Networking as a Barrier to Entry

and the Competitive Supply of Venture Capital [*] [†]

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Abstract

Many financial markets are characterized by strong relationships and networks, rather than arm's-length, spot-market transactions. We examine the potential entry-deterring effects of this organizational choice in the context of relationships established when VCs syndicate portfolio company investments using U.S. data for the period 1980 to 2003. Our results show that networking does help reduce entry: VC markets with more extensive networking among the incumbent players experience less entry, and the economic effect is sizeable. However, potential entrants can use their prior relationships with the incumbents as well as previous investment experience in the industry or state to overcome this barrier to entry. We also document that companies seeking venture capital raise money on worse terms in more densely networked markets, and that increased entry into a market is associated with companies receiving increased valuations.

Key words: Venture Capital, Start-up Financing, Networks, Syndication, Entry Deterrence.

JEL classification: G24, L13, L14, L22, L84.

Networks are widespread in many financial markets. In particular, networks are the predominant choice of organizational form in the venture capital (VC) industry, in the sense that VCs tend to syndicate their investments with other VCs rather than investing alone (Lerner (1994)). VCs are thus bound by their current and past investments into webs of relationships with other VCs. Hochberg, Ljungqvist, and Lu (2005) find that this organizational form has strong implications for success in the VC market: Better networked VC firms enjoy better performance, even after accounting for other performance drivers such as experience, skill, or access to deal flow.

In this paper, we ask how exactly networking improves performance. Clearly, syndication entails costs: It requires making a larger number of relatively smaller investments, which not only dilutes the lead VC's share in a promising startup but also entails a considerable increase in due diligence and monitoring costs. Among the many benefits of syndication that the academic literature has highlighted, one stands out: The ability to reduce competition for deal flow by syndicating deals with friendly VCs (Lerner (1994), Brander, Amit, and Antweiler (2002); Casamatta and Haritchabelet (2003)).[1] The idea that VCs network and thus co-operate, rather than compete, with a view to improving their bargaining power with entrepreneurs implicitly requires that incumbents can keep entrants out, for in the presence of free entry, their bargaining power should not increase. We focus on this missing link by examining whether networking indeed allows incumbent VCs to deter entry, and thereby improve their bargaining power.[2]

How do strong ties among incumbent VCs in a local market put entrants at a disadvantage? First, by referring promising deals they cannot fund themselves to their friends, VCs may be able

[1] Other benefits include diversification (Lerner (1994)), improved screening (Sah and Stiglitz (1986)), obtaining access to other VCs' deal flow on a reciprocal basis (Lerner (1994)), and the ability to draw on the expertise of other VCs when nurturing investments (Brander, Amit, and Antweiler (2002)).

[2] Anecdotal evidence supports the importance of such a link. For example, when planning its ultimately successful entry into the U.S. venture capital market, the president of Japan-based JAFCO Ltd. "suspected that the densely networked U.S.VC industry would present considerable barriers to entry" (Kuemmerle and Ellis (1999), p.3).

to reduce the time entrepreneurs spend searching for funding, with the result that entrants are less likely to see the deal flow (Inderst and Mueller (2004)). Indeed, knowing that cross-referrals are common among VCs, entrepreneurs may be more inclined to submit their business plans to incumbents than to entrants. Second, if a deal requires syndication, perhaps due to its size or risk profile, incumbents may refuse to co-invest with anyone except one another, making it harder for potential entrants to assemble funding for the deal. Third, to the extent that there are network externalities, incumbents may be able to provide better value-added services to their portfolio companies, or provide them at lower cost, than could an entrant that is denied access to the resources of network members. In sum, we conjecture that VCs may network strategically, with a view to deterring entry into their local markets. Reduced entry in turn would enable incumbents to obtain more favorable deal terms from the entrepreneurs they back.

Against this background, we seek to answer three empirical questions. (1) Do strong network ties among incumbent VCs in a given market deter entry, and if so, is the effect first-order economically? (2) Can potential entrants overcome this barrier to entry by establishing ties, in their own home markets, with the incumbent VCs of the target market? (3) What are the consequences of reduced entry for the valuations at which entrepreneurs raise VC funding?

VC investments are geographically concentrated and VCs tend to specialize in a small set of industries (Sorenson and Stuart (2001)). Thus, a natural definition of a VC market is an industry/state pair, such as the California software market or the Massachusetts life sciences market. Using six broad industries and 50 U.S. states gives us up to 300 local markets which we study over the time period 1980 to 2003. Because both entrepreneurial activity and the VC industry in the U.S. show pronounced geographic concentrations, we exclude industry/state combinations with no or little VC activity, leaving a set of 129 markets and 1,364 market-year observations.

For each of these markets, we construct two types of measures of the extent of networking borrowed from economic sociology, namely the "density" of ties in the market (i.e. the proportion of the *possible* relationships that are *actually* observed among incumbents) as well as the "centrality," or influence, of the typical (i.e., average) incumbent in the market. Controlling for other likely determinants of market entry such as demand for capital, investment opportunities, funding availability, and market size, we find that more densely networked markets see substantially less entry than more sparsely networked markets. The magnitude of the effect is large: All else equal, a one-standard deviation increase in the extent to which a market is networked reduces the number of entrants in the median market by more than a third.

Of course, how densely networked a market is is likely not exogenous; rather, it is the outcome of strategic decisions incumbents make, presumably partly with a view to deterring entry. To correct for this potential endogeneity problem, we follow two approaches. First, we use instrumental variables motivated by non-strategic and mechanical determinants of syndication decisions. This strengthens our results, but in the absence of a natural experiment, irrefutable instruments are of course not available to us.

Our second approach links observed networking at the level of a market to the entry decision of an individual potential entrant or to the valuations at which entrepreneurial companies raise venture money. This mismatch of the units of analysis lessens the impact of endogeneity, because it is hard(er) to argue that incumbents make their networking choices with respect to an individual potential entrant or an individual future funding round. For the purpose of an individual VC's entry decision or the negotiations with an entrepreneur, observed networking can reasonably be taken to be predetermined.

When we estimate the probability of a potential entrant successfully entering a market, we find, as in the market-level analysis, that strong networks among incumbents in the target market reduce the likelihood of entry. This increases our confidence that the density of network ties in a market truly affects entry decisions, in a causal fashion. But not every potential entrant is deterred. Controlling for geographic proximity to the target market and prior experience in the industry (which each double the likelihood of entry), we find that a potential entrant is significantly more likely to enter if it has previously established ties to the incumbents through inviting them into syndicates in its own home market. When we consider interaction effects crossing how densely networked the target market is with dummies capturing pre-existing ties between an entrant and the incumbents, we find that such ties are sufficient to completely overcome this particular barrier to entry.

Finally, we examine the price effect of reduced entry by comparing the valuations of companies receiving VC funding in relatively more protected and relatively more open markets. This analysis speaks directly to the conjecture in the literature that VCs syndicate to increase their bargaining power over entrepreneurs. Controlling as best we can for other value drivers, we find that valuations are significantly lower in more densely networked markets: A one-standard deviation increase in our networking measures is associated with an around 10% decrease in valuation, from the mean of $25.6 million. This indicates that incumbent VCs benefit from reduced entry through paying lower prices for their investments. On the other hand, the more market share entrants can capture, the higher are the valuations paid in a market in the following year, suggesting that entry is pro-competitive and, at least in that sense, benefits entrepreneurs. The industrial organization of a local VC market therefore has significant implications for entrepreneurs seeking startup capital.

Our contribution is fourfold. First, we provide evidence that networking can reduce entry in the VC market. We argue that this is a logical, though so far missing, link in one of the prominent explanations for VC networking, namely that VC syndicate in order to reduce competition for deal flow and thereby increase their bargaining power. Second, our results help explain prior empirical evidence that better networked VCs enjoy better performance. Part of the explanation for this may be due to the lower prices VCs pay for their investments in more densely networked markets. Third, we shed light on the process of entry. Successful entry appears to involve "joining the club" by offering the incumbents syndication opportunities in one's home market. This is interesting in light of Lerner's (1994) observation that "the process through which some of the entrants joined the core of established venture organizations remains unclear." Fourth, the IO literature has not previously considered the role of networking as an entry deterrent, and while we focus on venture capital, we believe that our results may generalize to other industries that make heavy use of networks, such as investment banking.

Our work is closely related to the industrial organization literature on market entry. Though there has been little empirical analysis of entry in response to the activities of incumbents, there is a rich literature focusing on the activities of entrants. Relevant contributions include Bresnahan and Reiss (1987, 1991) who estimate an equilibrium entry model applied to a sample of firms in isolated markets, but do not consider differences among firms; and Berry (1992) who examines a model of entry in the airline industry that considers the effect of the scale of an airline's operations at an airport on the profitability of routes it flies from there. Berry's model expressly focuses on the role of differences among firms. Our work combines an entry model which allows for differences among firms with an examination of how network ties among incumbents can serve as a barrier to entry and how network ties between potential entrants and incumbents can facilitate entry.

This paper is also related to a large literature examining the economic effects of networks. Saxenian (1994) examines the role of informal ties and network-like organizations among engineers in Silicon Valley's success. Powell, Koput, and Smith-Doerr (1996) examine similar network ties in the biotechnology industry. Belleflame and Bloch (2004) model the formation of networks of market-sharing collusive relationships among firms, focusing on agents' decisions whether to build and maintain a link, and which networks will emerge in equilibrium.

Finally, our paper is related to the literature examining the structure and organization of the venture capital industry. Sahlman (1990) examines the governance of VC firms with particular focus on the investor-fund manager relationship. Lerner (1994) and Brander, Amit, and Antweiler (2002) study the motivations for syndication among venture capitalists. Hochberg, Ljungqvist, and Lu (2005) examine the impact of syndication networks on VC performance.

