for the proposed mechanism to be relevant is that the companies incurring the certified-matching-market participation cost appropriate little surplus. When these companies' surplus is high, the amount transferred to partners is low. Everything else constant, this reduces the necessity of raising external capital, which in equilibrium is equal across types. A low level of external capital reduces low-types' relative financial slack, who can no longer disrupt the assortative-matching equilibrium.

Given the novelty of the mechanisms we propose, the paper includes a brief empirical analysis of inter-corporate alliances and VC deals. More specifically, we test two hypotheses. The first is whether the fact that company A receives funding from VC firm X increases the chances that company B—a partner of company A—also obtains funds from X later on. This hypothesis follows from the idea that VC-company links serve as channels for information transmission. We find that the increase in probability is very significant, both statistically and economically. In fact, when a company's partner is financed by a specific VC firm, the probability of that company being financed by that firm increases by 80%, compared to the unconditional probability. Moreover, these results are robust to including a rich set of controls for unobserved heterogeneity—namely, firm fixed effects, time fixed effects, firm location fixed effects, firm industry fixed effects, and firm deal size fixed effects.

We also investigate whether assortative matching occurs in data by looking at the correlation of company success rates, as measured by the companies going public. We find that when VC firm X has funded two partner companies, A (the initial venture) and B, then A being successful implies a higher likelihood that B is also successful. The regression results are again statistically and economically significant (14-17% increased probability of success), and in this analysis we include time fixed effects and an exhaustive set of company controls.

The remainder of the paper is organized as follows. Section 2 outlines how our results relate to existing literature. Section 3 contains the theoretical setup, section 4 presents the main theoretical results, and section 5 considers some theoretical extensions. Section 6 analyzes data on inter-company alliances and VC deals. Section 7 concludes. All proofs are presented in the appendix. An online appendix, containing a continuous-types version of the model and some additional empirical tables, is available from the authors' websites.

2 Connection to existing literature

This paper is related to several strands of research. First, VC financing is a salient aspect of the functioning of technological clusters;[2] and VC firms frequently operate in close proximity to their ventures (Zook, 2002). The location choice of VC firms presumably enhances their ability to collect information, especially in settings such as technological clusters; here, social networks are dense (Saxenian, 1994; Castilla et al., 2000), and much information on investment opportunities flows locally via interpersonal contacts (Sorenson and Stuart, 2001), including referrals from previously financed entrepreneurs (Fried and Hisrich, 1994).

[2] For a recent review of VC literature focusing on economics and finance, see Da Rin, Hellman, and Puri (2011).

Collecting information seems paramount for venture-capital firms, especially in light of some value-enhancing activities (e.g. screening and monitoring) that these financiers are believed to undertake.[3] Our model provides a rationale for the pervasiveness of VC firms in (successful) technological clusters that admittedly is less direct than screening and monitoring, but perhaps is also less stringent than traditional arguments about what is required in terms of ability of VC firms.[4] Furthermore, our argument does not rely on the advantages of information flowing through VC networks, as suggested by Hochberg, Ljungqvist, and Lu (2007), Shane and Cable (2002), and Higgins and Rodriguez (2006). Our model also provides an argument for industry specialization because we suggest that, by staying within the same sector, VC firms can capitalize on the private information being gathered as uncertainty about extant ventures resolves. This channel would also contribute to the clustering of VC firms.

Much empirical literature has studied the role of venture capital in promoting economic performance. Kortum and Lerner (2000) and Hirukawa and Ueda (2008a) show that VC financing correlates with contemporaneous patent production. Hirukawa and Ueda (2008b) and Chemmanur, Krishnan, and Nandy (2011) find that backing by VC firms predicts growth in total factor productivity, and Ozmel, Robinson, and Stuart (2013) find that both VC and alliance activity are positively correlated with going public. These findings are consistent with the predictions from our model.

The mechanism we propose is also consistent with the documented persistence in VC returns (Kaplan and Schoar, 2005): Learning that an initial venture is a high type is simultaneously associated with a high contemporaneous return and with access to subsequent

[3] Evidence also shows that venture capitalists provide value-added services in terms of management (Lerner, 1995; Hellman and Puri, 2002).

[4] We note that screening and monitoring are probably complementary to the explanation we suggest.

investment opportunities (the current venture's partners). Another related result, in the spirit of Sørensen (2008), is that a firm's initial ventures have low returns in equilibrium, given the presence of a valuable investment option attached to assortative-matching learning.

Some papers on technological clusters and VC also focus on matching (Inderst and Müller, 2004; Sorensen, 2007), but their focus is on the matching between venture capitalists and companies, whereas we focus on inter-company matching.

The empirical analysis we conduct also relates to papers studying the drivers of alliance performance—for example, Lindsey (2008) and Kellogg (2011).

Finally, our model is related to the general topic of finance and economic growth. Levine (2005) provides an overview of this literature, a subfield of which focuses on the role of financial intermediaries in alleviating informational frictions. For example, De la Fuente and Marín (1996) develop a model in which intermediaries monitor innovative activities and improve credit allocation; Lee (1996) models a process of financial development that is driven by information accumulation; and Keuschnigg (2004) proposes an endogenous growth model with venture capital. Although our paper is related to this strand of the macroeconomics literature, the mechanism we propose—by which a critical mass of financial intermediaries enables an efficient, large-scale, assortative-matching equilibrium—is novel.

3 Theoretical Setup

3.1 Description of the economy

The economy comprises companies in two technology sectors that need to pair up and collaborate sequentially to successfully complete a project. We use the terms "upstream sector" and "downstream sector" as shorthand for the two technologies. The exogenous risk-free rate is zero, and all agents are risk-neutral.

The upstream sector comprises a large, even number of companies F, each potentially producing one unit of the "primary good," which represents the first stage of the collaborative project. The two types of upstream companies are characterized by $\alpha_i = 0$ (low type) or $\alpha_i = 1$ (high type); the proportion of high types is normalized to $1/2$. Production is riskless and costs one unit upfront, and upstream companies have zero internal funds.[5]

There are F downstream companies attempting to deliver one unit of the "final good", each using exactly one unit of the input produced upstream. We also assume two types of downstream companies: high types and low types. The proportion of high types is $(F/2+1)/F$, so approximately $1/2$ for large F, but upstream high types are always scarce. Production of the final good (i.e., successfully completing the collaborative project) is risky and yields revenues R if success is attained and zero otherwise. The probability of success depends on the quality of both partners:

$$\text{Probab. of success} = \begin{cases} 1 & (\text{if} \quad \alpha_i \alpha_{P(i)} = 1) \\ \gamma & (\text{if} \quad \alpha_i \alpha_{P(i)} = 0), \end{cases} \tag{1}$$

where $P(i)$ represents i's upstream partner and $\gamma \in [0,1]$. Upfront production costs correspond to equilibrium input price plus η units. Downstream companies have internal funds $\delta\eta$, with $\delta \in [0,1]$.

There are $\mu \times F$ venture capitalists (VCs, or informed capital), with $\mu \le 1$, and a competitive financial market (uninformed capital). Each VC can service at most one company at a time, and each company can only have one VC. The presence of plausible exogenous

[5]The modeling of the upstream sector is simple so that we can keep the framework tractable; most of the results are driven by the characteristics of the downstream sector, where we introduce more economic complexity.

variation in the supply of informed capital in the economy is an implicit assumption of the paper. This assumption is consistent with the notion that having the necessary institutional framework in place for the VC industry to function appropriately is not trivial (Lerner, 1998). Next, we turn to the sequence of production and financing events.

$t = 1$ (**Upstream financing.**) VCs are randomly assigned to upstream companies and offer companies a debt contract.[6] If feasible, a competitive uninformed debt market for upstream companies also opens. Surplus from informed financing is split according to Nash bargaining.

$t = 2$ (**Type realization.**) Upstream companies that obtained financing invest their funds and produce, privately learning about their type; those with VC relationships reveal their type to the financier. Downstream companies' types are realized but not observable to VCs or other agents in the economy.

$t = 3$ (**Upstream-downstream matching market.**) Downstream companies choose whether to participate in a *certified* matching market or in a *residual* matching market.[7] In the certified matching market, downstream companies actively search for a high-type upstream partner. This search entails a cost ϕ, which represents, for example, performing extensive research about different potential partners. We model these costs as a success fee (as in a merger deal) mainly for technical simplicity,[8]

[6]Modeling debt instead of equity makes exposition easier. This choice is not material for the results since there are two states only (success/failure) and no moral-hazard problems.

[7]The setup of the matching markets is very close to the marriage market of Becker (1973), except that one of the markets includes a participation cost.

[8]First, it rules out the case where companies do not choose certified matching only because internal funds $\delta\eta$ are inferior to ϕ; this paper is not about such a mechanism. Second, it avoids having to consider two separate cases for downstream companies who participate in certified matching: those who paid ϕ and were matched, and those who paid ϕ but did not match.

but it seems likely they would many times in fact occur ex post.[9] Downstream companies in the certified-matching market also submit a bid X_i (the input price), to be transferred later to the upstream partner. Tentative matches are made for the top $F/2$ bids. If more than $F/2$ top bids are made, excess bids are taken out of the market randomly. Upstream companies are allowed to ultimately reject their tentative match. Figure 1 represents the sequence of events for this particular stage.

$t = 4$ (**Downstream financing.**) VCs choose whether to make a financing offer to their venture's downstream partner, whose type they never observe directly. Surplus from informed financing is split according to Nash bargaining. If feasible, an uninformed debt market for downstream companies also opens.

$t = 5$ (**Downstream production and transfers.**) Downstream companies who secure financing transfer agreed funds to upstream partners and receive the input in exchange. Principal plus interest of upstream companies debt is repaid up to the total transfer from the partner. Downstream companies that obtain financing produce. If enough funds are available, downstream companies repay debt plus interest.

Finally it is important to discuss what we mean by informed versus uninformed financial markets, especially since in high-tech clusters much financing comes from VCs. Our notion of informed financier aims to capture an ability to learn about current ventures' type. Therefore, an uninformed financier could simply be an unsophisticated VC. According to this interpretation, and in the extreme where only VC funding is available, μ would then

[9]For example, finding a great partner could make the employee/team involved in the process receive a bigger bonus after the match is realized. A more general argument is that the amount that a very early venture can spend upfront is negligible (relative to the potential payoff of the project). However, they can commit to large future amounts (in expected value).

