

Networking as a Barrier to Entry and the Competitive Supply of Venture Capital ^{* †}

Yael V. Hochberg, Alexander Ljungqvist, and Yang Lu

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ABSTRACT

We examine whether strong networks among incumbent venture capitalists in local markets help restrict entry by outside VCs, thus improving incumbents' bargaining power over entrepreneurs. More densely networked markets experience less entry, with a one-standard deviation increase in network ties among incumbents reducing entry by approximately one third. Entrants with established ties to target-market incumbents appear able to overcome this barrier to entry; in turn, incumbents react strategically to an increased threat of entry by freezing out any incumbents who facilitate entry into their market. Incumbents appear to benefit from reduced entry by paying lower prices for their deals.

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

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

* Hochberg is at the Kellogg School of Management, Northwestern University. Ljungqvist is at the Stern School of Business, New York University, ECGI, and CEPR. Lu is with Barclays Capital. The authors thank Campbell Harvey (the Editor), an anonymous referee, an anonymous Associate Editor, John Asker, Ola Bengtsson, Jan Eberly, Shane Greenstein, Arvind Krishnamurthy, Laura Lindsey, Andrew Metrick (our AFA discussant), Ramana Nanda, Leslie Papke, Mitchell Petersen, David Scharfstein (our EVI discussant), Morten Sørensen, Scott Stern, Per Strömberg (our RICAPE2 discussant), Toby Stuart (our NBER discussant), Toni Whited, Jeffrey Wooldridge, and seminar participants at the European Central Bank, Cornell University, Harvard Business School, Northwestern University, the University of Texas at Austin, the City University of New York, Hong Kong University of Science and Technology, the University of Pittsburgh, the University of Wisconsin-Madison, the Australian National University, the University of Zurich, Columbia University, London Business School, the Berkley Workshop at New York University, the 2007 American Finance Association meeting, the 2006 RICAPE2 Conference at the LSE, the Third EVI Conference at Harvard University, the 2006 NBER Entrepreneurship Meetings, and the 2007 Next Generation Conference at LBS for helpful comments and suggestions. Lu gratefully acknowledges funding from the Ewing Marion Kauffman Foundation. The views expressed in the paper are those of the authors and not of Barclays Capital.

† Address correspondence to: y-hochberg@kellogg.northwestern.edu (Hochberg) or al75@nyu.edu (Ljungqvist).

Entrepreneurship and innovation are commonly considered key determinants of an economy's capacity for wealth creation, job growth, and competitiveness. Venture capitalists serve a vital economic function by identifying, funding, and nurturing promising entrepreneurs, though whether they provide capital and services on competitive terms is much debated. In this paper, we examine whether U.S. venture capital firms engage in practices designed to increase their bargaining power over entrepreneurs by restricting entry into local VC markets, such as Silicon Valley in California or Route 128 in Massachusetts. Our results are consistent with the hypothesis that incumbents engage in strategic behavior that reduces entry and benefit from doing so through paying lower prices for their investments.

What does it take to enter a local VC market? There are no obvious natural or regulatory barriers to entry; VCs are free to open offices in any location they choose. But to do deals in what is, after all, a relatively opaque and above all private market, they need to be visible to local entrepreneurs who, moreover, must consider them a credible funding source worth approaching. If entrants wish to be proactive about sourcing deal flow, they need access to information about promising ideas, trends, and people, preferably ahead of other VCs. And once they have found start-ups to back, they need local knowledge and connections to provide them with "value-added services", such as help identifying managerial talent, suppliers, or customers.

Having to establish visibility, credibility, access to information, and local knowledge from scratch puts entrants at an obvious cost and time disadvantage relative to incumbents, but this ignores an additional important advantage to incumbency, namely network externalities. VCs routinely cooperate by referring deals and people to each other, helping to put funding together through investment syndicates, providing introductions to suppliers or customers, and sharing their resources in other ways. It is possible that they sometimes do so specifically to raise the cost of

entry. For instance, by referring promising deals they cannot fund themselves to their friends, incumbent VCs may be able 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)). Or they may refuse to join an entrant's syndicate, making it harder for the entrant to assemble funding for any deal that requires syndication, perhaps due to its size or risk profile.

Assuming network externalities make a VC's life easier for those that are already members of the club, we explore whether entry involves gaining an incumbent's cooperation (in the form of access to the incumbent's information, expertise, or contacts) with a view to eventually gaining admission to the club. This raises two questions: What incentives does an incumbent have to cooperate with an entrant? And how will the other incumbents react?