The remainder of the paper is organized as follows. Section I provides a brief overview of network analysis techniques. Section II discusses the VC setting, including the factors likely to affect entry, and describes the relevant data. Sections III and IV present the market-level and firm-level entry analyses, respectively, while Section V examines the link between valuations and entry barriers. Section VI concludes.

I. Network Analysis Methodology

Network analysis uses graph theory to describe network structure by focusing on the ties among economic actors. For instance, a network might be "dense" (if many actors are tied to one another via reciprocated relationships) or "sparse" (if actors tend to be more autarkic).[3]

Consider the networks illustrated in Figures 1 and 2. Figure 1 graphs the network that arises from syndication of portfolio company investments in the market for computer-related ventures

[3] See Wasserman and Faust (1997) for a detailed review of network analysis methods.

in Michigan over the five-year window 1979-1983. Nodes on the graph represent VC firms, and arrows represent syndicate ties between them. The direction of an arrow represents the lead/non-lead relationship between two syndicate members. The arrow points from the VC leading the syndicate to the non-lead member. Two-directional arrows indicate that both VCs have at one point in the time window led a syndicate in which the other was a non-lead member. Figure 2 shows the non-high-tech VC network in Pennsylvania in 1990-1994. Visually, it is quite apparent that the network in Figure 1 is dense; all the VC firms in the market have at least one tie to another VC, and often ties to multiple VCs. In contrast, the network illustrated in Figure 2 is clearly sparse; only two of the VC firms in this market have a tie to another VC.

In graph theory, networks are represented by a square "adjacency" matrix, the cells of which reflect the ties. In our setting, we code two VCs co-investing in the same portfolio company as having a tie.[4] Adjacency matrices can be "directed" or "undirected." Only directed matrices differentiate between the originator and the receiver of a tie. (Figures 1 and 2 illustrate directed networks.) In our setting, an undirected adjacency matrix records as a tie any participation by both VC firms *i* and *j* in a syndicate. The directed adjacency matrix differentiates between syndicates led by VC *i* versus those led by VC *j*.[5]

A. Density of the Network

One approach to measuring how strongly networked incumbents are is to examine the proportion of all logically possible ties present in their market. For example, the maximum number of possible ties in an undirected network of three incumbents A, B, and C is three – the

[4] As the example in Hochberg, Ljungqvist, and Lu (2005) illustrates, this coding produces a binary adjacency matrix. Though this is rarely done, it is possible to construct a valued adjacency matrix accounting not only for the existence of a tie between two VCs but also for the number of times there is a tie between them. All our results are robust to using network measures calculated from valued matrices.

[5] Unlike the undirected matrix, the directed matrix does not record a tie between VCs *j* and *k* who were members of the same syndicate if neither led the syndicate in question.

situation where all actors are tied to all other actors. Now suppose only A and C are connected to each other. The density of this market would then be 1/3 (one tie out of the three possible).

Density can be measured both for undirected and directed network representations, and we compute both. In an undirected network of n actors, the number of logically possible ties is $\frac{1}{2}n(n-1)$; in a directed network, it is $n(n-1)$. Let $p_{ijm}=1$ if at least one syndication relationship exists between VCs i and j in market m, and zero otherwise. Then the density of the undirected network is $\Sigma_j \Sigma_i p_{ijm} / (n(n-1))$. Let $q_{ijm}=1$ if at least one syndication relationship exists in market m in which VC i was the lead investor and VC j was a syndicate member, and zero otherwise. The density of the directed network then equals $\Sigma_j \Sigma_i q_{ijm} / (n(n-1))$.

B. Value-Weighted Average Centrality Measures

An alternative measure of networking in a market examines the centrality, or influence, of a typical incumbent VC. If incumbents are all highly networked among each other, their individual network centrality measures will be high. We would then consider such a market highly networked. Based on this principle, we compute two firm-level centrality measures as follows.

"Degree" centrality counts the number of unique VCs a VC has co-invested with: $\Sigma_j p_{ijm}$.[6] Clearly, degree is a function of network size, which in our dataset varies over time. To ensure comparability over time, we normalize degree by dividing by the maximum possible degree in an n-actor network (i.e., n–1).[7] To obtain an overall measure of how networked the market is, we compute the average degree in each market, value-weighted by VC firm size.[8]

While degree counts a VC's relationships, it does not take into account their quality.

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[6] Degree measures can also be calculated from directed adjacency matrices, giving two measures, "indegree" and "outdegree." These measure the extent to which a VC is invited into syndicates by others and the extent to which it invites other VCs into its own syndicates, respectively. Our results are robust to using indegree and outdegree.

[7] Whether or not we normalize has little effect on our results.

[8] Firm size is the sum of the capital under management by the VC firm at time t across all its funds in all markets.

Bonacich's (1972, 1987) "eigenvector centrality" weights a VC's ties to others by the importance of the VCs it is tied to. In essence, eigenvector centrality is a recursive measure of degree: $ev_{im} = \Sigma_j \, p_{ijm} \, ev_{jm}$. We normalize ev_{im} by the highest logically possible eigenvector centrality measure in a network of n actors. To obtain an overall measure of how networked the market is, we compute the value-weighted average eigenvector centrality for each market.

II. The VC Setting, Sample, and Data

Venture capital firms maintain extensive syndication networks which are easily observable, allowing us to directly measure the extent of networking among VC firms. As such, the VC industry is a prime example of a market where informal ties matter greatly. Furthermore, previous studies reveal strong evidence of localized exchange in the VC industry, both in terms of physical and industry distance (Sorenson and Stuart (2001)). Thus, the VC industry appears to be segmented into individual markets, making it a natural choice for examining issues of entry across heterogeneous markets. Below, we discuss the factors that are likely to drive market entry in the VC setting, and the relevant data used to estimate our entry models.

A. Primary Data Source

The majority of our data comes from Thomson Financial's Venture Economics (VE) database. We consider all investments in U.S. companies made by U.S. based VC funds between 1975 and 2003 which are included in the VE database. We exclude investments by angels and buyout funds. VE distinguishes between VC funds and management firms, and we will focus our analysis at the firm level. Because VC funds have a limited (usually ten-year) life, relationships are assumed to reside at the level of the VC management firms that manage the funds.

B. Market Definition

As Sorenson and Stuart (2001) show, VCs tend to invest locally, and many VCs specialize in a certain industry. Thus, an industry/state pair is a natural way to define the relevant market. Venture Economics classifies investments into six broad industry groups. Out of the 19,012 portfolio companies in the sample, 40.6% are “Computer related”, 25.3% are “Non-high-technology,” 15.4% are “Communications and media,” 9.4% are “Medical, health, life sciences,” 5.4% are “Semiconductors, other electronics,” and 3.8% are “Biotechnology.”

Our first empirical tests ask whether there is a link between entry and the extent of networking in a market. The unit of analysis in these market-level entry models is a market-year. To qualify for inclusion in the sample, a market-year has to have a history of at least 25 investments in the prior five years (to exclude markets with no real history of VC investment) and at least five VC deals in the year of analysis (to exclude inactive markets). There are 129 distinct markets with between one and 24 annual observations each. The total number of market-years in our sample is 1,364.

C. Incumbents and Entrants

We define an incumbent as a VC firm that has invested in the target market at some time prior to year *t* and continues to have investments in the market as of year *t*. Conversely, entrants are defined as those VC firms that invest in the market for the first time in year *t*.[9] Note that entrants are not necessarily inexperienced “rookies”; for the most part, entrants are themselves incumbents in other markets, and they may well be more experienced than the marginal incumbent in the market they are looking to enter.

To measure the extent of entry in a market in year *t*, we code four variables:

(a) the number of entrants in the market;

(b) the number of entrants that lead-manage deals in the market;

[9] For robustness purposes, we also consider as entrants firms for which some amount of time has passed since their last investment in a market. Our results are robust to considering a range of time limits on prior investment history.

(c) the number of deals lead-managed by entrants in the market; and

(d) the fraction of deals lead-managed by entrants in the market.

Lower values of these variables are an indication of less entry into a market, and thus potentially higher barriers to entry. As is common in the VC literature, a deal is defined as a collection of investments in a given portfolio company in a specific round of financing, and we identify the lead investor as the syndicate member making the largest investment in the round.

Table I, Panel A reports descriptive statistics for market entrants and incumbents. In the median market-year, there are 15 incumbents and nine entrants, five of which enter by leading syndicates for one deal each. The five deals won by entrants in the median market represent 28.6% of the deals by number and 29.9% of the deals by value.

D. Market-Level Network Measures

In common with the entry-deterrence literature, we focus on the network ties among the dominant incumbents and ignore ties among the competitive fringe, reasoning that the latter do not reflect an attempt to deter entry. We classify an incumbent as dominant if the VC firm is among the group of firms that contribute the first 80% of invested dollars in the target market measured over the prior five-year window; our results are not sensitive to this choice of cut-off.

VC firms that enter a market eventually become incumbents. To capture this dynamic, we construct a new network for each market for each year *t*, using data on syndications among the incumbents over the five years ending in *t*-1.[10] For example, for the "MA/Biotechnology" market in 1999, we construct the four network measures described in Section I from data on investments made in biotechnology companies in Massachusetts between 1994 and 1998. Table I, Panel B

[10] We make no distinction between relationships established earlier or later in these five-year windows. All our results are robust to using three-, seven-, or ten-year windows instead, with shorter windows generally being associated with stronger effects.

reports descriptive statistics of these network measures, each presented as a percentage of its theoretical maximum. The density of directed ties in the average market is 2.1%, the density of undirected ties averages 7.8%, the value-weighted average degree centrality is 8.4%, and the value-weighted average *eigenvector* centrality is 12.6%.

E. Market Characteristics

The level of entry we observe in the data is an equilibrium outcome of the interaction of the potential demand for and the potential supply of VC capital, both of which are difficult to observe, and hence challenging to measure. To proxy for demand and supply factors that affect the entry decision, our models include a range of controls, summarized in Table I, Panel C.