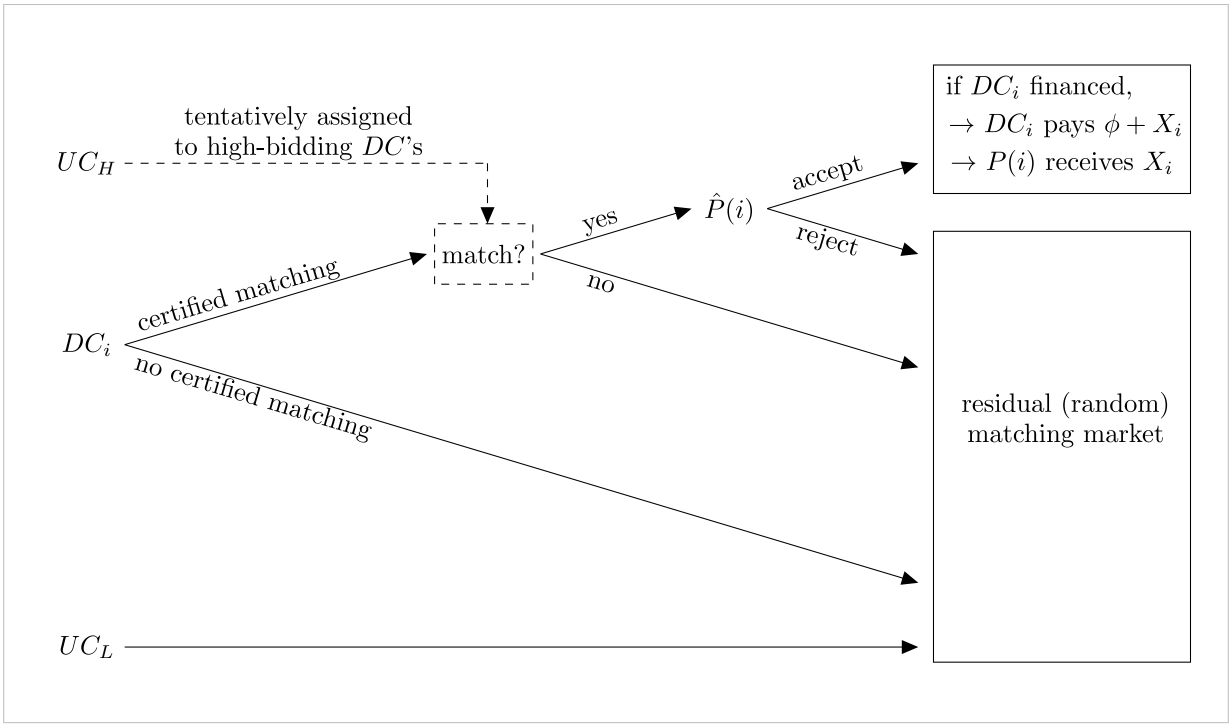

Figure 1: Matching markets. The figure details the sequence of events at $t = 3$. DC_i stands for downstream company with label i, UC_H (UC_L) stands for high-type (low-type) upstream companies, $P(i)$ ($\hat{P}(i)$) is i's (tentative) upstream partner.

represent the proportion of sophisticated VCs, and not, for example, the proportion of VCs relative to local banks. To avoid confusion, in the remainder of the paper the term VC denotes an "informed VC", whereas uninformed VCs are pooled together with other types of uninformed capital.

3.2 Preliminaries

Next, we make some assumptions regarding parameter relationships that are useful to make the subsequent analysis tractable. In particular, we take as a benchmark the state of the economy where all companies operate and no assortative matching occurs, and we require that this benchmark be economically unfeasible (assumption 1 below); this assumption emphasizes the role of assortative matching and simplifies the exposition. We also want to take as given that assortative matching is something desirable (net of certified matching costs), and this is reflected in assumption 2. The objective of the paper is not to study when/if assortative matching is efficient, but to study what determines whether efficient assortative matching is supported in equilibrium, and in particular how the structure of the financial sector can contribute toward this end. Finally, assumption 3 is made primarily for technical convenience, as is apparent in the proof of proposition 1.

Assumption 1 *All companies operating with no assortative matching generate a strictly negative aggregate surplus. Using (A.1) from lemma 1 in the appendix, this corresponds to*

$$R < \frac{4(1+\eta)}{1+3\gamma}. \tag{2}$$

Assumption 2 *Assortative matching with all companies operating generates a positive aggregate surplus. Using (A.2) from lemma 2 in the appendix, this corresponds to*

$$R \geq \frac{2(1+\eta)+\phi}{1+\gamma}. \tag{3}$$

Assumption 3 *Starting a downstream operation is never efficient if a downstream company and/or its supplier are low-type, even with sunk upstream costs. Formally,*

$$\gamma R < \eta. \tag{4}$$

3.3 Equilibrium: definition

We focus on symmetric pure-strategy perfect Bayesian equilibria, which we define in detail here.

Definition 1 *A symmetric pure-strategy perfect Bayesian equilibrium is characterized by the following four conditions:*

a) A collection of pure strategies for companies and VCs, where these strategies are homogenous across types at each information set.

b) A price for the certified matching market X_H (if it opens) and a price for the residual matching market X_L.

c) A rate for uninformed debt upstream r_u (if feasible) and a rate for uninformed debt downstream r_d (if feasible).

d) Every agent behaves optimally, given matching market prices, uninformed debt rates, and other agents' actions, and holds correct beliefs at every information set.

Eight (candidate) classes of equilibria are outlined in definition 1; these combine the status of the matching market (assortative matching or not) with the status of the upstream and downstream uninformed capital markets (feasible or not). The next section characterizes these equilibria, with a focus on the role played by the supply of informed capital.

4 Main theoretical results

4.1 Assortative matching with all companies operating

This section studies the main equilibrium of interest in the paper, where all companies operate and assortative matching obtains (henceforth, large-scale assortative matching (LSAM)). For all companies to operate, uninformed capital markets naturally need to be open, both upstream and downstream. For now, we take this as given; later, we investigate when uninformed financial markets break down.

The first step in characterizing the equilibrium is to derive an expression for matching-market prices, X_H and X_L, as well as the downstream cost of finance r_d, as a function of primitives. We delay the derivation of upstream costs of finance because this derivation is not crucial to an understanding of the LSAM equilibrium. Results are presented in proposition 1.

Proposition 1 *The following obtains in a LSAM equilibrium.*

1. *X_H and X_L are given by the following expressions:*

$$X_H = \frac{2R(1+\gamma-\mu)+\delta\eta(1-\gamma)(2-\mu)}{4-\mu(3-\gamma)} - (\phi+\eta) \tag{5}$$

$$X_L = \left[\frac{1}{4-\mu(3-\gamma)}\right]\Big(R\left[2(1+\gamma)-\mu(2+\gamma-\gamma^2)\right] + + \eta\left[\mu\left(3-\gamma+2\delta(1-\gamma)\right)-4-2\delta(1-\gamma)\right]\Big) \tag{6}$$

2. *The rate for uninformed downstream finance is given by:*

$$r_d = \frac{1-\gamma}{1+\gamma-\mu}. \tag{7}$$

3. The rate charged by VCs, denoted as $r_{VC,d}$, is

$$r_{VC,d} = \frac{r_d}{2}. \tag{8}$$

From equation (5) in the proposition, we can easily observe that X_H increases in both R and δ. This result occurs because high-type downstream companies are competing for high-type partners, and in equilibrium their surplus needs to be zero. Thus, downstream companies pass on more to their suppliers if the project yields higher revenues and/or if they have higher internal funds, which is intuitive. In addition, R pushes X_L up because, in equilibrium, the deviation payoff of a high-type downstream company to the residual matching market (which is equivalent to becoming a low type, given our technology assumptions) also needs to be zero (see proof for details). Thus the competition occurring in the certified matching market creates a latent demand in the residual matching market. The zero-surplus condition for low types would also obtain if, for example, we assume upstream firms are generally scarce (and not just high types). One of our key parameters, ϕ, influences X_H but not X_L, which follows from the fact that certified-matching costs are only paid by high types downstream.

The uninformed financial market rate r_d, given in equation (7), is high if γ is low (high probability that a low-type project fails) and if μ is high. The latter effect follows from the adverse selection faced by uninformed intermediaries whenever many good projects are retained by informed VCs. Intuitively, under Nash bargaining, the VC rate is one-half the market rate because seeking funds with the uninformed market is the best outside option for high-type downstream companies.

A key equilibrium condition, which delivers the main result of the paper, is that, for high-type upstream companies to accept the price in the certified matching market, we must see that $X_H \geq X_L$. This condition can be written as a minimum level for the supply of informed capital.

Proposition 2 *The minimum level for the supply of informed capital that sustains a LSAM equilibrium, denoted by μ_0, is given by*

$$\mu_0 = \begin{cases} 0 & \text{, if} \quad \phi < \phi_0 \qquad (9) \\ \dfrac{4\left[\phi - \delta\eta(1-\gamma)\right]}{\phi(3-\gamma) + (1-\gamma)(R\gamma - 3\delta\eta)} & \text{, if} \quad \phi \geq \phi_0, \qquad (10) \end{cases}$$

where ϕ_0 is a minimum level for certified-matching-market participation costs, given by

$$\phi_0 := \delta\eta(1-\gamma) \geq 0. \tag{11}$$

Now we turn to the intuition behind the result in proposition 2, which is illustrated numerically in table 1.

Table 1: Supply of informed capital and matching-market prices – numerical example. The table shows the equilibrium level of X_H and X_L for different μ. All scenarios refer to the LSAM equilibrium. Parameter choice: $R = 10.8$, $\eta = 6.2$, $\phi = 1.5$, $\gamma = 0.55$, $\delta = 0.5$.

Supply of informed capital	X_H	X_L
$\mu = 0.2$	1.32	1.32
$\mu = 0.3$	1.30	1.23
$\mu = 0.4$	1.26	1.12
$\mu = 0.5$	1.23	0.99

As explained, the market prices for upstream companies that support this equilibrium are high, in the sense that X_H exhausts all surplus of high-type downstream companies; and, in addition, X_L exhausts all surplus of low-type downstream companies. Given these characteristics of matching-market prices, the *wealth* of downstream companies, both high-type and low-type, ultimately determines these prices, and so a wedge between X_H and X_L is in essence a wedge between the wealth of high types downstream versus their low-type counterparts. One factor inducing a difference in wealth across types is precisely the cost at which they obtain funds. The difference in funding cost expands with the supply of informed capital μ, via two channels. First, a higher μ increases the likelihood that high types find informed finance, which is cheaper. Second, the equilibrium rate of the uninformed market r_d—the cost of financing for low types—increases with μ (i.e., these companies become poorer, via adverse selection). Although the cost of informed financing for downstream high-type companies is also increasing in μ (given Nash bargaining), it is increasing at a lower rate. For higher levels of μ, high-type downstream companies thus become wealthier *relative* to their low-type counterparts, and the fact that they have to spend ϕ in certified-matching costs still allows them to afford a high X_H. Naturally, this mechanism only matters if certified-matching costs are relatively high, as stated in the proposition. The cost ϕ of choosing the certified-matching-market generates the financial slack for low-type downstream companies, such that these agents find participating at all rational (because they do not pay ϕ).

So far we have implicitly assumed that uninformed financial markets are feasible; now we investigate this condition in detail. We start by analyzing the feasibility of upstream uninformed financial markets, under the assumption that downstream markets do not break down and that $X_H \geq X_L$. The result is contained in proposition 3.