One possible inducement an entrant can offer in return for cooperation in the target market is access to its home market. Bygrave (1987) and Lerner (1994) argue that reciprocity is expected when VCs syndicate investments, and Hochberg, Ljungqvist and Lu (2007) provide evidence to that effect.¹ Reciprocity benefits the cooperating incumbent but must be balanced against any negative reaction from the other incumbents. More formally, consider a group of incumbent VCs, each of which maximizes its profit while considering the effect of its actions on the behavior of the others. Individually, each VC chooses whether or not to help an entrant trying to break into the market. If an incumbent chooses to help, it expects to be punished by the other incumbents. The resulting Nash equilibrium is a function of the expected severity of punishment. The harsher is expected punishment, the more likely it is that incumbents will refrain from helping entrants. An incumbent's dominant strategy then depends on the gain from helping an entrant (such as reciprocal access to the entrant's home market), the expected punishment (such as refusal to

¹ The notion of reciprocity in economic exchange has been discussed extensively in the economics literature. See, for instance, Rabin (1993) and Fehr and Schmidt (2002).

cooperate with the deviating VC for one or more periods), and (because coordinating punishment becomes harder the more incumbents there are) the number of incumbents.

While network externalities are not directly observable, it is possible to use data on syndication relationships to proxy for how interdependent incumbents have chosen to be in a market. VC firms that are prone to sharing their investments with other incumbents presumably also share other network resources.² All else equal, we expect more densely networked markets to be harder to enter, not only because of the relatively greater network externalities that incumbents (but not entrants) enjoy in such markets, but also because withdrawal of network access (“suspension from the club”) may provide an effective threat of punishment against the offender.³

Our results are consistent with the hypothesis that networking among VCs reduces entry. First, we find that there is less entry in VC markets in which incumbents are more tightly networked with each other, as evidenced by their past syndication patterns. The magnitude of the effect is large: Controlling for other likely determinants of entry, a one-standard deviation increase in the extent to which incumbents are networked (using measures borrowed from economic sociology) reduces the number of entrants in the median market by around a third.

The networking patterns we observe in the data may not be exogenous; rather, they may reflect omitted variables affecting both networking and entry. For example, unobserved variation in the cost of doing business in a given industry or location could induce networking (say, to economize on information costs) and *independently* reduce entry. To correct for this potential endogeneity problem, we follow two approaches. First, we use instrumental variables motivated by non-

² Reasons to syndicate include pooling capital and diversifying risk (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)).

³ Anecdotal evidence supports a link between entry and networking. Kuemmerle and Ellis (1999) report that 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.”

strategic and mechanical determinants of syndication decisions. This strengthens our results. Second, we exploit the three-way panel structure of our data (which span time, location, and industry) to identify omitted time-varying factors that are either location-specific or industry-specific. This produces results that are very similar to the IV estimates.

Our second test focuses on the determinants of an individual VC firm's entry decision. Strong networks among the incumbents in the target market reduce the likelihood of entry. But not every potential entrant is deterred. Controlling for industry experience and geographic proximity to the market (which each double the likelihood of entry), we find that a VC firm is significantly more likely to enter if it has previously established ties to incumbents by inviting them into syndicates in its own home market. Moreover, it is with these very same incumbents that the entrant does business in the target market. In the context of the entry deterrence game sketched out above, this suggests that incumbents deviate from the strategy of non-cooperation with entrants when the gain from deviating – reciprocal access to the entrant's home market – is sufficiently tempting.

The cost of deviation is punishment, in the form of reduced syndication opportunities with fellow incumbents. We show that after doing business with a potential entrant, an incumbent's probability of being invited into fellow incumbents' syndicates decreases considerably and significantly, for up to five years after the event. This effect is concentrated in markets with a small number of incumbents, consistent with the notion that a small number of players can more easily prevent free-riding when called upon to execute a punishment strategy.

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. Controlling as best we can for other value drivers, we find significantly lower valuations in more densely networked markets: A one-standard deviation increase in our networking measures is

associated with a 10% decrease in valuation, from the mean of \$25.6 million. This suggests that incumbent VCs benefit from reduced entry by paying lower prices for their deals. On the other hand, the more market share entrants capture, the higher are valuations in the following year, suggesting that entry is pro-competitive and, at least in that sense, benefits entrepreneurs. An unanswered question is whether networks provide offsetting benefits to entrepreneurs. We leave an examination of the overall welfare effects of networking to future research.

Our contribution is threefold. First, we show that networking can have the effect of reducing entry in the VC market.⁴ This result may generalize to other heavily networked industries, such as investment banking. Second, our results help explain prior evidence that better networked VCs enjoy better performance (Hochberg, Ljungqvist, and Lu (2007)). Part of the explanation for this may be due to the lower prices VCs pay for investments in more densely networked markets. Third, we shed light on the process of entry in the VC industry. 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.”

The remainder of the paper is structured as follows. Section I describes our sample and data. Section II presents the market-level analysis, while Section III presents the firm-level analysis. Section IV examines strategic versus efficient networking. Section V presents an analysis of valuation effects. Section VI discusses alternative explanations for our findings. Section VII concludes.