Better investment performance in a particular target market may attract entrants. Absent data on investment returns, we follow Hochberg, Ljungqvist, and Lu (2005) and compute the fraction of incumbent portfolio companies in the target market that were exited successfully through an IPO or an M&A transaction between *t*-5 and *t*-1. We then compute the target market's excess exit rate as the market exit rate relative to the median exit rate across all markets in the same industry in that five-year window. This ranges from -25% to +54%, with an average of 4.7%.

Markets with more volatile deal flow may provide more opportunity for entry if incumbents cannot easily meet unexpected increases in demand. To proxy for swings in market demand, we compute the coefficient of variation of the monthly number of deals over the prior five years. The average market has a coefficient of variation of 1.161.

Larger markets and those less economically developed generally have a higher demand for external capital and more capacity for new VC funding, and thus are more likely to attract entrants. We use the number of deals completed in a market in year *t*-1 as a proxy for market size, with the average market having 37.9 deals a year. To proxy for a state's economic development, we include both its gross state product (GSP), as reported by the U.S. Department of Commerce's Bureau of Economic Analysis (BEA), and its annual GSP growth rate. Since our sample covers more than 20 years of data, we use the BEA's implicit GNP deflator to adjust for inflation. The mean real GSP is $323 billion, with an average growth rate of 3.3%.

It is possible that certain types of deals are more attractive to potential entrant. For instance, larger and later-stage deals are more likely to be syndicated (Lerner (1994), Brander, Amit and Antweiler (2002)), primarily due to individual VCs' capital constraints and diversification needs. If, as we have conjectured, incumbents refuse to help entrants syndicate such deals, we would expect less entry in markets where deals are predominantly large and/or later-stage. Thus, we calculate the fraction of deals raising more than $3 million[11] and the fraction of later-stage deals. In the average market, 29.3% of deals exceed $3 million while 53.2% of deals are later-stage.

Investment opportunities are a reasonable proxy for a demand-side factor affecting entry. Controlling for investment opportunities in a private market is not easy. We follow Gompers and Lerner (2000a) who use *public*-market pricing multiples as a proxy for private-market investment climates. Specifically, we construct annual book-to-market ratios from Compustat data for each of the six Venture Economics industries. The mean value-weighted industry book-to-market ratio in our data is 0.524. Of course, this variable varies by year and industry but not by state.

If VC firms raise funds in response to perceived investment opportunities in a particular industry, fund inflows are another useful proxy for the industry investment climate. VC fund inflows average $7 billion per year and industry over the sample period.

Many start-up companies develop and commercialize cutting-edge technologies, and so require skilled and educated workers. Education levels in a particular geographic region may

[11] Our results are robust to alternative specifications.

hence be related to the probability of entrepreneurial success and consequently to the supply of VC funding. We obtain data on annual state-level science and engineering degree completions from the National Science Foundation (NSF).[12] This averages 2.6 per a thousand inhabitants.

F. Characteristics of Potential Entrants

All else equal, we expect more entry if there is a larger pool of "qualified" potential entrants (see Berry (1992)). A VC firm is considered to be a potential entrant if (1) it was founded (i.e. raised its first fund) in or before year *t*; (2) it has at least one fund under management that was raised in the previous six years; and (3) it has not invested in this particular market prior to year *t*.[13] We consider three key characteristics of potential entrants.

VC investments require substantial monitoring and active management and so tend to be local. We therefore control for the geographic distance between each potential entrant's location and the target market. Following Coval and Moskowitz (1999), we compute the geographic distance for each pair of VC *i* and target market *m* as follows:

$$D_{im} = \arccos\{\cos(lat_i)\cos(lon_i)\cos(lat_m)\cos(lon_m) + \cos(lat_i)\sin(lon_i)\cos(lat_m)\sin(lon_m) + \sin(lat_i)\sin(lat_m)\}2\pi r / 360 \qquad (1)$$

where *lat* and *lon* are the latitudes and longitudes (measured in degrees of arc) and *r* is the radius of the earth ($\approx$3,963 miles).[14] We then compute the fraction of potential entrants that are located within 100 miles of the target market. (Our results are robust to alternative cut-offs.)

Presumably, previous investment experience in the industry and/or state make a potential

[12] Science and engineering includes the following subjects: Engineering, physical sciences, geosciences, mathematics and computer sciences, life sciences, and science and engineering technologies.

[13] Condition (2) ensures that we capture active funds. A typical VC fund spends its first few years nurturing portfolio companies and the remainder of its life exiting them (Ljungqvist, Richardson, and Wolfenzon (2005)).

[14] We use zip codes to identify the coordinates of a VC firm's headquarters, assuming it is located in the center of the zip code area. To find the coordinates of a market, we cluster the zip codes of all portfolio companies in the market to locate the unique zip code where most economic activity takes place.

entrant more likely to actually enter a market. We therefore group potential entrants into three groups: Firms that in the prior five years have invested (1) in the state and the industry (but not in the specific state/industry combination); (2) in the industry (but not in the state); and (3) in the state (but not in the industry). In the average market, 6.8% of potential entrants have invested in both the industry and state, 31% have invested in the industry before but not in the state, and 5.9% have in invested in the state but not in the industry; see Table I, Panel D.

A key question we address is whether an entrant's *prior* relationships with incumbents, established in *other* markets, can facilitate entry. Sorenson and Stuart (2001) argue that the VCs' network ties can decrease both geographic and industry-based constraints on economic exchange. Similarly, one might argue that pre-existing network ties between incumbents and entrants may lead to entry being accommodated. For each potential entrant, we generate indicator variables capturing whether, in the prior five years, the potential entrant (a) participated in a deal lead-managed by an incumbent; or (b) lead-managed a deal in another market in which an incumbent was a co-investor. In the jargon of network analysis, these correspond to positive indegree and outdegree, respectively. In the average market-year, 20% of potential entrants have served as co-investors for incumbents elsewhere during the prior five years, while 13.1% have lead-managed syndicates in which incumbents were co-investors.

III. Market-Level Analysis

A. A Descriptive Model of Entry in Venture Capital

To see if there is a link in the data between the extent of entry in a VC market and the density of the incumbents' network ties, we regress the number of entrants in year t in market m on the four networking measures as of year t-1 (which we add one by one to avoid collinearity problems) as well as suitably lagged variables controlling for the pool of qualified potential entrants and the aforementioned market characteristics. Given the count nature of the dependent variable, and the fact that we have repeated observations per market, the models are estimated using conditional fixed-effects Poisson. We also include year fixed effects.

Table II reports the resulting estimates. The pseudo-R^2 exceeds 69% indicating good explanatory power. In each of the four models (one for each network measure), we find a strongly negative and significant relation between the extent of networking and the number of entrants, consistent with our conjecture that networking can help deter entry.

The controls behave as expected. There is significantly more entry if there is a larger pool of qualified potential entrants for the market, in the sense of geographical proximity to the market, prior investment experience (either having invested both in the state and the industry or having invested in the industry though not yet in the state[15]), and the prevalence of past network ties between potential entrants and incumbents. The latter result is consistent with syndication (and the networks that result from syndication) in part being a product of and contributing to reciprocity among VC firms (Lerner (1994), Hochberg, Ljungqvist, and Lu (2005)): By sharing deal flow today, a VC firm may be allowed to enter another market at a later date.

As for the market characteristics, as expected, the number of entrants increases in the market's lagged performance history, investment opportunities (as proxied by industry book-to-market ratios), variability of demand, flows of capital into the industry, the size of the VC market (as measured by the number of deals in the previous year), and state education levels (though this is significant only in two of the four models). There is less entry in larger states (based on state GSP) and in markets where late-stage deals predominate. As late-stage deals usually require syndication, this result is consistent with incumbents often refusing to syndicate with entrants.

[15] Sensibly, experience in the state by VCs focused on other industries is associated with less entry.

B. Causality

The results in Table II provide clear evidence of a link between the extent of entry in a VC market and the density of the incumbents' network ties, but is it causal? This is a tough question to answer. It is conceivable that both entry and networking are simultaneously determined by a third variable whose omission creates a spurious correlation between them. For instance, *perhaps* entrants avoid markets where deals are unusually risky, and *perhaps* there is more syndication (and hence potentially more networking) among incumbents seeking to diversify in such risky markets. In this example, failure to control adequately for risk would induce a spurious correlation between entry and networking.[16] While our empirical entry model includes as many market characteristics as we can measure, we cannot rule out the possibility of omitted variables.

Equivalently, interpreting the negative coefficients on networking causally is problematic given the (strong) likelihood that networking is endogenous to entry. If entry deterrence is indeed strategic, we should think of incumbents as optimizing their investment in networking in part with a view to minimizing entry. This too could result in a spurious correlation.

To better understand whether there is indeed a causal link, we take two approaches. The first is an instrumental-variables approach that seeks to deal directly with the potential endogeneity of networking, discussed in the remainder of this section. Our second approach links observed networking at the level of a market to entry decisions at the level of a potential entrant (in Section IV) or to the valuations at which entrepreneurial companies raise venture money (in Section V). Changing the unit of observation in this way should lessen the impact of endogeneity, because it is hard(er) to argue that incumbents optimize networking with respect to an individual potential entrant or an individual funding round. This is a standard way to

[16] Though this hypothetical example seems inconsistent with our finding of more entry in markets in which seed and early-stage deals (which are usually riskier) predominate.

circumvent endogeneity concerns (see Bottazzi, da Rin, and Hellmann (2006) for a recent application of this reasoning to the venture capital setting).

C. A Two-stage Model of Market-level Entry

For our first approach, we use three instruments. They are chosen to satisfy the standard IV exclusion restriction; that is, the instruments likely correlate with the extent of networking in a market but are unlikely to affect entry directly.