Proposition 3 *A sufficient condition for the failure of* upstream *uninformed capital mar-*

kets is that the supply of informed capital be above the following threshold:

$$\mu_1 := \frac{4\left[R(1+\gamma) - 2(1+\eta) - \phi\right]}{R(4+\gamma-\gamma^2) - \eta\left[6 - 2\gamma + \delta(1-\gamma)\right] - (2+\phi)(3-\gamma)} \tag{12}$$

The intuition for the result in proposition 3 is that, as μ increases, the expected cost of financing for all downstream companies also increases (see proposition 1). As a result, a lower amount is transferred to upstream companies in equilibrium, which at some point makes the financing of these companies uneconomical (from the perspective of the uninformed capital market). This result is also illustrated in table 1 above.

Next, we study the conditions for the failure of downstream uninformed capital markets. These markets stop being feasible when downstream companies obtaining financing in this market do not generate enough funds to repay their debt. The result is contained in proposition 4 and follows from standard adverse-selection arguments.

Proposition 4 *A sufficient condition for the failure of* downstream *uninformed capital markets is that the supply of informed capital be above the following threshold:*

$$\mu_2 := \frac{4\delta\eta}{2\delta\eta + R(1-\gamma)} \tag{13}$$

Finally, note that the breakdown of the upstream uninformed capital market is a necessary and sufficient condition for the same to happen downstream. If the downstream uninformed capital market closes, even high-type pairs (without a VC) cannot operate downstream; hence incentives to produce/finance upstream in absence of VC financing disappear. On the other hand, if the upstream uninformed capital market does not open, then high-type pairs lose the incentives to access the downstream uninformed capital market, which becomes attractive only for low types that did not get financing from a VC. As a consequence, uninformed financiers do not have incentives to provide financing downstream. This result is stated formally in corollary 1.

Corollary 1 *A necessary condition for the LSAM equilibrium to obtain is that the supply of informed capital be below* $\min(\mu_1, \mu_2)$.

4.2 Other Equilibria

After having characterized the main equilibrium of interest, we can address the possibility that other equilibria exist. We still focus on the equilibria from definition 1, which includes eight candidate classes. With the result from corollary 1, this number reduces to four, combining whether assortative matching is present with whether uninformed financial markets are feasible.

Given our assumption regarding the surplus of the economy when all companies operate and assortative matching does not occur (assumption 1), it follows immediately that having uninformed capital markets and no assortative matching cannot be an equilibrium. Basically, in this economy collaborative projects have negative NPV ex ante. Therefore only two other potential equilibria might exist: one in which companies are backed by VCs only and assortative matching is happening; the other in which companies are backed by VCs only and assortative matching is not happening.[10] The results regarding these two economic regimes are contained in proposition 5.

Proposition 5 *The following statements hold in economies where the parameters verify assumptions 1-3:*

[10]Note that in this case VCs are not equivalent to uninformed financial markets because learning about the type of the upstream company is occurring, which affects the conditional expected payoff of the collaborative project (even without assortative matching).

1. *The economic regime in which neither uninformed finance nor assortative matching is happening is never an equilibrium.*

2. *The economic regime in which no uninformed finance is happening but assortative matching obtains is an equilibrium for $\mu \notin [\mu_0, \min(\mu_1, \mu_2)]$, with corresponding surplus*

$$S = \mu \left[\frac{R - (2 + \eta + \phi)}{2} \right]. \tag{14}$$

3. *In the no-uninformed-finance/assortative-matching equilibrium, low-type downstream companies do not participate.*

4.3 Efficiency results

This section analyzes the desirability of the LSAM equilibrium. To facilitate exposition, we use an illustrative numerical example, together with more general results.

Figure 2 shows the variation in equilibrium aggregate surplus—normalized by F, the number of companies in each sector—for varying levels of μ, the supply of informed capital (equation (14)). Region 1 in the figure represents a state (or stage) of the economy in which very few companies operate and all are backed by informed capital. Aggregate surplus is low because few companies operate; the surplus per operating company is actually high because no low-type downstream companies operate. If we look at the picture as representing the life cycle of a high-tech/VC cluster, this image would correspond to an initial phase of slow and steady growth, similar to the initial stage of an S-shaped technology curve.[11]

Figure 2 shows that as the critical threshold μ_0 is hit, the size of the economy experiences

[11]For an early example of the patterns of technological expansion (and the famous S-curve), see Rogers (1962).

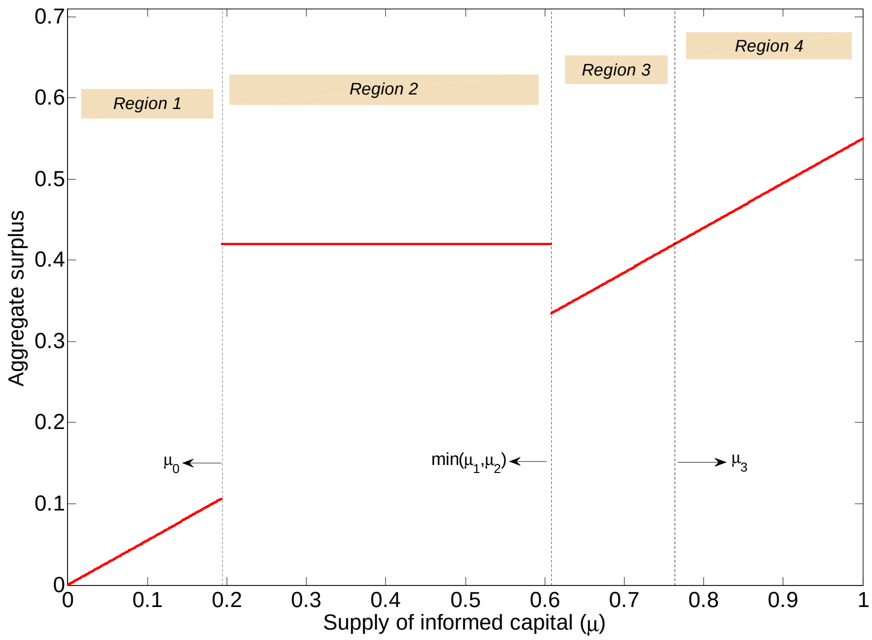

Figure 2: Supply of informed capital and aggregate surplus. The figure plots the aggregate equilibrium surplus, normalized by F, for varying supplies of informed capital μ. μ_0 ($\min(\mu_1, \mu_2)$) is the minimal (maximal) threshold necessary to sustain the assortative-matching equilibrium where all companies operate. Parameter choice: $R = 10.8$, $\eta = 6.2$, $\phi = 1.5$, $\gamma = 0.55$, $\delta = 0.5$.

a strong jump; in a dynamic interpretation, this jump compares to the accelerating stage of an S-curve. The jump in economic surplus is driven entirely by an increase in the size of the financial sector because the number of companies F and their characteristics are kept unchanged. The equilibrium in region 2 has all companies in the economy operating, but under an efficient LSAM regime. This equilibrium is possible because now uninformed capital markets can operate and many more companies can be financed. Perhaps interesting to note is that, in this model, uninformed financial markets are initially enabled by the presence of enough informed intermediaries. Only after a second threshold is hit (region 3) do uninformed markets break down. In regions 3 and 4, aggregate surplus again increases linearly in μ.

Figure 2 also shows that the transition from region 2 to region 3 is welfare-destroying.

This destruction of welfare stems from a bargaining externality: VCs extract a high surplus ex post (downstream) via Nash bargaining, and this limits the amount of funds that downstream companies can pass to upstream partners.[12] At some point, starting an uninformed-financed upstream operation is economically efficient, but the company will not have high enough sales to make the funding opportunity viable for uninformed (upstream) investors. (Note how X_H and X_L decrease in μ in table 1.) We do not focus on this result because it depends critically on the assumption about Nash bargaining. The main result holds even when informed capital is provided at competitive rates (see section 5.4); and in this case, the bargaining externality that leads to a drop in surplus from region 3 to region 4 is absent.

The result that the LSAM regime "dominates" at μ_0 and $\min(\mu_1, \mu_2)$ is actually more general than the numerical example, as shown in proposition 6.

Proposition 6 *Under assumptions 1-3, and assuming that a non-trivial ($\mu_0 > 0$) LSAM exists, the aggregate surplus generated by the LSAM equilibrium is larger than the aggregate surplus of a hypothetical no-uninformed-finance/assortative-matching regime as $\mu \to \mu_0$ and $\mu \to \min(\mu_1, \mu_2)$.*

After threshold μ_3 in the figure, the economy starts operating at a higher level of surplus than in region 2—a result that is general, as shown in proposition 7. But if having an arbitrarily large supply of informed capital is inexpensive, the main point of the paper becomes immaterial; the preferable scenario is to function in a regime where most high types downstream operate in a partnership with high types upstream, and no low types downstream operate. The argument of the paper is not that a significant amount of informed capital is beneficial, but that increasing the supply of informed capital beyond a *critical threshold* creates a significant jump in economic surplus.

[12] Consistent with this explanation, in figure 2, we see that $\min(\mu_1, \mu_2) = \mu_1$.

Proposition 7 *Under assumptions (1)-(3), a threshold for the supply of informed capital exists, defined as*

$$\mu_3 := \frac{R(1+\gamma) - 2(1+\eta) - \phi}{R - (2+\eta+\phi)}, \tag{15}$$

such that for all $\mu \geq \mu_3$ the surplus of the economy is larger in the no-uninformed-finance/assortative-matching equilibrium than in the LSAM regime; and it is always true that $\mu_3 \leq 1$.

5 Additional theoretical analyses

5.1 The role of internal funds

So far we have focused on the role played by a minimum supply of (outside) informed capital (μ) in supporting an LSAM equilibrium. However, another important factor for this equilibrium to obtain is the level of internal funds δ. Figure 3 presents five possible regions in which the economy may be operating, as a function of the level of internal funds (horizontal axis) and the supply of informed capital (vertical axis). The figure can also be interpreted as capturing two other dimensions of the economy: the aggregate informed funding availability (which expands along the NE direction); and the aggregate capital structure (where going NW implies a higher ratio of outside-to-inside funds). The five regions are defined mainly by the conditions that sustain the assortative-matching equilibrium of interest: $\mu \geq \mu_0$ represents the minimum-VC-supply condition; $\mu \leq \min(\mu_1, \mu_2)$ guarantees that uninformed markets do not break down.