I. Sample and Data

Most of our data comes from Thomson Financial’s *Venture Economics* (VE) database. We

⁴ While networking may reduce entry into local markets, thus restricting the competitive supply of venture capital, it is also likely that networks offer benefits to portfolio companies, such as reduced search time (Inderst and Mueller (2004)) and more efficient information and resource sharing among VCs (Hochberg, Ljungqvist and Lu (2007)).

consider all investments in U.S. companies made by U.S. based VC funds between 1975 and 2003 that are included in the VE database. We exclude investments by angels and buyout funds.

A. Market Definitions

Sorenson and Stuart (2001) show that VCs tend to specialize in a certain industry and invest locally, not least because VC investments require substantial monitoring. Thus, the VC industry appears to be segmented into industry-specific, localized markets. We use the six broad industry groups defined by *Venture Economics* and cross each with either states or metropolitan statistical areas (MSAs).⁵ States usually cover larger geographic areas, resulting in a broader market definition, while MSAs can usefully aggregate economic activity across state borders, where appropriate. In practice, our results are nearly identical using either definition.

For inclusion in the sample, a market-year must have 25 or more VC deals in the prior five years (to exclude markets with no real history of VC activity) and at least five deals in the year of analysis (to exclude inactive markets). This results in 129 state/industry markets and 130 MSA/industry markets. Our panels have between one and 24 annual observations per market. The panels are nested: There are multiple industries for each location in year t , and vice versa for each industry. The total number of market-years is 1,375 using states and 1,292 using MSAs.

B. Incumbents and Entrants

We define incumbents as VC firms that have invested in the target market at some time prior to year t and continue to have investments in the market as of year t . Entrants are defined as VC firms that invest in the market for the first time in year t .⁶ Entrants are not necessarily inexperienced “rookies”; for the most part, they are themselves incumbents in other markets.

To measure the extent of entry in a market in year t , we examine the *number* and *fraction of*

⁵ The 19,012 sample companies break down as follows. Computer related: 40.6%; Non-high-tech: 25.3%; Communications/media: 15.4%; Medical, health, life sciences: 9.4%; Semiconductors: 5.4%; and Biotech: 3.8%.

⁶ Results are robust to coding as entrants firms for which some time has passed since they last invested in a market.

deals entrants are involved in as well as the *number of entrants*. We analyze separately cases where an entrant acts as a lead investor,⁷ so we use six measures of entry in total. Table I, Panel A reports descriptive statistics. In the median state-market-year, there are 15 incumbents and nine entrants, five of which enter by leading syndicates for one deal each, giving a combined market share of 28.6%. In the median MSA-market-year, there are 16 incumbents and eight entrants, four of which enter by leading one deal each with a market share of 25%.

C. Market-level Network Measures

We use social network analysis to measure how interconnected incumbents are. Fig. 1 graphs the network that arises from syndication of computer-related investments located in Michigan in 1979-1983. Nodes represent VC firms and arrows represent syndicate ties.⁸ Arrows point from the VC leading a syndicate to the non-lead member. (Two-way arrows indicate that each VC has led a syndicate in which the other was a non-lead member.) Fig. 2 shows the non-high-tech VC network in Pennsylvania in 1990-1994. Visual inspection suggests that the network in Fig. 1 is dense; every VC firm has at least one tie to one or more VCs. In contrast, the network illustrated in Fig. 2 is sparse; only two of the VC firms in this market have a tie to another VC.

Networks are represented as matrices. Cells reflect whether two VCs co-syndicated a deal, and can be coded in two ways. The “undirected” matrix records as a tie any participation by both VC firms i and j in a syndicate. The “directed” matrix records a tie between i and j only if one of them lead-managed the syndicate. Directed ties embody a more demanding notion of a relationship.

A natural measure of how interconnected incumbents are is “density”, defined as the proportion of all logically possible ties that are present in a market. For example, the maximum

⁷ In common with the VC literature, a deal is defined as a collection of investments in a given portfolio company in a specific round of financing. We identify the lead as the investor making the largest investment in the round.

⁸ Venture Economics distinguishes between VC funds and management firms. A VC fund has a limited (usually ten-year) life, so we assume relationships reside at the level of the VC firm.

number of undirected ties among three incumbents is three. If only two incumbents are connected to each other, the density is $1/3$ (one tie out of the three possible). With n incumbents, there are at most $\frac{1}{2}n(n-1)$ undirected and $n(n-1)$ directed ties. Let $p_{ijm}=1$ if VCs i and j have an undirected tie in market m , and zero otherwise. Then market m 's symmetric density equals $\sum_j \sum_i p_{ijm} / (n(n-1))$. Let $q_{ijm}=1$ if VCs i and j have a directed tie in market m , and zero otherwise. Then the market's asymmetric density equals $\sum_j \sum_i q_{ijm} / (n(n-1))$.⁹

In common with the industrial organization literature, we focus on relationships 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.