C.1. Geographical Clustering of Demand

If more frequent interaction helps VCs form ties, it is more likely that dense, entry-reducing networks will result. Markets in which demand is spread over a wide geographic area presumably offer fewer opportunities for VCs to interact than markets in which demand is concentrated in a few clusters of economic activity. Silicon Valley is an obvious case in point. More generally, VCs tend to meet while attending board meetings of their portfolio companies (Kuemmerle and Ellis (1999)) and during "pitch events" for local startups seeking capital. The more clustered are portfolio companies and start-ups, the greater the chances that any two VCs will meet and establish a relationship. Thus, our first instrument is based on the geographic distribution of demand in a market, measured as the coefficient of variation of the distance between each pair of portfolio companies in a market, calculated using equation (1) above.[17]

C.2. Presence of Corporate VCs

For reasons unrelated to entry considerations, markets with a heavy presence of corporate venture programs are likely to be less densely networked. According to Gompers and Lerner (2000b), corporate VCs differ from traditional VCs both in terms of investment objectives (which are often strategic rather than financial) and their longevity (which averages a mere four

[17] An alternative measure of geographic proximity can be calculated using the distances among incumbent VC firms rather than among portfolio companies. Our results are robust to the use of this alternative measure.

years). This alone makes them less likely to view networking as a way to reduce long-run entry into a given market: It may be something they are content to free-ride on, but their incentives to contribute to entry deterrence are clearly much lower. Corporate VCs also tend to form less dense syndication networks, for a simple reason. Because of compensation issues, they are typically staffed with managers seconded from the parent corporations, as opposed to dedicated venture capital professionals (Gompers and Lerner (2001)). These individuals are likely to be considerably less well networked (at the personal level) than are dedicated VC professionals, and this tends to lead to opportunistic as opposed to strategic syndication (and hence networking).

In summary, the presence of corporate VCs in a market is expected to be associated with lower levels of networking in the market, a prediction that is borne out empirically in Zheng (2004). At the same time, it is hard to see why the presence of corporate VCs should encourage or deter entry directly.

C.3. Number of Incumbents

Presumably, the greater the number of incumbents in a market, the more difficult it becomes to network strategically and hence to co-ordinate on entry-deterrence. (This is a standard result in oligopoly theory.) This makes the inverse of the number of incumbent VCs in a market a potential instrument for the extent of networking in that market. It may be a weak instrument to the extent that the number of incumbents itself influences the entry decision, though empirically this is not what we find.[18] Nonetheless, we will attach greater weight to any results that are identified through our other two instruments.

C.4. First-stage Results

The first-stage regression in our IV models predicts the extent of networking in the market as

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[18] It is important to recall that the network measures do not decrease mechanically in network size, as each is normalized by its theoretical maximum.

a function of our three instruments, the second-stage control variables (as per Table II), and market fixed effects. Table III reports the estimates for each of our four networking measures. Overall, the models appear to be well specified. The within-group R^2 ranges from 26.7% in the eigenvector centrality model to 57.0% in the asymmetric density model.

Having valid instruments that satisfy the exclusion restriction is not sufficient to ensure unbiased two-stage estimators in finite samples. The instruments also need to correlate 'strongly' with the endogenous first-stage variable. Staiger and Stock (1997) recommend a critical value of 10 in an F-test for the joint significance of the instruments in the first stage. The F-tests suggest our instruments are collectively strong in all four models, though the eigenvector centrality measure is only identified off our least convincing instrument, the lagged inverse number of incumbents.

The significance of each instrument varies across the models. Consistent with our hypothesis that markets in which demand is concentrated geographically experience more networking, we find that the coefficient of variation of within-market pairwise distances among portfolio companies is negatively and significantly related to the two density measures and to degree. The same is true of the fraction of corporate VCs in a market. Finally, the inverse number of incumbent VCs in a market is positively and significantly related to all four networking measures, as expected.

C.5. Determinants of Market Entry: Second-stage Results

Table IV presents the results of the instrumental-variables entry models. The dependent variables in Panels A, B, and C are the number of VC firms entering a market, the number of VCs entering as lead-managers, and the number of deals won by new entrants in year t, respectively. As in Table II, we estimate conditional fixed-effects Poisson models, though we now instrument the networking measures using predicted values from Table III. The dependent variable in Panel D is the fraction of deals by number lead-managed by entrants, which has support on [0,1] and positive mass at both 0 and 1.[19] To avoid the well-known biases of OLS in this situation, we estimate fractional logit models using quasi-MLE, modeling the conditional mean as $E(y|x)=\exp(x\beta)/(1+\exp(x\beta))$; see Papke and Wooldridge (1996). As fractional logits cannot currently accommodate fixed effects, Panel D pools repeated observations on each market. To conserve space, we report only the coefficients for the instrumented network measures and the R^2; the coefficients on the controls mirror those shown in Table II.

For all four networking measures, we find a negative and statistically significant effect on the number of entrants in the market.[20] Comparing Table II to Panel A of Table IV, it is clear that the failure to account for endogeneity imparts a small positive bias to the coefficient estimates. Economically, the effect of networking is large. Holding all other covariates at their sample means, a one-standard deviation increase in degree, for instance, reduces the expected number of entrants in Panel A by 3.6. This is large compared to the median number of entrants, which is nine. The predicted difference in the number of entrants in the most and least networked markets (again using degree) is -21.7. (The corresponding numbers for the other three networking measures range from -6.0 for eigenvector to -15.6 for symmetric density.) Networking has the second largest economic effect in this specification, after variation in state GSP.

Similar results obtain for the three alternative measures of entry. Both the number of entrants that *lead* syndicates and the number of deals won by entrants are negatively and significantly related to networking. The effects are again large economically. In Panel B, for instance, a one-

[19] We obtain qualitatively similar results when we instead use the fraction of deals by *value* won by entrants.
[20] Consistent IV standard errors are obtained using the procedure derived in Murphy and Topel (1985, Section 5).

standard deviation increase in incumbents' degree centrality is associated with a decrease of 1.67 in the number of entrants that lead-manage a deal, compared to a median of five. The corresponding effect in Panel C, which focuses on the number of deals entrants win, is 1.81, also compared to a median of five. (Note that the coefficient estimated for eigenvector in Panel C is only significant at the 10% level; this is also the specification that appears to have the weakest identification according to the Table III first-stage results.) In Panel D, we find that the *fraction* of deals lead-managed by entrants is significantly lower in more networked markets, with the exception of the eigenvector specification. Economically, the effect is quite large. A one-standard deviation increase in symmetric density, for instance, reduces the fraction of deals lead-managed by entrants by 12.3%, from the unconditional mean of 30.1% to 26.4%.

Collectively, the results from the market-level entry models shown in Table IV suggest that even after accounting for the endogeneity of networking in the target market, networking by incumbents can present a barrier to entry for potential entrants, and thus may restrict the competitive supply of venture capital to entrepreneurial firms.

IV. Firm-Level Analysis

How persuasive the findings of the previous section are depends on how plausible our instruments are judged to be. At minimum, we find evidence of less entry in more networked markets, though this may or may not be causal. We therefore turn to our second approach, which calls for a change of unit of analysis. In this section, we ask whether the probability that an individual potential entrant successfully enters a given market depends on the density of the relationships among market incumbents. This helps break endogeneity problems because while a potential entrant reasonably conditions its entry decision on the entry barriers it faces, the incumbents decide on the optimal level of entry deterrence with a view to minimizing entry overall, not to minimizing the probability of a given individual entrant entering their market.

Focusing on the entry decision of an individual potential entrant also allows us to shed light on how determined entrants can overcome entry barriers. Our market-level results indicate more entry in markets with larger pools of qualified potential entrants. We now ask whether proximity to the market, prior investment experience, and pre-established ties to incumbents increase the likelihood that a given potential entrant successfully enters a given market.

Table V presents summary information on the characteristics of potential entrants in the 129 target markets used in our analysis. Panel A focuses on geographic location, Panel B on prior investment experience, and Panel C on prior syndication ties to incumbents. In each case, we report the number of potential entrants that do and do not have a particular characteristic as well as the number and fraction of potential entrants that actually enter the market. The results suggest that investors located closer to a target market, that have previous industry- and/or state-related experience, and that have prior ties to incumbents are consistently more likely to enter a market than other potential entrants. For example, the entry rate among VCs located within 100 miles of the target market is 5.01% compared to 1.28% among those located further away (the difference is significant at $p<0.001$). Similarly, the entry rate for potential entrants with both previous industry and state investment experience is 4.42%, compared to 1.21% among other VCs.[21]

To control for other influences on the entry decision, we estimate firm-level probit models in which the dependent variable equals one if the potential entrant enters the market successfully and zero otherwise. The main variables of interest are: Our four measures of how networked a target market is; a dummy set equal to one if the VC firm is headquartered within 100 miles of

[21] Similar patterns obtain if we define entrants as firms that enter as lead investors rather than syndicate members.

the center of the market, since VCs tend to invest locally;[22] a set of indicators for previous experience investing in either the industry, the state, or both; and two indicator variables for the potential entrant's prior network ties which equal one, respectively, if the potential entrant has previously lead-managed one or more syndicates in another market where one of the incumbents was a participant (positive outdegree) or has co-invested with one or more incumbents in another market (positive indegree). We also include interactions of the network measure and the indegree and outdegree indicators to test if ties to incumbents are sufficient to overcome the entry barrier. If so, we expect the partial derivatives with respect to the networking measures to be zero in the presence of prior ties to incumbents. Other control variables included in the model are the performance history, investment opportunities, demand variation, market size, overall supply of VC capital, and state economic development measures described in Section II.

The results are reported in Table VI. As before, we report four models, one for each alternative measure of how densely networked the market is. The models have good overall fit, with pseudo R^2 of around 15%. Regardless of how we measure networking, we find that a potential entrant is significantly less likely to enter the more networked the market. This mirrors the main result of the market-level models discussed in Section III. (These effects become a little stronger if we use a more restrictive definition of entry, coding the dependent variable one if the potential entrant entered the market as a lead investor, and zero otherwise.)