Inspection of figure 3 immediately reveals that a substitution effect occurs between internal funds and the supply of informed capital because the μ_0 threshold is (weakly) downward sloping. Regions 1.a and 1.b in the figure depict the case where the μ_0-threshold is not sat-

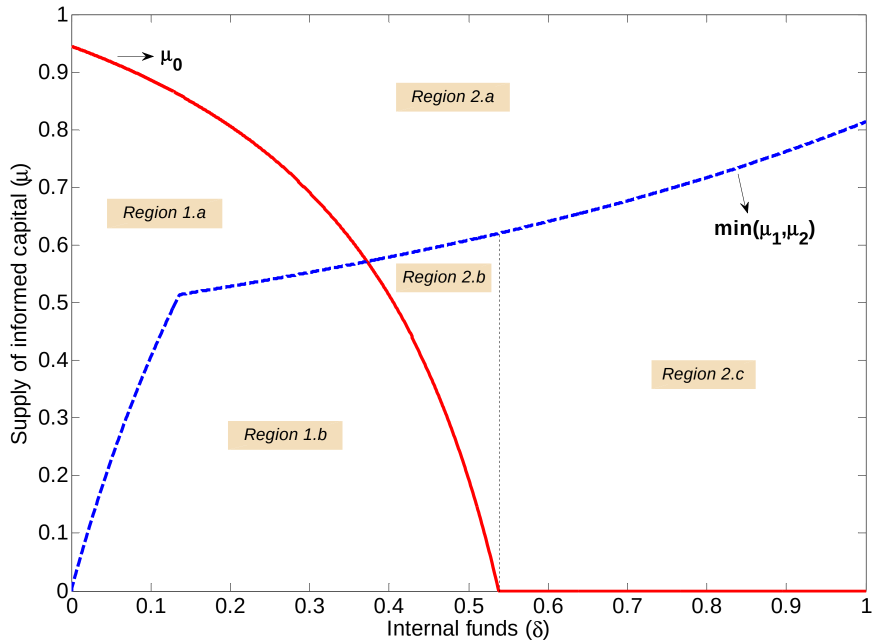

Figure 3: Internal funds, supply of informed capital, and economic regimes. The red solid line represents the minimum level of informed capital required to support an assortative-matching equilibrium, where all companies operate (μ_0), as a function of internal funds δ. The blue dashed line maps the maximum level of informed capital ($\min(\mu_1, \mu_2)$) that that prevents uninformed markets from breaking down, also as a function of internal funds δ. The remaining parameter choice is the same as in figure 2: $R = 10.8$, $\eta = 6.2$, $\phi = 1.5$, $\gamma = 0.55$.

isfied, which implies that the economy is necessarily in a VC-only equilibrium, as explained in section 4.2. Region 2.a. represents the case where the minimum-VC-supply criterion is satisfied but where uninformed financial markets fail. Region 2.b is the one relevant for the paper's main argument: A minimum positive supply of VCs is required to sustain the equilibrium in which all companies operate. Region 2.c shows that this argument is no longer binding if internal funds are large enough.

Perhaps the most interesting feature of figure 3 is that it reveals both a minimum and a maximum level for internal funds that needs to be verified for the mechanism of interest to be relevant. This result is more general than just the numerical example in figure 3, as stated in corollaries 2 and 3, which follow directly from propositions 2 and 4.

Corollary 2 *A strictly positive level of internal funds δ is necessary to prevent downstream uninformed markets from breaking down.*

Corollary 3 *If internal funds δ are smaller than the following threshold:*

$$\overline{\delta} := \frac{\phi}{\eta(1-\gamma)}, \tag{16}$$

then a positive supply of informed capital is not a necessary condition to obtain the LSAM equilibrium.

The intuition for corollary 3 is that the minimum-VC-supply mechanism matters only because companies are financially constrained (small δ); otherwise, the wealth differential comes simply from the fact that good projects are valuable enough. As for corollary 2, the reason why downstream uninformed markets break down is that under the intense competition for upstream targets in the certified matching market, high-type downstream companies with little internal funding are willing to increase their bid (X_H) to value-destroying levels, as long as this increase in the bid is achieved via the expropriation of outside financiers. Because these financiers anticipate this problem, no uninformed capital is available in these conditions.

5.2 Equilibrium rate of informed upstream capital

This section briefly discusses how the equilibrium VC rate for upstream companies is obtained (denoted as $r_{VC,u}$), focusing on the LSAM equilibrium. First consider that $r_u = 0$ (i.e. $X_L \geq 1$). The surplus of VC financing is assumed to be split according to Nash bargaining.

If agreement is achieved, the ex ante payoffs for the company and for the VC are, respectively,

$$\begin{cases} \frac{1}{2}\left(X_L + X_H\right) - (1 + r_{VC,u}) & \text{(Upstream company)} \quad (17) \\ r_{VC,u} + \frac{1}{2}\left(D\frac{r_d}{2}\right) & \text{(VC).} \quad (18) \end{cases}$$

In turn, the disagreement payoffs correspond to a situation where the company declines the VC opportunity and goes to the uninformed market; these payoffs are given by:

$$\begin{cases} \frac{1}{2}\left(X_L + X_H\right) - 1 & \text{(Upstream company)} \quad (19) \\ 0 & \text{(VC)} \quad (20) \end{cases}$$

Combining the agreement and disagreement payoffs, we arrive at the result stated in proposition 8.

Proposition 8 *If $r_u = 0$, the equilibrium rate charged by a VC to the upstream company they initially are matched with is negative, and given by the following expression:*

$$r_{VC,u} = -\frac{(1-\gamma)(R-\delta\eta)}{4[4-\mu(3-\gamma)]} \tag{21}$$

Average upstream companies obtain a discounted rate because VCs obtain a positive ex post surplus from this associative activity (they may find a high-quality downstream company later on). This result mimics the one in Montgomery (1991), where the initial employee obtains a higher-than-market wage because of the option value associated with a future potential hiring of her high-type "friend." According with this theory, we would thus expect to empirically find that VCs initial ventures exhibit low average returns. The argument that VC choices are influenced by learning considerations has been previously made by Sørensen (2008), although learning is not occurring via the assortative-matching mechanism.

Perhaps interesting to note is that $r_{VC,u}$ declines with μ, the supply of informed capital, although this decline is totally unrelated to competitive forces in the VC market. In fact, in our setting this obtains because a higher μ implies that VCs extract a higher absolute surplus ex post (higher r_d).

If we analyze the case in which $r_u \neq 0$ (i.e., initial financing is risky), then the model delivers persistence in VC returns, which is an empirically documented regularity of VC investments (Kaplan and Schoar, 2005). This result is stated in proposition 9 and follows directly from the assortative-matching mechanism: Either the VC finds a high type initially, which delivers a high initial return upstream and a good investment opportunity downstream; or the VC learns that the initial venture is a low type, in which case it earns a low return initially and the competitive return subsequently.

Proposition 9 *If X_L is smaller than a threshold $\underline{X}_L$ (defined in the appendix), then two cases occur with equal probability:*

1. *The VC experiences a high realized return upstream (greater than the average return for VCs), which is followed by a high realized return downstream (greater than the competitive average return of zero).*

2. *The VC experiences a low realized return upstream (lower than the average return for VCs), which is followed by non-participation (or earning the competitive average return of zero).*

5.3 A closer look at the role of scarcity

The scarcity of upstream high types plays an important role in the preceding analysis. This scarcity is what drives up the price of the certified matching market and, indirectly, the price of the residual matching market as well. This section shows that this setting is not the only one in which the main result obtains. In fact, what is required is a scarcity of upstream companies, either just for high types, as previously assumed, or in general. We still focus on the sustainability of an assortative-matching equilibrium in which all companies operate.

Assume now that upstream companies are generally scarce; for example, assume $F-2$ upstream companies (but keep considering a large, even F). Also, assume that 1/2 of these companies are high types, but that high types downstream are now scarcer, totaling $\beta \times F$, with $\beta < 0.5$. In this setting, the participation constraint of low types downstream is binding, given the general scarcity of upstream companies; this participation constraint pins down X_L. In this equilibrium, we need to have $X_H = X_L = X$ because it represents the minimum amount that high types downstream need to bid to secure a partner via the certified matching market. Using equations (A.3) and (A.7), we obtain an expression for X:

$$X = \frac{1}{1+r_d}\left[R - \left(\frac{\delta\eta - \phi}{\gamma}\right)\right] - \phi - \eta(1-\delta) \tag{22}$$

To see that the main mechanism is still at play, we can assume otherwise; in particular, we set the supply of informed capital as $\mu = 0$ and check whether the incentive-compatibility constraint for high types downstream is verified. According to equation (A.5) (or equation (A.6)), high types downstream have a positive surplus as long as the following holds:

$$X \leq \frac{R-\delta\eta}{1+r_d(1-\mu/2)} - \phi - \eta(1-\delta) \quad = \Big|_{\mu=0} \; \frac{R-\delta\eta}{1+r_d} - \phi - \eta(1-\delta). \tag{23}$$

Combining expressions (22) and (23), we have

$$\frac{1}{1+r_d}\left[R-\left(\frac{\delta\eta-\phi}{\gamma}\right)\right]\leq\frac{R-\delta\eta}{1+r_d}\Leftrightarrow\phi\leq\delta\eta(1-\gamma),$$

which is the threshold for the certified-matching costs previously derived in proposition 2. This condition establishes that a minimum level for the supply of informed capital is still necessary in this case. In fact, this level is the same as the one derived in proposition 2 because μ_0 is implicitly determined by $X_H = X_L$, an equality we assumed at the outset for this new setting. The difference relative to the first case is that now $X_H = X_L$, even for $\mu > \mu_0$; previously, this slack in the incentive-compatibility constraint of high types downstream was actually transferred to high types upstream, via $X_H > X_L$.

Another way to make the argument that an abundance of parties incurring the certified-matching costs is what drives the results is to show that the equilibrium breaks down otherwise. More specifically, consider now that upstream companies are abundant—in general and in terms of high types—and their participation constraint is binding. This abundance implies, in equilibrium, $X_L = X_H = 1$. Using equations (A.5) and (A.7), the incentive-compatibility constraint of high types downstream is satisfied as long as the following holds:

$$\mu[R-D(1+r_d/2)]+(1-\mu)[R-D(1+r_d)]-\delta\eta\geq\gamma[R-D(1+r_d)]-\delta\eta-\phi\Leftrightarrow$$
$$R(1-\gamma)\geq D[\mu(1+r_d/2)+(1-\mu)(1+r_d)-\gamma(1+r_d)]-\phi.$$

Assuming $\mu = 0$, this equation simplifies to

$$R(1-\gamma)\geq D(1+r_d)(1-\gamma)-\phi\Leftrightarrow R\geq D(1+r_d)-\frac{\phi}{1-\gamma}. \tag{24}$$

Because in the conjectured equilibrium uninformed financial markets do not break down,[13] it must be true that $R > D(1 + r_d)$. This implies that condition (24) is verified. In short, even with $\mu = 0$ the LSAM equilibrium would obtain.

5.4 Competitive informed capital

As is intuitive, for the main mechanism to operate, informed financiers cannot extract too high a surplus. If they do so, the wedge in cost of financing across types might be compromised. But what happens if VCs provide capital at more favorable terms than those associated with Nash bargaining? Presumably, this situation would facilitate, at the margin, the beneficial effect of informed capital in terms of matching. To analyze this setting, we consider the extreme case of competitive rates offered by informed capitalists. Proposition 10 contains the main result, which confirms the intuition.

Proposition 10 *If informed capital to downstream companies is provided at a competitive rate, then the minimum supply of informed capital that sustains an assortative-matching equilibrium where all companies operate is given by:*

$$\tilde{\mu}_0 := \frac{2[\phi - \delta\eta(1-\gamma)]}{\phi(2-\gamma) + (1-\gamma)(R\gamma - 2\delta\eta)}. \tag{25}$$

This new threshold is always lower than the threshold derived in proposition 2.

[13] Notice that adverse selection is at its minimum because $\mu = 0$.

6 Empirical analysis

6.1 Approach

Our empirical analysis studies the plausibility of the key mechanisms that operate in the model. To that end we combine data on inter-company alliances and VC financing. More specifically, we test two hypotheses: first, whether companies exhibit a higher probability of obtaining first-round funding from their partner's VC (section 6.3.1), which is consistent with the idea that VC-company links serve as channels for information transmission; and second, whether two partners funded by the same VC *both* have a higher-than-average performance (section 6.3.2), which would follow from the assortative-matching pattern. The empirical results are very consistent with the model. For computational reasons the analysis focuses on the top 250 VCs.

6.2 Data construction and summary statistics

We use data from Thomson Reuters SDC Platinum for VC investment rounds, and Alliances and Joint Ventures (1984-2010). Data for VC characteristics was taken from Thomson's Venture Expert (1980-2011).

We extracted all venture-related deals for companies based in the United States, which resulted in records for 35,186 companies, many with multiple rounds of investment. Each investment round by a firm per company was counted as a single observation, for a total of 288,082 individual observations. We dropped observations for which no investment round date was given and observations for which the investor or company was "Undisclosed." Of the remaining sample of 215,019 observations, we saw 14,958 unique fund names that we were able to match to 9,274 VC firms. Within this data we recorded values for company name, disclosed amount, round date, company location, company industry, and investor. The characteristics of the VCs were extracted from the Venture Expert Private Equity Funds database and merged with the venture deals data.

Sorting on the number of deals completed by each firm provided us with our top 250 VC firms, used later in the empirical analysis presented in table 4. The average deal size was $3.39 million and $2.97 million for deals involving a top-250 VC firm. The Venture Expert database provides only the aggregate round amounts; therefore, with rounds involving multiple VC firms, we allocated the total deal amount equally to each firm. For example, if the round was for $10 million and four firms were involved, each firm would be allocated $2.5 million as its investment. We also focused on the first round of financing that a company received by a VC firm as recorded by the Venture Expert database. We had data on first-round financings for 32,086 companies, and many of these rounds involved investment by multiple VC firms; thus, the total number of first-round deals was 54,131, of which 22,513 were completed by a top-250 firm. The average first-round deal size was $4.25 million and $3.45 million for deals involving a top-250 firm. Although we might have expected that first-round financing would generally be smaller than later rounds of financing, our deal-size variable (which is per VC firm) showed no such pattern. Later round financing often involves multiple VC firms, and although the per deal number is smaller, the aggregated number for later rounds is often larger. Summary statistics for these data are provided in table 2.

The data for alliances and joint ventures was extracted from Thomson Financial Strategic Alliances and Joint Ventures database. In 45,069 observations, each observation was an alliance name and the participants in the alliance, so one observation per alliance (we use “alliance” to describe either a strategic alliance or a joint venture). We reformatted the data so that an alliance that included three participants would count as three observations.

Table 2: Summary statistics. In this table we present the number of VC firms, number of companies, and number of deals considered in the empirical analysis. We also present average deal size and average proceeds for companies that completed a successful initial public offering (IPO). For computational tractability, part of the empirical analysis uses a subsample of deals completed by the top 250 firms; a description of this subsample is also provided in the table.

Summary Statistics	
General Deal Information	
Number of firms	9,274
Number of deals	215,019
Number of deals by Top 250 firms	102,433
Avg deal size ($Mil)	$ 3.39
SE deal size ($Mil)	$ 0.05
Avg deal size by Top 250 firms ($Mil)	$ 2.97
SE deal size by Top 250 firms ($Mil)	$ 0.03
1st Round Deal Information	
Number of firms participating in 1st round financing	6,893
Number of Companies with 1st round financing	32,086
Number of 1st round deals	54,131
Number of 1st round deals by top 250 firms	22,513
Avg 1st round deal size ($Mil)	$ 4.25
SE 1st round deal Size ($Mil)	$ 0.18
Avg 1st round deal size by Top 250 firms ($Mil)	$ 3.45
SE 1st round deal size by Top 250 firms ($Mil)	$ 0.08
Partnership Information	
Number of partnerships	28,992
Number of partnerships with both parties VC funded	2,692
IPO Information	
Average IPO proceeds all deals ($Mil)	$ 47.38
SE IPO proceeds all deals ($Mil)	$ 1.66
Average IPO proceeds all deals involved in partnership both VC funded ($Mil)	$ 45.81
SE IPO proceeds all deals involved in partnership both VC funded ($Mil)	$ 2.94
IPO rate all deals	0.07
IPO rate all deals involved in partnership both VC funded	0.33

We kept information only on U.S.-based participants. We merged this data with the VC funding data, so that each participant was matched with each of its VC investors. We saw 28,992 unique participants, which is much larger than the 16,818 unique firms in Lindsey (2008), but our sample is expanded by 11 years. Of these participants, 3,828 were matched with at least one VC investor, or roughly 13% (also larger in number than Lindsey (2008) but smaller in proportion). The highest number of investors any single company had was 31. We then created a sample that paired each participant with all other companies that participated in the alliance. So four participants in an alliance would result in six pairwise alliance observations. Finally, we merged these data with the participant-VC investor data so that each participant pair had a listing of all its VC investors. This pairing resulted in 41,572 observations, of which each observation is a pairing of participants involved in the same alliance. The number of partnerships in which each member of the partnership was backed by a VC totaled 2,692.

In addition, we used the Thomson Global New Issues Database to record information related to company IPOs. We extracted all original IPOs for U.S.-based issuers from 1980 to 2011. We recorded values for IPO dates, company name, and total IPO proceeds. These data were then merged on company name with the participant/VC investor database, resulting in 2,203 matches for an approximate 7% IPO rate of all deals. The average IPO proceeds for matched companies totaled $47.38 million for all matched companies and $45.81 million dollars for matched companies involved in partnerships in which both partners were VC-funded. The IPO rate for companies involved in partnerships in which both partners were VC-funded was approximately 33%. Summary statistics for these data are provided in table 2.

6.3 Empirical results

6.3.1 Alliance partners and access to VC funds

In table 3 we present anecdotal evidence that a company is more likely to receive funds from a VC that previously funded its partner. For example, the first row presents the unconditional probability of obtaining funds in a first-round deal from J.P. Morgan (1.56%) and the probability of obtaining funds from J.P. Morgan if one of the company's partners also was previously funded by J.P. Morgan (2.94%). For the top-five VCs, table 3 shows that the average probability of obtaining funds from a specific VC is about five times larger if a partner firm obtained funds from that VC. Moreover, it is always true that the difference between conditional and unconditional probabilities is positive and significant (statistically and economically) for each of the five firms.

Table 3: Probability of obtaining funds from a top-five VC in the first financing round. This table presents the probability that a company, in its first financing round, obtains funds from one of the top-five VC firms. In column (1) we present the unconditional probability that a company obtains funds from each VC, and in column (2) we present the probability that a company that has a partnership with one of the VC's ventures obtains funds from that VC. * represents significance at the 10% level, ** represents significance at the 5% level, and *** represents significance at the 1% level.

	(1)	(2)	(2)-(1)
J.P. Morgan Partners	1.56%	4.50%	2.94%**
New Enterprise Associates, Inc.	1.51%	6.82%	5.31%**
Intel Capital	0.71%	8.11%	7.40%*
Kleiner Perkins Caufield & Byers	1.22%	12.71%	11.49%***
Sequoia Capital	1.11%	6.15%	5.04%***
Average	1.22%	7.66%	6.44%***

We extend the findings from table 3 to a more representative sample using data on more than 30,000 first-round VC deals for the 250 largest VCs (according to the number of deals closed).[14] We use the logistic model in equation (26) to capture how different variables affect the probability that a given firm invests in a specific company. Table 4 reports the estimation results using a panel at the firm-company level.[15]

$$\begin{aligned}\log\left(\frac{p_{ij}}{1+p_{ij}}\right) &= \beta_1 \times \tilde{P}\_VC_{ij} + \beta_2 \times LAR_j \times \tilde{P}\_VC_{ij} + \beta_3 \times \tilde{P}\_250_i + \beta_4 \times \tilde{P}\_ANY_i + \\ &\quad \beta_5 \times \tilde{P}_i + \eta_j + \mu_t + \pi_{j-st(i)} + \gamma_{j-ind(i)} + \tau_{j-s(i)} + \varepsilon_{ij} \qquad (26)\end{aligned}$$

In this equation, p_{ij} is the probability that firm j invests in company i's first round of financing, $\tilde{P}\_VC_{ij}$ is a dummy variable that takes the value of one if at least one partner of company i gets funding from firm j before i's first round of VC financing, and zero otherwise; LAR_j is a dummy variable that takes the value of one if firm j is one of the 50 largest firms in terms of number of deals, and zero otherwise; $\tilde{P}\_250_i$ is a dummy variable that takes the value of one if at least one partner of company i gets funding from one of the largest 250 firms before i's first round of VC financing, and zero otherwise; $\tilde{P}\_ANY_i$ is a dummy variable that takes the value of one if at least one partner of company i gets VC funding before i's first round of financing, and zero otherwise; and $\tilde{P}_i$ is a dummy variable that takes the value of one if company i has at least one partnership in place before its first round of VC financing, and zero otherwise. η_j is a firm fixed effect; μ_t is a time fixed effect; $\pi_{j-st(i)}$, $\gamma_{j-ind(i)}$, and $\tau_{j-s(i)}$ are firm-state, firm-industry, and firm-size fixed effects, where $st(i)$ is the state in which company i operates; $ind(i)$ is the industry in which company i operates;

[14] We focus on the top 250 firms for reasons of computational tractability.

[15] Given that the unconditional probability of a specific company getting funds from a given VC firm is relatively small, the interpretation of a logistic model is intuitive. The logit regression is $\log\left(\frac{p}{1-p}\right) = C+\beta X$, thus $\frac{\frac{\partial p}{\partial X}}{p} = \beta(1-p)$. Therefore, if p is small enough, β represents the percent change in p associated with a marginal change in X.

and $s(i)$ is the size of company i.[16] For example, if j is J.P. Morgan Partners, and company i operates in California, $st(i)$ is California, and $\tau_{j-st(i)}$ is the J.P. Morgan Partners-California fixed effect.

Table 4: Probability of obtaining funds from your partner's VC – Logit Model. The table presents the probability that a company, in its first financing round, obtains funds from a specific top-250 VC, and how this probability increases if the VC previously financed the company's partner. For the interaction term in the second row, the largest 50 firms are considered *large*. We use a logistic model. The standard errors are presented in parentheses. * represents significance at the 10% level, ** represents significance at the 5% level, and *** represents significance at the 1% level.