We also find a positive and significant relation between prior syndication ties to incumbents and the likelihood of entry in all four models, for both indegree and outdegree. Moreover, the interaction terms crossing indegree and outdegree with the networking measures are each positive and statistically significant, indicating that prior ties to incumbents can indeed mitigate

[22] We define the center as the modal location of portfolio companies (in a given industry) in the state. Our results are not sensitive to the 100-mile cutoff. However we measure it, closer VCs are more likely to enter.

the effects of this particular barrier to entry. To see if they can overcome it entirely, we test the following three linear restrictions, which correspond to the aforementioned partial derivatives:

- network measure · (1 + indegree) = 0
- network measure · (1 + outdegree) = 0
- network measure · (1 + outdegree + indegree) = 0

In none of the four models in Table VI are the combined effects significantly negative, suggesting that networking presents a significant barrier to entry only for entrants that lack ties to the incumbents. In fact, entrants that have both positive indegree and positive outdegree are actually significantly *more* likely to enter the more densely networked the market.[23]

The single most significant determinant of the entry decision in Table VI appears to be location. VC firms located within 100 miles of the center of the target market are 128% more likely to enter than those located farther away. Previous related investment experience also makes entry more likely, whether in the state or the industry or both. Economically, these effects too are large. Prior experience in the same industry and state increases the likelihood of entry by around 1.8 percentage points from the unconditional mean of 1.5%, that is, an increase of around 120%. Prior industry experience in the absence of prior investments in the state has a smaller economic effect, increasing the likelihood of entry by around 36%, while experience in the state but not the industry increases it by 29%.

The effects of the remaining control variables largely mirror those found in the market-level analysis. Worse investment opportunities, as measured by higher average industry book-to-

[23] An interesting related question is who entrants syndicate with when they enter. Our data show that entrants are more likely to syndicate with incumbent VC firms that they have done business with elsewhere before. Specifically, we find that the probability that an entrant syndicates with a related incumbent is 18.3%. The median probability under the null that pairings conditional on entry are random is 10.8%, based on 200 draws from a bootstrapped sample. The observed and simulated probabilities are significantly different at $p<0.0001$.

market ratios, reduce the likelihood that a potential entrant will actually enter the market. More volatile deal flow increases the probability of entry, as do larger inflows of VC capital into the industry, larger market size (measured by the number of deals), and higher GSP growth.

V. Valuation Effects

Our results support the existence of the conjectured missing link between networking and a reduction in competition for deal flow: Networking does appear to deter at least some entrants. As a result, we expect incumbent VCs to exploit their increased bargaining power by negotiating more favorable funding terms at the expense of entrepreneurs. While we do not observe any qualitative funding terms (such as control rights, liquidation preferences, anti-dilution protection, and so on), we can examine the consequences of reduced entry by looking at the valuations at which venture-backed companies raise VC funding.

Companies typically receive funding in distinct stages, which provides VCs with the option to cease funding if a business model turns out not to work. Not surprisingly, the average company's valuation increases over a sequence of funding rounds and with its maturity. It also appears to be related to networking. Sorting markets into quartiles based on asymmetric density, for instance, the average valuation is $39 million in the most densely networked markets versus $71 million in the least densely networked ones.

Of course, these figures do not control for other reasons why valuations might differ. In Table VII, we estimate ordinary least squares regressions where the unit of observation is a funding round and the dependent variable is the log of the round valuation. The explanatory variables of interest are our four networking measures, included one at a time and treated as exogenous to the valuation of each deal in the market in the following year; the lagged fraction of deals entrants managed to win in the company's market the previous year; and an indicator identifying whether the company's lead investor is an entrant (=1) or an incumbent (=0). If entry deterrence is effective, we expect lower valuations in more densely networked markets. Where entrants manage to overcome the entry barriers put in their way, we expect higher valuations. Finally, entrants likely have to offer higher valuations to compete with incumbents.

Absent data on sales, earnings, or book values in the Venture Economics database, there are no company-specific value drivers we can control for beyond stage of development and funding round number. Following Gompers and Lerner (2000a), we instead control for the book-to-market ratio of the company's industry (to proxy for investment opportunities), a valuation index of publicly listed companies in the same industry, constructed as in Gompers and Lerner (2000a), and the amount of money raised in the previous year by VC funds focusing on the company's industry (to capture any "money chasing deals" phenomena). We also include a proxy for the lead investor's investment experience (the log size of assets under its management), the lagged number of deals completed in the company's market, an indicator identifying seed- or early-stage companies, a set of funding round dummies (the omitted category is a first-round investment), and market fixed effects to control for otherwise unobserved heterogeneity across markets.

The resulting regressions have excellent fit, in view of the around 40% adjusted R^2. Regardless of how we measure it, companies in more densely networked markets are valued significantly less highly, suggesting that incumbent VCs benefit from reduced entry through paying lower prices for their investments. Economically, a one-standard deviation increase in asymmetric or symmetric density is associated with a more than 10% decrease in round valuation from the unconditional mean of $25.6 million, all else equal. On the other hand, the more market share entrants have captured in the recent past, the higher are the valuations paid, suggesting that entry benefits entrepreneurs through higher prices. Also, perhaps not surprisingly, entrants pay significantly higher valuations than do incumbents, all else equal.

The results for the controls mirror those in Gompers and Lerner (2000a). Higher public-market valuations for the industry are associated with higher valuations being paid in the private markets, while increases in the amount of money chasing deals drive valuations up significantly. Valuations are also higher in more active markets (based on the number of completed deals) and when a more experienced VC leads the round . Early-stage companies receive lower valuations while valuations increase significantly as a company progresses through follow-on funding rounds.

While these results support the notion that entry deterrence has real, detrimental effects for the terms on which entrepreneurs can access the VC market, the Venture Economics round valuation data we use have two shortcomings. First, they are self-reported, and there is every reason to expect companies to disclose valuations strategically; for instance, a company may choose not to disclose a "down-round" valuation (i.e., a lower valuation than it achieved in a previous round). Indeed, VE has valuation data for only around one fifth of all the funding rounds in its database. Second, the absence of company-level data on potential value drivers is troubling. We address each shortcoming in turn.

To correct for strategic disclosure, we follow Hwang, Quigley, and Woodward (2005) who estimate an ordered probit model of the following events: 1) Revelation of value through shutdown; 2) funding through acquisition, without revelation of value; 3) no funding at all; 4) VC funding without revelation of value; 5) VC funding with revelation of value; 6) funding through acquisition with revelation of value; 7) funding and revelation of value through an IPO. The explanatory variables are the company's development status (as per its most recent funding round), its VE industry group and geographic location, the stock market capitalization at the time, year effects, and the elapsed time since the most recent funding round, the importance of which is allowed to vary with the type of the previous round (seed, late-stage, and so on). From the ordered probit estimates, they construct the inverse Mill's ratio for each company and round.

We replicate their ordered probit model in our data, and obtain results that are at least as strong as theirs (not shown). When we include the inverse Mill's ratio in the specifications of Table VII, we continue to find to find that round valuations are lower in more densely networked markets, but increase after entrants have won more market share and if an entrant leads a round. As Panel B of Table VIII shows, all coefficients bar one are highly statistically significant (the *p*-value for eigenvector is 0.062). Compared to the relevant coefficients from the Table VII specifications, which are reproduced in Panel A for ease of comparison, the selection-corrected model produces slightly smaller economic effects for the network measures.

There is little doubt that our valuation models leave out many factors that influence valuations, such as the company's track record, the quality of its management, or the strength of its intellectual property. However, we can exploit the panel structure of the data – companies receive multiple funding rounds – to remove the effect of unobserved company-specific factors. We do so while also controlling for unobserved market-specific factors that might bear on valuation, such as local pricing anomalies, conditions in the managerial labor market, and so on. The resulting model is a mixed linear model with two levels of random effects (for the company and for the market), which can be estimated using maximum residual likelihood; see Baltagi, Song, and Jung (2001). The coefficients of interest are reported in Panel C of Table VIII. The likelihood ratio tests strongly reject the null that market and company-level effects are jointly zero (indeed each level is significant, though this is not shown). Still, we continue to find, as before, that networking reduces valuations while entry increases them. (Again, the significance of eigenvector is only marginal, with a p-value of 0.056.) Including company-level effects reduces the coefficients for the networking variables compared to Panel A.

Our final models, shown in Panel D, adjust for both selective disclosure and unobserved company-level heterogeneity by including the inverse Mill's ratios in the mixed effects model. While this reduces the coefficient estimates for the networking a bit further, our conclusions remain unaffected.

VI. Conclusion

Venture capitalists are often said to prefer syndicating deals in part because doing so reduces competition for deal flow, which in turn strengthens their bargaining power vis-à-vis entrepreneurs. As we point out, this explanation must implicitly assume that syndication can reduce market entry, for in the presence of free entry there is no reason to expect incumbents' bargaining power to increase. In this paper, we provide evidence that markets in which incumbents maintain dense syndication networks with each other are indeed associated with reduced entry, controlling for a wide variety of other influences that bear on entry. Moreover, evidence derived from plausible instruments for networking suggests that prevailing network conditions in a target market causally influence entry decisions. The magnitude of these effects is economically large, and robust to a wide range of specifications.

One way to overcome this particular barrier to entry is through establishing ties to the incumbents in other markets, i.e., by "joining the club." The price of admission appears to be letting incumbents in on the entrant's deal flow in unrelated markets. In addition, previous investment experience in the targeted industry or a prior presence in the targeted state facilitates entry into a market. However, entrants also appear to enter by offering to pay higher prices.

Having established a link between syndication networks and reduced entry, we ask whether incumbents' bargaining power vis-à-vis entrepreneurs increases. We show that the valuations at which companies can raise VC funding depend on the extent of networking and the degree of entry that results, consistent with networking providing an effective barrier to entry.