	(1)	(2)	(3)	(4)
Partner has the same VC	0.959***	0.889***	0.780***	0.794***
	(0.182)	(0.193)	(0.191)	(0.221)
Large × partner has the same VC	0.002	0.052	0.053	-0.013
	(0.218)	(0.228)	(0.220)	(0.246)
Partner has funds from top 250 VC	0.024	0.061	0.035	0.038
	(0.080)	(0.080)	(0.083)	(0.087)
Partner has VC funds	0.203*	0.113	0.114	0.156
	(0.123)	(0.125)	(0.131)	(0.140)
Has a partner	0.046	0.011	0.019	0.070
	(0.082)	(0.083)	(0.086)	(0.090)
N	387,672	162,402	118,522	63,792
$pseudo - r^2$	0.076	0.058	0.085	0.109
time f.e.	YES	YES	YES	YES
firm f.e.	YES	YES	YES	YES
firm × deal size f.e	NO	YES	YES	YES
firm × industry f.e.	NO	NO	YES	YES
firm × location f.e.	NO	NO	NO	YES

In table 4, we present the maximum likelihood estimation of equation (26). We show that the probability that a company obtains funds from a given VC increases by 80% (significant

[16]Industry is obtained from the one-digit Venture Economics codes, and size is the total VC funding amount for each company divided into quintiles.

at the 1% level) if a partner of the company had previously obtained funds from the same VC. For example, if the unconditional probability of getting funds from firm A is 5%, a company that is partners with a company previously funded by A has 5%+5%*80%=9% probability of getting funds from A. For completeness we present the linear probability model in the online appendix.[17] As seen in the interaction term presented in the second row of the table, the increase in the probability that a company obtains funds from a given VC associated with a partner obtaining funds from the same VC is independent of firm size; thus, we do not seem to lose generality by working with the largest 250 firms.

The specification in equation (26) addresses several endogeneity issues. In particular, one might be concerned that the increase in funding probability is driven by industry, by location, or by size VC specificity. For example, if a VC specializes in software in California, the VC that funded a given software development company in California naturally has a higher probability of financing that company's partner that also develops software in California. To mitigate this problem, we include the firm-state, firm-industry, and firm-size fixed effects previously described. Going back to our example, the VC-industry dummy $J.P.Morgan - software$ would capture the probability that J.P. Morgan invests in the software industry, and the VC-location dummy $J.P.Morgan - California$ captures the probability that J.P. Morgan invests in a deal in California. Thus, if we observe an increased probability that J.P. Morgan invests in software developer B when B is partners with developer A and A was already funded by J.P. Morgan, the increase is likely driven by the companies partnership and not by the fact that they both work in the same industry and geographic location.

One might also be concerned that the companies that have a partner, or those that have

[17] The results in table 4 in the main text and table 1 in the online appendix suggest a geometric increase in the probability that a company obtains funds from a given VC when a partner of the company obtained funds from the same firm. As a consequence, a linear probability model does not capture correctly any marginal changes in the probability of obtaining funds from a given firm.

a partner that was able to obtain funds from a VC or from a top-250 VC, have increased probability of obtaining funds from a VC in our sample. To address these concerns, we explicitly include a dummy that captures the effect of having a partner, a dummy that captures the effect of having a partner that has VC funds, and a dummy that captures the effect of having a partner that has funds from a top-250 VC.

6.3.2 Alliance partners and company success rates

In this section we study whether companies match assortatively, as predicted by the model. We test this hypothesis using a sample of all partnerships between companies with VC funding, and we use company IPO as proxy for quality.[18] We estimate the likelihood that a company goes public using the following linear probability model.[19]

$$
\begin{aligned}
p_i \;=\; & \beta_1 \times P(i)\_IPO + \beta_2 \times VC(i)\_VC(P(i)) + \beta_3 \times P(i)\_IPO \times VC(P(i))\_VC(i) + \\
& \varphi_{st(i)} + \chi_{ind(i)} + \omega_{s(i)} + o_{st(P(i))} + \delta_{ind(P(i))} + \nu_{s(P(i))} + \varsigma \times st(i)\_st(P(i)) + \\
& \varpi_{ind(i)\times ind(P(i))} + \rho_{s(i)\times s(p(i))} + \mu_t + \varepsilon_i \qquad (27)
\end{aligned}
$$

In this equation, p_i is the probability that company i goes public; $P(i)$ is the partner of company i; $VC(i)$ is the VC investing in company i; $P(i)\_IPO$ is a dummy variable that takes the value of one if the company's partner goes public, and zero otherwise; $VC(i)\_VC(P(i))$ is a dummy variable that takes the value of one if the company received funds from a VC that previously invested in its partner, and is zero otherwise; and $P(i)\_IPO \times VC(P(i))\_VC(i)$

[18] A natural alternative measure of success is an acquisition, however many companies are acquired for assets (and not for performance) which makes acquisitions a noisier measure than IPO (Ozmel, Robinson, and Stuart, 2013).

[19] Logit model presented in the online appendix provides similar results.

is the interaction between the two dummies. $\varphi_{st(i)}$ is the state of the company fixed effect; $\chi_{ind(i)}$ is the industry of the company fixed effect; $\omega_{s(i)}$ is the size of the company fixed effect; $o_{st(P(i))}$ is the state of the partner fixed effect; $\delta_{ind(P(i))}$ is the industry of the partner fixed effect; $\nu_{s(P(i))}$ is the size of the partner fixed effect; $st(i)\_st(P(i))$ is a dummy variable that takes the value of one if the company and its partner operate in the same state, and zero otherwise; $\varpi_{ind(i)\times ind(P(i))}$ is a fixed effect at the industry of the company–industry of the partner pair level; $\rho_{s(i)\times s(p(i))}$ is a fixed effect at the size of the company–size of the partner pair level; and μ_t is a time fixed effect. Note that if the number of industries is 10, 10 dummies will capture the industry of the company fixed effect; 10 dummies will capture the industry of the partner fixed effect; and 100 dummies will capture the industry of the company–industry of the partner pair fixed effect. Also note that the industry of the company–industry of the partner pair fixed effect is more stringent than a company-industry or a partner-industry fixed effect. Indeed, by using the fixed effect at the pair level, we are comparing company i's probability of going public to other companies that both work in the same industry as i and that have partners that operate in the industry where company i's partner operates. Similarly the size of the company–size of the partner pair fixed effect is more stringent than a company-size fixed effect or a partner-size fixed effect.

In our model β_1 captures the possibility that companies that go public partner with other companies that also go public; β_2 captures the advantage associated with the VC investing in the company's partner; and β_3 captures the assortative-matching channel.

The OLS estimation of equation (27) is presented in table 5. The results suggest that assortative matching is borne out in the data. Indeed, the probability that a company goes public is 16.5% larger for companies that obtain funds from a VC that previously invested in a successful partner, compared to companies that obtain funds from a VC that invested in a

Table 5: Probability that a VC venture goes public – Linear Probability Model. In this table we estimate the probability that a company with VC funding goes public, and how this probability is different when the company obtains funds from a VC that previously invested in one of its partners. We use a linear probability model. The *standard errors* are presented in parentheses. * represents significance at the 10% level, ** represents significance at the 5% level, and *** represents significance at the 1% level.

	(1)	(2)	(3)	(4)
Partner completed IPO	0.020	0.006	-0.001	0.008
	(0.020)	(0.020)	(0.021)	(0.021)
VC invested in partner	-0.005	-0.053	-0.083	-0.070
	(0.057)	(0.055)	(0.057)	(0.058)
VC invested in partner and partner completed IPO	0.169**	0.136*	0.173**	0.165**
	(0.071)	(0.070)	(0.071)	(0.072)
N	2,692	2,627	2,559	2,559
$adj - r^2$	0.052	0.145	0.154	0.158
time f.e.	YES	YES	YES	YES
company controls	NO	YES	YES	YES
partner controls	NO	NO	YES	YES
company $\times$ partner controls	NO	NO	NO	YES

random company, and 9.5% (16.5%-7%) higher compared to a company that does not share a VC with its partner. These magnitudes are virtually unchanged in the logit regression we present in the online appendix.[20] Perhaps surprisingly, the likelihood that a company goes public is not affected by its partner going public (by itself). But this finding is consistent with the hypothesis that VCs quickly offer funding to *any* partner of a venture that is perceived to be high quality (which is consistent with assortative-matching-based inference). Thus, we simply would not observe pairs with perceived high-quality that did not share the same

[20]The increase in the probability of going public associated with obtaining funds from a VC that invested in a successful partner is $\beta_{OLS} = 16.5\%$ using the linear probability model. The same estimate using the logit model in the online appendix is $\beta_{logit} * p * (1 - p) = 76.5\% * 32.7\% * (1 - 32.7\%) = 16.8\%$, where we use the average probability of going public presented in table 2. To make the analysis more intuitive, we use the linear probability model for the analysis of this subsection.

VC.[21] This finding also suggests that the correlation in success cannot be solely explained by synergies among partners or by alliances solving contractual problems, otherwise we would observe a positive correlation between partners' success rates even if they did not share a VC. These results are robust to explicit controls for characteristics of the company, characteristics of the partner, and characteristics of the company–partner pair.

Our findings are consistent with the results in Lindsey (2008) and Ozmel, Robinson, and Stuart (2013), but we explore a new dimension associated with company success: the informational advantage a VC has, given that firms match assortatively. In fact, Ozmel, Robinson, and Stuart (2013) show that VC activity increases the likelihood of success, and Lindsey (2008) shows that within-portfolio alliances (i.e., alliances that share a VC) have a higher likelihood of success. We show that the success of companies that form a within-portfolio alliance not only is higher than the unconditional probability of success, but also is strongly correlated; that is, good firms funded by VC_j are more likely to be partners with other good firms funded by VC_j. Note that this correlation can hold even if within-portfolio alliances was not a driver of success and if VC did not affect the quality of their investments.

7 Conclusion

We develop a novel theory of informed capital, proposing that in an economy with heterogeneous companies, financiers gradually learn about company type via the pattern of inter-corporate relationships. The model predicts that companies can increase their probability of obtaining funds from a specific financier if one of their partners is financed by that firm. This hypothesis is confirmed in the data. We also establish empirically that the success

[21] Also note that all companies in table 5 are required to have some VC financing.

rates of companies that have been financed by the same firm are strongly correlated, which is consistent with the model's assumption that assortative matching is efficient (and occurs). Our main theoretical result is that a critical threshold of informed capital needs to be met for the economy to operate in an efficient, large-scale regime, where many organizations produce. That assortative matching obtains is crucial for the feasibility of such a regime, and a critical supply of informed capital is precisely what incentivizes high-quality companies to incur the costs required to find a high-quality partner. The paper thus contributes to our understanding of how the structure of the financial sector affects the functioning of the "real economy."

A Appendix

A.1 Lemmas

This section presents intermediate results that are useful for proving the propositions in the main body of the paper.

Lemma 1 *If all companies operate (downstream and upstream) and there is only residual matching, the (ex ante) aggregate surplus S (normalized by F) is given by:*

$$S = \frac{R}{4}(1 + 3\gamma) - (1 + \eta). \tag{A.1}$$

Lemma 2 *If all companies operate and there is assortative matching, aggregate surplus is given by:*

$$S = \frac{R}{2}(1 + \gamma) - \left(1 + \eta + \frac{\phi}{2}\right). \tag{A.2}$$

A.2 Proofs

Proof of lemma 1. If all companies are matched at random, then 1/4 of all pairs comprise a high-type upstream company and a high-type downstream company. For these pairs, and noting that certified-matching costs are not incurred in this case, total surplus is $R-(1+\eta)$; for other pairs in the economy, surplus corresponds to $\gamma R - (1 + \eta)$. We thus obtain an expected surplus (normalized by F) of

$$S = \frac{1}{4}[R - (1 + \eta)] + \frac{3}{4}[\gamma R - (1 + \eta)].$$

Simplifying this expression yields equation (A.1) in the lemma.■

Proof of lemma 2. With assortative matching, and for large F, approximately all high-type upstream companies match up with all high-type downstream companies; but the latter incur certified-matching costs. Total surplus for these pairs is $R-(1+\eta+\phi)$. For other pairs in the economy, surplus corresponds to $\gamma R-(1+\eta)$. Combining the two types of surplus, in the aggregate we thus obtain:

$$S = \frac{1}{2}[R-(1+\eta+\phi)] + \frac{1}{2}[\gamma R-(1+\eta)],$$

which simplifies into expression (A.2) in the lemma.■

Proof of proposition 1. The derivation is presented in six steps:

STEP 1. Both types of downstream companies raise debt D in the following amount:

$$D = X_H + \phi + \eta(1-\delta). \tag{A.3}$$

This amount of financing is strictly required by high-type downstream companies with a high-type supplier; the low types simply mimic this amount.[A.1]

STEP 2. Under assumption 3, rational VCs make financing offers only to downstream companies that are partnered with high-type suppliers; that is, only half of VCs will end up making offers. Recall that the rate associated with these offers is denoted by $r_{VC,d}$.

STEP 3. Because VCs only make financing offers if their downstream potential client is a high type, the measure for the total number of high-quality downstream companies that receives an offer is $\mu/2$. All other companies seek financing with the uninformed market, which we assume cannot observe whether a company was "rejected" by a VC. The equilibrium rate

[A.1] Companies could in principle raise an amount greater than D, but for simplicity we rule this out. (Formally we could have an off-the-equilibrium-path belief that only low types would try to raise more than D, which does not seem unreasonable.)

for the downstream uninformed market, r_d, is set to solve:

$$\underbrace{\left[\frac{1/2-\mu/2}{1-\mu/2}\right]D(1+r_d)}_{\text{high type}}+\underbrace{\left[\frac{1/2}{1-\mu/2}\right][\gamma D(1+r_d)+(1-\gamma)0]}_{\text{low type}}=D, \tag{A.4}$$

which, using equation (A.3) and simplifying, yields equation (7) in the proposition.

STEP 4. The ex ante surplus for a downstream company i, denoted by $\pi_{d,i}$, conditional on i being a high type and also matching with a high-type supplier, is the following:

$$\begin{aligned}\mathrm{E}[\pi_{d,i}|\alpha_i\alpha_{P(i)}=1] \quad = \quad & \underbrace{\mu\times[R-D(1+r_d/2)]}_{\text{finds VC-financed high-type supplier}} \quad + \\ & + \quad \underbrace{(1-\mu)\times[R-D(1+r_d)]}_{\text{finds non-VC-financed high-type supplier}} \quad -\delta\eta,\end{aligned} \tag{A.5}$$

where we used the fact that, with Nash bargaining, the informed rate is simply going to be one-half of the market rate. (Recall the real interest rate is 0.) In other words, $r_{VC,d} = r_d/2$.[A.2] Because high-type downstream companies are competing among themselves (given the scarcity of high-type suppliers), in equilibrium their ex ante surplus needs to be zero. Equating expression (A.5) to zero and using expression (A.3) for debt D, we obtain the following expression for X_H:

$$X_H=\frac{R-\delta\eta}{1+r_d\left(1-\frac{\mu}{2}\right)}-\phi-\eta(1-\delta) \tag{A.6}$$

This zero-surplus condition is naturally sufficient for low-type downstream companies not wanting to deviate to the certified matching market because doing so would violate their

[A.2]The disagreement payoffs correspond to financing being conducted in the uninformed market (i.e., $R-D(1+r_d)$ for the downstream company and 0 for the VC).

participation constraint.

STEP 5. Under the assumption that companies' insiders are able to appropriate all ex ante excess funds (e.g., via higher wages (not modeled)), the surplus of a downstream company, conditional on its being partnered with a low-type supplier, is given by:

$$\begin{aligned} \mathrm{E}[\pi_{d,i}|\alpha_{P(i)}=0] &= \gamma\left[R-D(1+r_d)\right]-\overbrace{(X_L+\eta-D)}^{\substack{\text{necessary own funds for}\\ \text{low-type downstream}}} \\ &= \gamma\left[R-D(1+r_d)\right]-\delta\eta+(X_H-X_L)+\phi. \end{aligned} \tag{A.7}$$

The surplus in this equation must be zero in equilibrium to prevent high-type downstream companies from deviating to residual matching; because with this deviation a high-type upstream company would undoubtedly be partnered with a low-type supplier, expression (A.7) is indeed the deviation payoff. This zero-surplus condition pins down X_L:

$$X_L=(X_H+\phi-\delta\eta)\left[1-\gamma(1+r_d)\right]+\gamma\left[R-\eta(1+r_d)\right], \tag{A.8}$$

where in the simplification we made use of expression (A.3) for debt D.

STEP 6. Expressions (5) and (6) in the proposition are obtained by inserting the expression for the uninformed rate in equation (7) into equations (A.6) and (A.8).■

Proof of proposition 2. The denominator in expressions (5) and (6) is positive for all $\mu\in[0,1]$ (our domain of interest). Therefore, $X_H\geq X_L$ is equivalent to:

$$\begin{aligned} &2R(1+\gamma-\mu)+\delta\eta(1-\gamma)(2-\mu)-(\phi+\eta)[4-\mu(3-\gamma)]\geq \\ &2R(1+\gamma)-\mu R(2+\gamma-\gamma^2)+\eta\left[\mu(3-\gamma+2\delta(1-\gamma))-4-2\delta(1-\gamma)\right]. \end{aligned}$$

Simplifying this expression with respect to μ yields the threshold in equation (10). The next step is to establish that expression (10) increases with certified-matching costs ϕ:

$$\frac{\partial \mu_0}{\partial \phi} \geq 0 \Leftrightarrow \frac{4}{\phi(3-\gamma)+(1-\gamma)(R\gamma-3\delta\eta)} \geq \frac{4(3-\gamma)[\phi-\delta\eta(1-\gamma)]}{[\phi(3-\gamma)+(1-\gamma)(R\gamma-3\delta\eta)]^2} \Leftrightarrow$$
$$(1-\gamma)(R\gamma-3\delta\eta) \geq -(3-\gamma)\delta\eta(1-\gamma) \Leftrightarrow R \geq \delta\eta,$$

which is always true under assumption 2 and because of the fact that $\delta < 1$. The threshold ϕ_0 is obtained by setting the numerator in (10) to zero.■

Proof of proposition 3. The upstream uninformed financial market sets the rate r_u competitively for a total debt amount of one unit, knowing that one-half of financed companies will turn out to be low-type. The formal condition for expected breakeven to be zero is given by:

$$\frac{1}{2}\min\left((1+r_u), X_H\right) + \frac{1}{2}\min\left((1+r_u), X_L\right) = 1, \tag{A.9}$$

which solving for r_u yields

$$r_u = \begin{cases} 0 & \text{, if } X_L \geq 1 \quad \text{(A.10)} \\ 1 - X_L & \text{, if } X_L < 1. \quad \text{(A.11)} \end{cases}$$

The lowest threshold for upstream-company expected revenues that sustains an uninformed financial market is given by

$$\frac{1}{2}X_H + \frac{1}{2}X_L = 1. \tag{A.12}$$

Combining the expressions for X_H and X_L (equations (5) and (6)) with equation (A.12), the breakdown condition $X_H + X_L < 2$ is equivalent to:

$$\frac{R[4(1+\gamma-\mu)-\mu(\gamma-\gamma^2)]-(\phi+2\eta)[4-\mu(3-\gamma)]+\delta\eta\mu(1-\gamma)}{2[4-\mu(3-\gamma)]} < 2.$$

Simplifying this expression with respect to μ yields threshold (12) in the proposition.■

Proof of proposition 4. The boundary condition for default for downstream companies facing the uninformed market is that all funds available are used to pay for debt (principal plus interest). Formally, this condition is expressed as:

$$\left(\frac{1/2-\mu/2}{1-\mu/2}\right) R + \left(\frac{1/2}{1-\mu/2}\right)\gamma R = D. \tag{A.13}$$

Using equations (A.3) and (A.13), the breakdown condition for downstream uninformed financial markets can be written as:

$$\begin{aligned} R\left(\frac{1/2-\mu/2+1/2\gamma}{1-\mu/2}\right) &< X_H + \phi + \eta(1-\delta) \Leftrightarrow \\ R\left(\frac{1-\mu+\gamma}{2-\mu}\right) &< \frac{2R(1+\gamma-\mu)+\delta\eta(1-\gamma)(2-\mu)}{4\mu(3-\gamma)} - \eta\delta, \end{aligned} \tag{A.14}$$

where in the second step we used equation (5) to substitute for X_H. The inequality appears to be quadratic in μ, but it simplifies to a linear relationship; equation (A.14) is equivalent to:

$$R(1+\gamma-\mu)[4-\mu(3-\gamma)-2(2-\mu)] < \delta\eta(2-\mu)[2-\mu-\gamma(2-\mu)-4+\mu(3-\gamma)] \Leftrightarrow$$
$$R(1+\gamma-\mu)\mu(\gamma-1) < \delta\eta(2-\mu)2(\mu-1-\gamma) \Leftrightarrow R\mu(1-\gamma) > \delta\eta(2-\mu)2.$$

Further simplification with respect to μ yields expression (13).■

Proof of proposition 5. The proof of the proposition is presented in three steps:

STEP 1. Let us momentarily conjecture that an equilibrium without uninformed finance and without assortative matching can exist. Any one high type would prefer to deviate to the certified matching market (offering $X_L + \epsilon$ and definitely obtaining a high-type partner) and significantly improve its chances of success (because assortative matching is assumed to be efficient, from assumptions 1 and 2). Thus, such an equilibrium cannot exist.[A.3]

STEP 2. Assuming that a no-uninformed-finance/assortative-matching equilibrium can exist, we first show that it cannot be an equilibrium whenever $\mu \in [\mu_0, \min(\mu_1, \mu_2)]$. To see this fact, note that upstream companies that did not obtain VC financing at $t = 0$ still create value on average, as long as high-type downstream companies demand them later (i.e., choose to participate in the certified matching market). Because participating in the certified matching market later also creates value for these downstream companies, the only possible subgame-perfect equilibrium necessarily implies that all companies operate and that uninformed financial markets open.[A.4]

STEP 3. Next, assuming that a no-uninformed-finance/assortative-matching equilibrium can exist (for $\mu \notin [\mu_0, \min(\mu_1, \mu_2)]$), we compute its associated surplus. 1/2 of upstream companies that partnered with a VC are a high type, and so their downstream partner will receive a financing offer. For these pairs, which represent a measure of $\mu/2$ in the economy, total surplus is then $R - (1 + \eta + \phi)$. The other 1/2 upstream companies turn out to be low types, and their downstream partners accordingly do not obtain the funding necessary to engage in production (nor will they pay certified matching costs). Because upstream companies' type is only revealed via production, low types upstream still need to incur the

[A.3] However, such a regime can be shown as feasible under conditions compatible with assumptions 1-3.