Our results illustrate the role of networking as an entry deterrent. While we focus on the VC setting, we believe our results generalize to other industries that make heavy use of networks, such as investment banking. In addition, our results shed light on the industrial organization of the VC industry in general and the dynamics of entry in this industry in particular. Finally, our findings present interesting policy implications. If networking poses an effective barrier to entry, this may lead to a more restricted supply of capital to entrepreneurial ventures and to harsher funding terms. The structure of the local VC market therefore has significant implications for entrepreneurial ventures seeking startup capital. More broadly, we may ask how strategic behavior in the VC market affects the funding of new ventures and their eventual success.

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Figure 1. Example of a Densely Networked Market

The figure shows the network that arises from syndication of portfolio company investments in the market for computer-related ventures in Michigan over the five-year window 1979-1983. Nodes on the graph represent VC firms, and arrows represent syndicate ties between them. The direction of the arrow represents the lead/non-lead relationship between syndicate members. The arrow points from the VC leading the syndicate to the non-lead member. Two-directional arrows indicate that both VCs on the arrow have at one point in the time window led a syndicate in which the other was a non-lead member.

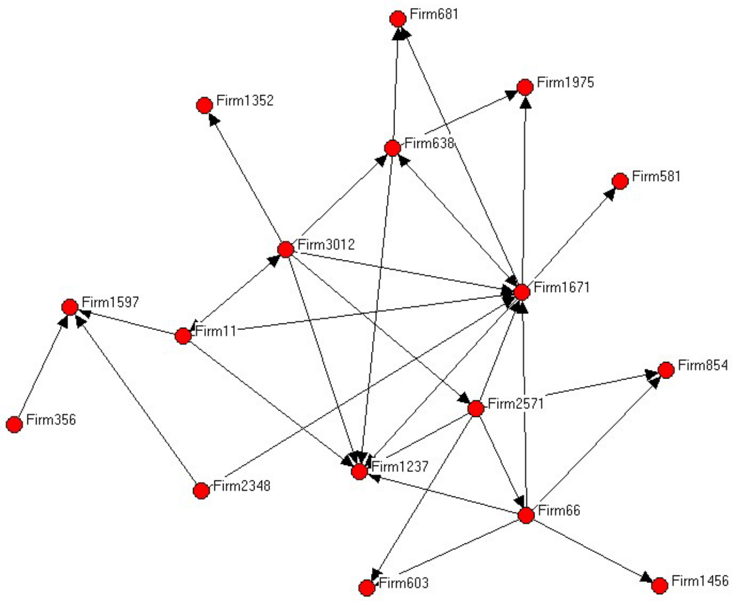

Figure 2. Example of a Sparsely Networked Market

The figure shows the network that arises from syndication of portfolio company investments in the market for non-high-tech ventures in Pennsylvania over the five-year window 1990-1994.

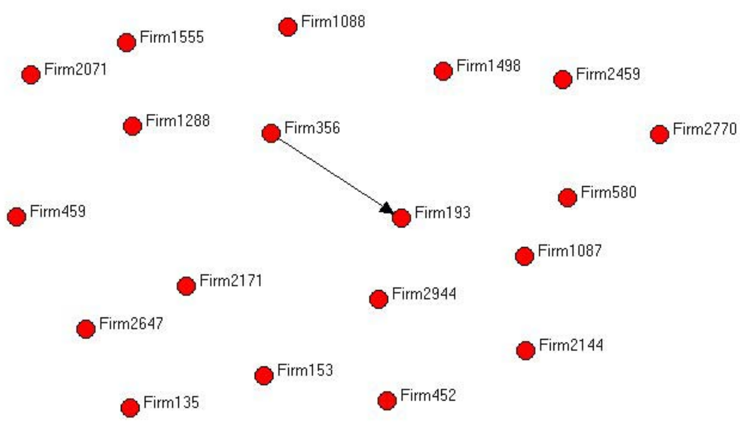

Table I. Descriptive Sample Statistics.

The unit of observation in this table is a market-year. We define a market as a combination of one of the six Venture Economics industries and a U.S. state. Venture Economics classifies investments into the following industries: Biotechnology; communications and media; computer related; medical/health/life science; semiconductors/other electronics; and non-high-technology. To qualify for inclusion in the sample, a market-year has to have a minimum of 25 investments in the prior five years and five investments in the current year. There are 129 distinct markets with between one and 24 annual observations each. The total number of market-years in our sample is 1,364. Entrants in Panel A are defined as VC firms investing in a given market in year *t* that had never invested in this market before year *t*. For a market in year *t*, we use data from the previous five years (from *t*-5 to *t*-1) to construct four network measures. Density in Panel B is defined as the proportion of all logically possible ties among incumbents that are present in that market. Asymmetric density is calculated from directed networks (i.e., conditioning on lead vs. syndicate participant ties) and symmetric density is calculated from undirected networks. Mean degree is the size-weighted average degree centrality measure of individual VC firms active in the market in the previous five-year window, where degree counts the number of relationships an actor in the network has, normalized by the maximum possible number of ties. Mean eigenvector is the size-weighted average eigenvector centrality measure of individual VC firms active in the market in the previous five-year window, where eigenvector centrality weights an actor's ties to others by the importance of the actors he is tied to. Panel C characterizes the markets. To control for performance in a market, and in the absence of return data, we calculate the fraction of venture-backed firms in a market that were successfully exited through an IPO or an M&A transaction during the prior five years. To measure excess performance in a market, we subtract from this the median exit rate across all geographic markets in the same Venture Economics industry. "Later-stage" deals include "expansion" financing, as coded by Venture Economics. B/M is the value-weighted book/market ratio of *public* companies in the relevant industry. We map public-market B/M ratios to industries based on four-digit SIC codes. The VC inflows variable is the aggregate amount of capital raised by VC funds specializing in the industry. We take a fund's industry specialization to be the Venture Economics industry that accounts for the largest share of its portfolio, based on dollars invested. Potential entrants in Panel D are defined as the VC firms satisfying the following three conditions: (1) the firm was founded (i.e., raised its first fund) in or before year *t*; (2) the firm has at least one fund under management that was raised in the previous six years; and (3) the firm has not invested in this particular market prior to year *t*. We use trailing five-year windows to construct the characteristics of potential entrants. A potential entrant VC firm's indegree is the normalized number of unique VCs in the market in question that have led syndicates the firm was a non-lead member of. A potential entrant VC firm's outdegree is the normalized number of unique VCs in the market that have participated as non-lead investors in syndicates lead-managed by the firm. (The lead investor is identified as the VC firm that invests the largest amount in the portfolio company in a given round.)

Table I. Descriptive Sample Statistics (Continued).

	Mean	Std. Dev.	Min	Median	Max
Panel A: Entry measures					
# incumbents	28.3	40.9	1	15	499
# entrants	14.7	19.9	0	9	291
# entrants that lead syndicates	7.2	9.6	0	5	145
# deals won by entrants	8.5	12.2	0	5	194
# deals won by incumbents	24.1	57.5	0	10	1,118
fraction of deals by # lead-managed by entrants	0.301	0.182	0	0.286	0.900
fraction of deals by value lead-managed by entrants	0.343	0.254	0	0.299	0.991
Panel B: Network measures					
asymmetric density	0.021	0.013	0	0.018	0.118
symmetric density	0.078	0.052	0	0.067	0.467
mean degree	0.084	0.058	0	0.069	0.362
mean eigenvector	0.126	0.083	0.001	0.108	0.556
Panel C: Market, state, and industry characteristics (*t*-1)					
excess investment performance in market	0.047	0.095	-0.250	0.038	0.540
coefficient of variation of monthly # deals in market	1.161	0.346	0.332	1.171	3.609
# deals in market	37.9	78.0	6	18	1,497
fraction of deals with size >$3m (real)	0.293	0.140	0	0.273	0.761
fraction later-stage deals	0.532	0.115	0.111	0.528	0.900
real GSP ($billion)	323.0	262.1	17.3	237.2	1,352.1
real GSP growth rate	0.033	0.026	-0.051	0.032	0.136
value-weighted mean industry B/M ratio	0.524	0.225	0.161	0.489	1.264
inflow into VC funds in industry ($m)	6,954.6	12,309.6	5.6	2,247.0	63,995.8
# science & eng. degrees awarded/1000 inhabitants	2.6	0.8	0.8	2.5	11.8
Panel D: Potential entrants					
fraction located within 100 miles of market	0.065	0.073	0	0.025	0.289
fraction investing in same industry and same state	0.068	0.028	0.005	0.064	0.156
fraction investing in same industry but not same state	0.310	0.157	0.021	0.291	0.732
fraction investing in same state but not same industry	0.059	0.081	0	0.028	0.505
fraction w/ positive indegree	0.200	0.096	0.003	0.193	0.521
fraction w/ positive outdegree	0.131	0.054	0.001	0.132	0.270

Table II. Number of Entrants.

The dependent variable is the number of VC firms entering a market in year *t*. Given the count nature of the dependent variable, and the fact that we have repeated observations per market, we estimate conditional fixed-effects Poisson models. Intercepts are not shown. Heteroskedasticity-consistent standard errors (clustered on market) are shown in italics. We use ***, **, and * to denote significance at the 0.1%, 1%, and 5% level, respectively.

	Dependent variable: # entrants			
	asymmetric density	symmetric density	degree	eigenvector
network measure	-4.281***	-1.949***	-1.598***	-0.386**
	1.288	*0.347*	*0.273*	*0.145*
Potential entrants				
fraction headquartered within 100 miles	0.593*	0.592*	0.612*	0.607*
	0.247	*0.247*	*0.247*	*0.247*
fraction investing in same industry and same state	1.879**	1.808**	1.571*	1.838**
	0.633	*0.633*	*0.637*	*0.634*
fraction investing in same industry but not in state	0.859***	0.766***	0.715***	0.887***
	0.208	*0.209*	*0.210*	*0.208*
fraction investing in same state but not in industry	-1.301***	-1.358***	-1.476***	-1.353***
	0.399	*0.400*	*0.401*	*0.400*
fraction w/ positive indegree	1.105***	1.045**	1.253***	1.177***
	0.337	*0.338*	*0.337*	*0.336*
fraction w/ positive outdegree	2.562***	2.672***	2.426***	2.511***
	0.545	*0.546*	*0.545*	*0.544*
Market, state, and industry characteristics (*t*-1)				
excess investment performance in market	0.251*	0.260*	0.276*	0.271*
	0.121	*0.121*	*0.121*	*0.121*
value-weighted mean industry book/market ratio	-1.295***	-1.278***	-1.237***	-1.287***
	0.133	*0.133*	*0.133*	*0.133*
coeff. variation of monthly no. of deals in market	0.252***	0.235***	0.232***	0.259***
	0.044	*0.044*	*0.044*	*0.044*
log inflow into VC funds in industry ($m)	0.236***	0.233***	0.232***	0.237***
	0.014	*0.014*	*0.014*	*0.014*
log no. deals in market	0.135***	0.125***	0.128***	0.141***
	0.027	*0.027*	*0.027*	*0.027*
fraction of deals with size >$3m (real)	-0.244	-0.141	-0.119	-0.251
	0.134	*0.135*	*0.136*	*0.134*
fraction later stage deals	-0.441***	-0.400***	-0.415***	-0.469***
	0.124	*0.124*	*0.124*	*0.124*
# science & engineering degrees awarded/1000 inhabitants	0.067	0.070	0.098**	0.080*
	0.036	*0.036*	*0.036*	*0.036*
log real GSP ($m)	-0.882***	-0.966***	-0.952***	-0.824***
	0.190	*0.192*	*0.191*	*0.189*
real GSP growth rate (%)	0.005	0.005	0.005	0.003
	0.005	*0.005*	*0.005*	*0.005*
Diagnostics				
Pseudo-R^2	69.1 %	69.2 %	69.2 %	69.1 %
Wald-test: all coeff. = 0 (χ^2)	18,299***	18,320***	18,322***	18,295***
No. of markets	129	129	129	129
No. of observations	1,364	1,364	1,364	1,364

Table III. First-stage Models.

The models are estimated using OLS with fixed (market) effects. The motivation for our three instruments can be found in the text. Following Coval and Moskowitz (1999), we measure the distance between portfolio companies in terms of the average distance in miles between every pair of portfolio companies in the market, using the zip code of companies to pinpoint location. All control variables are defined as in Table I. Intercepts are not shown. Heteroskedasticity-consistent standard errors (clustered on market) are shown in italics. We use ***, **, and * to denote significance at the 0.1%, 1%, and 5% level (two-sided), respectively.

	Dependent variable:			
	asymmetric density	symmetric density	degree	eigenvector
Instruments				
st.dev. / mean distance between portfolio companies	-0.004***	-0.021***	-0.011*	-0.001
	0.001	*0.004*	*0.005*	*0.010*
fraction of $ invested by corporate VCs in market	-0.020***	-0.089***	-0.084***	-0.024
	0.004	*0.015*	*0.017*	*0.033*
1/(# distinct VC firms in market)	0.278***	0.222*	0.234*	2.031***
	0.024	*0.098*	*0.111*	*0.213*
Potential entrants				
fraction headquartered within 100 miles	0.011	0.045	0.104	0.131
	0.007	*0.031*	*0.035*	*0.067*
fraction having invested in same industry and same state	-0.047**	-0.045	-0.124	-0.409**
	0.016	*0.067*	*0.076*	*0.145*
fraction having invested in same industry but not in state	-0.018***	-0.072***	-0.115***	-0.095*
	0.005	*0.021*	*0.024*	*0.045*
fraction having invested in same state but not in industry	-0.011	-0.031	-0.135*	-0.191
	0.012	*0.049*	*0.056*	*0.106*
fraction w/ positive indegree	-0.008	-0.056	0.044	0.143
	0.009	*0.037*	*0.042*	*0.080*
fraction w/ positive outdegree	0.006	0.078	-0.012	-0.085
	0.014	*0.060*	*0.068*	*0.130*

Continued over.

Table III. First-stage Models (Continued).

	Dependent variable:			
	asymmetric density	symmetric density	degree	Eigenvector
Market, state, and industry characteristics (*t*-1)				
excess investment performance in market	0.005	0.028*	0.046***	0.076**
	0.003	*0.011*	*0.013*	*0.025*
value-weighted mean industry book/market ratio	0.005	0.031*	0.046**	0.044
	0.003	*0.014*	*0.016*	*0.031*
coeff. of variation of monthly no. of deals in market	-0.004***	-0.008	-0.011*	-0.013
	0.001	*0.005*	*0.006*	*0.011*
log inflow into VC funds in industry ($m)	0.000	-0.002	-0.003	-0.002
	0.000	*0.002*	*0.002*	*0.004*
log no. deals in market	0.000	-0.005	-0.004	0.003
	0.001	*0.003*	*0.003*	*0.006*
fraction of deals with size >$3m (real)	0.002	0.051***	0.086***	0.040
	0.003	*0.013*	*0.015*	*0.029*
fraction later stage deals	0.002	0.025*	0.033*	0.023
	0.003	*0.011*	*0.013*	*0.025*
# science & engineering degrees awarded/1000 inhabitants	-0.004***	-0.007	0.008	-0.003
	0.001	*0.004*	*0.005*	*0.009*
log real GSP ($m)	-0.019***	-0.082***	-0.127***	-0.085*
	0.004	*0.019*	*0.021*	*0.040*
real GSP growth rate (%)	0.034**	0.065	0.088	-0.014
	0.012	*0.050*	*0.057*	*0.109*
Diagnostics				
Within-groups R^2	57.0 %	54.1 %	52.8 %	26.7 %
Wald-test: all coeff. = 0 (*F*)	37.7***	33.5***	31.8***	10.4***
F-test: all FE = 0	6.6***	7.2***	8.1***	4.0***
Instrument strength test (*F*-test with critical value of 10)	64.3***	21.0***	11.6***	31.5***
No. of markets	129	129	129	129
No. of observations	1,364	1,364	1,364	1,364

Table IV. Entry Models using Two-stage Estimators.

The table reports the results of two-stage (instrumental variables) entry models similar to the one-stage entry models shown in Table III. We treat the network measures as endogenous and replace them with the predicted values generated from the regressions shown in Table II. The dependent variables in Panels A, B, and C are the number of VC firms entering a market in year *t*, the number of VC firms entering a market that lead-manage syndicates in year *t*, and the number of deals won by VC firms entering a market in year *t*, respectively. Given the count nature of these dependent variables, and the fact that we have repeated observations per market, the models in Panels A-C are estimated using conditional fixed-effects Poisson. The dependent variable in Panel D is the fraction of deals by number lead-managed by entrants in a market in year *t*. This dependent variable has support on [0,1] and positive mass at both 0 and 1. To avoid the resulting well-known biases of OLS in this situation, we estimate fractional logit models using quasi-MLE; see Papke and Wooldridge (1996). This involves modeling the conditional mean $E(y|x)=\exp(x\beta)/(1+\exp(x\beta))$. Note that fractional logits cannot currently accommodate fixed effects. Thus, we pool repeated observations on each market in Panel D. To save space, we report only the coefficient estimates for the network measures; the coefficient estimates for the controls mirror those shown in Table II. Standard errors, shown in italics, are based on the Murphy-Topel (1985) adjustment. We use ***, **, and * to denote significance at the 0.1%, 1%, and 5% level (two-sided), respectively. The number of markets is 129 and the number of observations is 1,364.

	Network measure used:			
	asymmetric density	symmetric density	degree	eigenvector
Panel A: Number of entrants				
instrumented network measure	-14.273***	-6.838**	-7.680*	-1.419*
	3.031	*2.349*	*3.168*	*0.632*
Pseudo-R^2	69.4 %	69.4 %	69.4 %	69.3 %
Panel B: Number of entrants leading syndicates				
instrumented network measure	-12.909***	-5.805**	-6.890**	-1.440*
	3.989	*2.010*	*2.568*	*0.688*
Pseudo-R^2	55.9 %	55.9 %	55.9 %	55.8 %
Panel C: Number of deals entrants lead				
instrumented network measure	-10.966***	-5.852*	-6.589*	-0.994
	3.320	*2.356*	*2.993*	*0.592*
Pseudo-R^2	59.5 %	59.6 %	59.5 %	59.5 %
Panel D: Fraction of deals entrants lead				
instrumented network measure	-13.821***	-4.179***	-2.667***	-0.418
	3.065	*0.845*	*0.650*	*0.428*
R^2	47.8 %	48.2 %	47.5 %	46.8 %

Table V. Entry Levels and Rates.

We define a market as a combination of one of the six Venture Economics industries and a U.S. state. Venture Economics classifies investments into the following industries: Biotechnology; communications and media; computer related; medical/health/life science; semiconductors/other electronics; and non-high-technology. To qualify for inclusion in the sample, a market has to have a minimum of 25 investments in the prior five years and five investments in the current year. There are 129 markets with between one and 24 annual observations, giving a total number of observations of 1,364. Potential entrants are defined as U.S. VC firms that have never invested in a given market prior to year *t*. Entrants are defined as potential entrants that invest in the market in year *t*. The fractions of potential entrants that enter in the final column are pairwise significantly different at the 0.1% level for each question in the table.