[A.4] The possibilities potentially would be different if the companies were moving simultaneously, and where a coordination failure could obtain.

initial cost of 1. Combining the two cases, we thus obtain the following for the aggregate surplus:

$$S = \frac{\mu}{2}[R - (1 + \eta + \phi)] + \frac{\mu}{2}(-1),$$

which simplifies into expression (14); and we note S is positive under assumptions 2 and 3. Finally, we show that no agent wants to deviate from its equilibrium strategy when $\mu \notin [\mu_0, \min(\mu_1, \mu_2)]$ for the following reasons : (1) uninformed markets cannot open because of the arguments given in the proof of the LSAM equilibrium; (2) downstream high types are competing for upstream high types and obtaining a surplus of zero; no downstream high types strictly prefer to deviate to the residual matching market because doing so undoubtedly would mean being partnered with a low type, and the low-type upstream companies' partners do not get funding (thus the deviating downstream high type would obtain a deviation payoff of zero); (3) downstream low types certainly do not participate in the certified matching market (doing so is too costly, given competition) and do not obtain financing otherwise, so these companies actually do not participate at all; (4) upstream high types share the total positive surplus with the VC and thus verify their participation constraint; (5) for the same reason VCs also verify their participation constraint; and (6) upstream low types default and have a payoff of zero.■

Proof of proposition 6. If a non-trivial LSAM equilibrium exists, then necessarily $\mu_1 > 0$ because $\min(\mu_1, \mu_2) \geq \mu_0 > 0$. Given that $\mu_1 > 0$ and that the numerator in expression (12) is always positive under assumption 2, the denominator in expression (12) must also be positive. Noting that the denominator in the expression for μ_3, equation (15), is also positive, it follows that the sign of the difference $\mu_3 - \mu_1$ is the sign of the following function:[A.5]

$$F(R) := A\,R^2 + B\,R + C, \tag{A.15}$$

where

$$A := \gamma(1-\gamma^2) \tag{A.16}$$

$$B := (2+\phi)(2\gamma^2+\gamma+1) + \eta\left[4\gamma^2 - 2\gamma - 2 - \delta(1-\gamma^2)\right] \tag{A.17}$$

$$C := [2(1+\eta)+\phi]\,[\eta(1-\gamma)(2+\delta) - (2+\phi)(1+\gamma)]\,. \tag{A.18}$$

Next, we claim that if $F(R)$ is positive for any R larger than the threshold defined in assumption 2, this result is equivalent to the surplus of the LSAM being larger than the surplus of the no-uninformed-finance/assortative-matching regime around the points μ_0 and $\min(\mu_1, \mu_2)$. To see that this claim is true, note that the LSAM surplus is independent of μ and the no-uninformed-finance/assortative-matching surplus increases linearly with μ. Thus, it suffices to show that $\mu_3 \geq \mu_1$, which is equivalent to $F(R) \geq 0$. Noting that A is positive, we can see two possible cases. In the first, $F(R)$ is always positive; for this case, the proof ends. In the second case, $F(R)$ has two zeros. However, the larger zero actually corresponds to the lower bound for R, defined in assumption 2:

$$\frac{-B+\sqrt{B^2-4AC}}{2A} = \frac{2(1+\eta)+\phi}{1+\gamma} \Leftrightarrow$$

$$-(1+\gamma)^2 C = A\,[2(1+\eta)+\phi]^2 + B(1+\gamma)\,[2(1+\eta)+\phi] \Leftrightarrow$$

$$-\left[\eta(1-\gamma^2)(2+\delta) - (2+\phi)(1+\gamma)^2\right] = \gamma(1-\gamma)(2+2\eta+\phi) + (2+\phi)(2\gamma^2+\gamma+1) +$$

[A.5] We are omitting rather lengthy, although trivial, algebra.

$$\eta\left[4\gamma^2-2\gamma-2-\delta(1-\gamma^2)\right] \Leftrightarrow -\eta(1-\gamma^2)(2+\delta)=\eta\left[2\gamma^2-2-\delta(1-\gamma^2)\right] \Leftrightarrow 1=1.$$

This concludes the proof.■

Proof of proposition 7. The expression in the proposition for μ_3 is obtained by combining the surplus from lemma 2 (equation (A.2)) with the surplus from equation 14:

$$\mu\left[\frac{R-(2+\eta+\phi)}{2}\right] \geq \frac{2(1+\eta)+\phi}{1+\gamma}.$$

To prove that μ_3 is smaller than 1, and using expression (15), we have:

$$R(1+\gamma)-2(1+\eta)-\phi \leq R-(2+\eta+\phi) \Leftrightarrow \gamma R \leq \eta,$$

which is true by assumption (3).■

Proof of proposition 8. Using equations (17)-(20), the normalized agreement payoffs for the upstream company and the VC are:

$$\begin{cases} -r_{VC,u} & \text{(Upstream company)} \\ \dfrac{Dr_d}{4}+r_{VC,u} & \text{(VC).} \end{cases}$$

According to Nash bargaining, total (normalized) surplus is now shared equally, that is,

$$r_{VC,u}=-\frac{Dr_d}{8}.$$

Using expressions (A.3), (7), and (5), one can write the preceding equation as a function of primitives only:

$$-\frac{Dr_d}{8}=-\frac{r_d[X_H+\phi+\eta(1-\delta)]}{8}=-\frac{r_d}{8}\left[\frac{R-\delta\eta}{1+r_d(1-\mu/2)}\right]=$$
$$\left[\frac{\gamma-1}{8(1+\gamma-\mu)}\right]\left[\frac{R-\delta\eta}{1+\left(\frac{1-\gamma}{1+\gamma-\mu}\right)(1-\mu/2)}\right]$$

Further simplification yields equation (21) in the proposition.■

Proof of proposition 9. The disagreement payoffs are the same as with $r_u=0$; under the assumption that upstream debt is risky for the VC (i.e. low types default), the agreement payoffs are given by:

$$\begin{cases}\frac{1}{2}\left[X_H-(1+r_{VC,u})\right] & \text{(Upstream company)}\\ \frac{1}{2}\left(r_{VC,u}+D\frac{r_d}{2}\right)+\frac{1}{2}(X_L-1) & \text{(VC).}\end{cases}$$

Equating the normalized payoffs, we can write:

$$X_H-1-r_{VC,u}-X_H-X_L+2=r_{VC,u}+D\frac{r_d}{2}+X_L-1\Leftrightarrow$$
$$2=2r_{VC,u}+D\frac{r_d}{2}+2X_L\Leftrightarrow r_{VC,u}=1-X_L-D\frac{r_d}{4}.$$

Using the expression for downstream debt (A.3), we can simplify the preceding equation:

$$r_{VC,u}=1-X_L-[X_H+\phi+\eta(1-\delta)]\frac{r_d}{4}.$$

Replacing X_H using equation (A.6), we obtain:

$$r_{VC,u} = 1 - X_L - \left[\frac{X_L - \gamma[R - \eta(1+r_d)]}{1-\gamma(1+r_d)} + \eta\right]\frac{r_d}{4}. \tag{A.19}$$

The condition that low types default is equivalent to $r_{VC,u} < X_L - 1$; combining this condition with (A.19), we can write:

$$\begin{aligned} X_L - 1 < 1 - X_L - \frac{r_d}{4}\left[\frac{X_L - \gamma R + \eta}{1-\gamma(1+r_d)}\right] \Leftrightarrow \\ X_L < \frac{8[1-\gamma(1+r_d)] - r_d(\eta - \gamma R)}{8[1-\gamma(1+r_d)] + r_d} =: \underline{X}_L, \end{aligned}$$

which is the threshold in the proposition. If the parameters are such that this threshold is met, then in the conjectured equilibrium, a high realized return of $r_{VC,u}$ (no default) happens if, and only if, the upstream company is a high type; and this return is naturally higher than the average return for VCs upstream (simple average of r_{VC_u} and $X_L - 1$). The fact that the return downstream is higher than the competitive return follows directly from the fact that $r_{VC,d}$ is positive and certain for high types.■

Proof of proposition 10. The surplus for high-type pairs downstream in equation (A.5) now becomes:

$$\mathrm{E}\left[\pi_d | \alpha_i \alpha_{P(i)}\right] = \mu(R - D) + (1-\mu)[R - D(1+r_d)] - \delta\eta.$$

Setting this expression to zero, and using equation (A.3) for debt D, the price of the certified matching market is given by:

$$X_H = \frac{R - \delta\eta}{1 + r_d(1-\mu)} - \phi - \eta(1-\delta), \tag{A.20}$$

instead of expression (A.6). The surplus of low types is still given by equation (A.7), and accordingly X_L is given by expression (A.8). Using equations (A.8) and (A.20), the condition for sustainability of the equilibrium, $X_H \geq X_L$, can now be written as:

$$\begin{aligned}
& X_H \geq (X_H + \phi - \delta\eta)\left[1 - \gamma(1 + r_d)\right] + \gamma\left[R - \eta(1 + r_d)\right] \Leftrightarrow \\
& (1 + r_d)\gamma\left[\frac{R - \delta\eta}{1 + r_d(1-\mu)}\right] \geq \phi - \delta\eta + \gamma R \Leftrightarrow \\
& r_d\left[\phi - \delta\eta - \mu(\phi - \delta\eta + \gamma R)\right] \leq \delta\eta(1-\gamma) - \phi. \qquad \text{(A.21)}
\end{aligned}$$

The equilibrium uninformed rate is still given by equation (7). Combining this equation with (A.21), the condition becomes:

$$(1-\gamma)\left[\phi - \delta\eta - \mu(\phi - \delta\eta + \gamma R)\right] \leq \left[\delta\eta(1-\gamma) - \phi\right](1 + \gamma - \mu).$$

Solving for μ yields the threshold in the proposition. To prove the second statement in the proposition, we need to show that:

$$\begin{aligned}
& \frac{2[\phi - \delta\eta(1-\gamma)]}{\phi(2-\gamma) + (1-\gamma)(R\gamma - 2\delta\eta)} \leq \frac{4\left[\phi - \delta\eta(1-\gamma)\right]}{\phi(3-\gamma) + (1-\gamma)(R\gamma - 3\delta\eta)} \Leftrightarrow \\
& \phi(\gamma - 1) - R\gamma(1-\gamma) - \delta\eta(1-\gamma) \leq 0,
\end{aligned}$$

which is always true, given that every individual term in the previous expression is negative.■

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