	Total # of potential entrants	# entering	% entering
Panel A: Proximity to target market			
Is the potential entrant located within 100 miles of the center of the target market?			
Yes	74,963	3,757	5.01
No	1,215,246	15,499	1.28
Panel B: Prior investment experience			
Has potential entrant invested in the same industry and same state in prior 5 years (but not in this market)?			
Yes	91,891	4,061	4.42
No	1,355,277	16,415	1.21
Has potential entrant invested in the same state but not the same industry in prior 5 years?			
Yes	81,409	2,245	2.76
No	1,365,759	18,231	1.33
Has potential entrant invested in the same industry but not the same state in prior 5 years?			
Yes	484,014	7,180	1.48
No	963,154	13,296	1.38
Panel C: Prior syndication ties to incumbents			
Has potential entrant participated in deals led by incumbents in prior 5 years? (positive indegree)			
Yes	260,399	8,786	3.37
No	1,186,769	11,690	0.99
Has potential entrant led deals with incumbents as co-investors in prior 5 years? (positive outdegree)			
Yes	170,659	6,483	3.80
No	1,276,509	13,993	1.10

Table VI. Firm-level Entry Models: Syndicate Membership.

The dependent variable is an indicator variable equaling one if the potential entrant enters the market successfully, and zero otherwise. There are 1,364 market-years and 3,025 distinct potential entrants. All models are estimated using probit MLE. Intercepts and year fixed effects are not shown. Heteroskedasticity-consistent standard errors are shown in italics. We use ***, **, and * to denote significance at the 0.1%, 1%, and 5% level (two-sided), respectively.

	Dependent variable: =1 if VC firm enters, =0 else			
	asymmetric density	symmetric density	degree	eigenvector
Network measure	-1.430**	-0.404***	-0.220*	-0.290***
	0.473	*0.120*	*0.099*	*0.060*
Potential entrants				
=1 if positive outdegree	0.131***	0.136***	0.148***	0.138***
	0.014	*0.014*	*0.015*	*0.016*
… x network measure	2.974***	0.700***	0.446**	0.382***
	0.698	*0.179*	*0.156*	*0.119*
=1 if positive indegree	0.117***	0.120***	0.143***	0.135***
	0.013	*0.013*	*0.013*	*0.015*
… x network measure	3.046***	0.750***	0.340*	0.286**
	0.662	*0.168*	*0.146*	*0.111*
=1 if located within 100 miles of center of market	0.514***	0.514***	0.515***	0.515***
	0.009	*0.009*	*0.009*	*0.009*
=1 if has invested in same industry and same state (-5 yrs)	0.500***	0.500***	0.500***	0.501***
	0.011	*0.011*	*0.011*	*0.011*
=1 if has invested in same industry but not in state (-5 yrs)	0.231***	0.231***	0.232***	0.232***
	0.008	*0.008*	*0.008*	*0.008*
=1 if has invested in same state but not in industry (-5 yrs)	0.170***	0.169***	0.168***	0.169***
	0.013	*0.013*	*0.013*	*0.013*
Market, state, and industry characteristics (*t*-1)				
excess investment performance in market	0.063	0.059	0.059	0.063
	0.039	*0.039*	*0.039*	*0.039*
value-weighted mean industry book/market ratio	-0.317***	-0.321***	-0.325***	-0.335***
	0.023	*0.024*	*0.024*	*0.022*
coeff. variation of monthly no. of deals in market	0.164***	0.165***	0.166***	0.169***
	0.015	*0.015*	*0.015*	*0.015*
log inflow into VC funds in industry ($m)	0.038***	0.038***	0.038***	0.037***
	0.004	*0.004*	*0.004*	*0.004*
log no. deals in market	0.321***	0.320***	0.319***	0.319***
	0.006	*0.006*	*0.006*	*0.006*
log real GSP ($m)	-0.002	-0.002	-0.002	-0.003
	0.005	*0.005*	*0.005*	*0.005*
real GSP growth rate (%)	0.005**	0.005**	0.005**	0.005**
	0.002	*0.002*	*0.002*	*0.002*
Diagnostics				
Pseudo-R^2	15.0 %	15.0 %	14.9 %	15.0 %
Wald test: all coeff. = 0 (χ^2)	26,372***	26,416***	26,576***	26,494***
Wald test: network measure · (1+ outdegree) = 0	4.1*	2.3	1.8	0.6
Wald test: network measure · (1+ indegree) = 0	5.6*	3.9*	0.7	0.0
Wald test: network measure · (1+ indegree + outdegree) = 0	60.9***	48.2***	18.4***	16.3***

Table VII. Round-level Valuation Models.

The unit of observation is a funding round and the dependent variable is the log of the valuation put on the company in that round. All models are estimated using OLS with market fixed effects. Year effects are jointly and individually insignificant and so excluded. Intercepts are not shown. Standard errors are shown in italics. We use ***, **, and * to denote significance at the 0.1%, 1%, and 5% level (two-sided), respectively.

	Dependent variable: log valuation			
	asymmetric density	symmetric density	degree	eigenvector
network measure	-10.421***	-2.695***	-2.107***	-0.622*
	2.161	*0.587*	*0.491*	*0.282*
fraction of deals won by entrants in previous year	0.616***	0.623***	0.593***	0.524***
	0.122	*0.122*	*0.121*	*0.120*
Lead investor characteristics				
=1 if lead investor in current round is entrant	0.282***	0.283***	0.281***	0.283***
	0.027	*0.027*	*0.027*	*0.027*
investment experience (log dollars under management)	0.075***	0.076***	0.076***	0.076***
	0.004	*0.004*	*0.004*	*0.004*
Market, state, and industry characteristics				
value-weighted mean industry book/market ratio	-0.283*	-0.199	-0.127	-0.255
	0.136	*0.135*	*0.138*	*0.136*
price index of publicly traded equity in same industry	0.289***	0.291***	0.289***	0.279***
	0.024	*0.024*	*0.024*	*0.024*
log inflow into VC funds in industry ($m)	0.137***	0.137***	0.135***	0.133***
	0.012	*0.012*	*0.012*	*0.012*
log no. deals in market	0.063	0.069	0.089**	0.134***
	0.036	*0.036*	*0.034*	*0.032*
Company characteristics				
=1 if seed or early-stage	-0.656***	-0.656***	-0.656***	-0.659***
	0.023	*0.023*	*0.023*	*0.023*
=1 if second funding round	0.460***	0.461***	0.462***	0.463***
	0.027	*0.027*	*0.027*	*0.027*
=1 if third funding round	0.802***	0.802***	0.804***	0.805***
	0.031	*0.031*	*0.031*	*0.031*
=1 if fourth or later funding round	0.966***	0.966***	0.966***	0.968***
	0.030	*0.030*	*0.030*	*0.030*
Diagnostics				
Adjusted R^2	39.9 %	39.9 %	39.9 %	39.8 %
Wald test: all coeff. = 0 (F)	546.8***	546.5***	546.1***	544.3***
No. of rounds	11,108	11,108	11,108	11,108

Table VIII. Alternative Round-level Valuation Models.

The unit of observation is a funding round and the dependent variable is the log of the valuation put on the company in that round. To save space, we report only the coefficient estimates of interest; the coefficient estimates for the controls mirror those shown in Table VII. Panel A is the OLS with market fixed effects specification taken from Table VII and is included for ease of comparison. Panel B corrects for possible endogenous disclosure of round valuations by including the inverse Mill's ratio from an ordered probit following Hwang, Quigley, and Woodward (2005). Panel C is a mixed linear model with two levels of random effects: For the company and for the market. This hierarchical model, which assumes that company effects are nested within market effects, allows us to control for unobserved company-level valuation drivers. Panel D combines the selection correction of Panel B with the two-level model of Panel C. Standard errors are shown in italics. We use ***, **, and * to denote significance at the 0.1%, 1%, and 5% level (two-sided), respectively.

	Dependent variable: log valuation			
	asymmetric density	symmetric density	degree	eigenvector
Panel A: Market fixed effects model (from Table VII)				
network measure	-10.421***	-2.695***	-2.107***	-0.622*
	2.161	*0.587*	*0.491*	*0.282*
fraction of deals won by entrants in previous year	0.616***	0.623***	0.593***	0.524***
	0.122	*0.122*	*0.121*	*0.120*
=1 if lead investor in current round is entrant	0.282***	0.283***	0.281***	0.283***
	0.027	*0.027*	*0.027*	*0.027*
Panel B: Heckman-selection corrected model				
network measure	-8.982***	-2.326***	-1.837***	-0.526
	2.175	*0.590*	*0.493*	*0.282*
fraction of deals won by entrants in previous year	0.635***	0.642***	0.616***	0.558***
	0.122	*0.122*	*0.121*	*0.120*
=1 if lead investor in current round is entrant	0.291***	0.292***	0.290***	0.293***
	0.027	*0.027*	*0.027*	*0.027*
inverse Mill's ratio	0.122***	0.124***	0.126***	0.132***
	0.023	*0.023*	*0.023*	*0.023*
Panel C: Two-level mixed effects model				
network measure	-7.379***	-1.582**	-1.422***	-0.477
	1.919	*0.517*	*0.425*	*0.249*
fraction of deals won by entrants in previous year	0.472***	0.464***	0.451***	0.430***
	0.104	*0.104*	*0.103*	*0.103*
=1 if lead investor in current round is entrant	0.220***	0.220***	0.219***	0.220***
	0.024	*0.024*	*0.024*	*0.024*
LR test vs. linear model (χ^2)	2,399.7***	2,418.0***	2,421.4***	2,421.3***
Panel D: Heckman-correct mixed effects model				
network measure	-5.837**	-1.188*	-1.150**	-0.383
	1.934	*0.521*	*0.427*	*0.249*
fraction of deals won by entrants in previous year	0.486***	0.479***	0.470***	0.453***
	0.103	*0.104*	*0.103*	*0.103*
=1 if lead investor in current round is entrant	0.227***	0.228***	0.227***	0.228***
	0.024	*0.024*	*0.024*	*0.024*
inverse Mill's ratio	0.129***	0.132***	0.132***	0.135***
	0.020	*0.020*	*0.020*	*0.020*
LR test vs. linear model (χ^2)	2,436.4***	2,455.2***	2,428.1***	2,459.9***