Networks change as entrants become incumbents, so we construct a new network for each market and year from data on syndications among incumbents over the five years ending in $t-1$. Table I, Panel B reports descriptive statistics. The density of directed and undirected ties in the average state market is 2.1% and 7.8%, respectively, with somewhat larger densities in MSA markets. To illustrate, the Massachusetts biotech industry ranks among the most densely networked markets in every year in our panel, while the New York non-high-tech industry is the least densely networked market in most years.¹⁰ Variation in our network measures within markets (across time) is nearly identical in magnitude to variation between markets (across geographies).

⁹ Our results are not driven by the $n(n-1)$ normalization. We obtain results that are about as strong statistically and economically if we use the absolute rather than the relative number of ties present in a market.

¹⁰ Supplemental Table 1 in the Internet Appendix breaks down our six entry measures by quintile of density. In the case of the number of entrants or the number of deals, more densely networked markets are associated with less entry. This holds for the full sample, in the most active VC markets (Silicon Valley and Route 128, or California and Massachusetts), and when we partition the sample in 1993. In the case of the fraction of deals entrants lead or are involved in, we do not find a monotonic relation in this simple cut. As we will see later, the raw correlation appears to cover up the evidence of strategic behavior among VCs we find in our multivariate regressions.

D. 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 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 (2007) and compute the fraction of portfolio companies that were successfully exited 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.

Markets with more volatile deal flow may be easier to enter if incumbents cannot quickly meet unexpected increases in demand, so we include the coefficient of variation of the monthly number of deals. Larger markets and those less economically developed generally have a higher demand for external capital and thus are more likely to attract entrants. We use the lagged number of deals completed in a market as a proxy for market size and the lagged level and change in real gross state product (GSP) to proxy for economic development. Additionally, all else equal, a larger number of incumbents could make entry harder if companies seeking capital already have ample funding options. We therefore control for the number of incumbents.

Where deals are typically syndicated (perhaps because they tend to be large or late-stage), incumbents might reduce entry simply by refusing to syndicate with entrants. To capture this possibility, we control for the fraction of syndicated deals in a market in the prior five years.

To control for demand-side factors affecting entry, we use two proxies for investment opportunities for private companies. First, 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 which we map to the six *Venture Economics* industries. This variable varies by year and industry but not by state or MSA.¹¹ Second, 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.

Finally, many start-ups depend on skilled labor, so education levels in a particular geographic region may be related to the probability of success and hence to the supply of VC funding.

E. Characteristics of Potential Entrants

We code a VC firm as a potential entrant if it was founded in or before year t ; has at least one fund under management that was raised in the previous six years (to capture funds that are actively investing as of t); and has not invested in this particular market prior to year t .

All else equal, we expect more entry if there is a larger pool of “qualified” VC firms that could potentially enter the market (see Berry (1992)). We hypothesize three relevant characteristics, shown in Panel D. First, we control for the fraction of potential entrants that are located within 100 miles of the target market.¹² Since demand for funding tends to be local, far-away VCs may have a harder time entering. (Our results are robust to alternative cut-offs.)

Second, experience investing in the industry or area may facilitate entry. Based on their investment patterns in the prior five years, in the mean state market, 6.8% of potential entrants have done deals in both the industry and state, 31% have invested in the industry before but not in

¹¹ Our results are robust to using a location-and-industry-specific book-to-market measure, constructed by weighting book-to-market ratios for each industry by their respective weights within the geographical area in question. The weights are determined using VC investments by location and industry over the prior five years.

¹² We use zip codes to identify the coordinates of a VC’s headquarters, assuming it is located in the center of the zip code area. To find the coordinates of a market, we use the modal zip code of all portfolio companies in the market. Our results are generally robust to ignoring potential entrants located more than 100 miles away altogether. Specifically, as shown in Supplemental Tables 2 and 3 in the Internet Appendix, we continue to find a negative relation between entry and network density in every specification, and while some coefficients are more noisily estimated, their economic magnitudes are similar to those reported in the paper. The results are statistically weakest for the fraction of deals proximate entrants lead. We thank the referee for suggesting this robustness test.

the state, 5.9% have invested in the state but not in the industry, and the remainder in neither.

A key question we address is whether an entrant's *prior* relationships with incumbents, established in *other* markets, can facilitate entry. We code whether a potential entrant, in the prior five years, lead-managed a deal in another market in which an incumbent was a co-investor. This corresponds to positive “outdegree” in economic sociology. In the mean market-year, around 13% of potential entrants have lead-managed syndicates in which incumbents were co-investors.

II. Market-Level Analysis

A. A Descriptive Model of Entry in Venture Capital

To see if the data support a link between the extent of entry in a VC market and the density of the incumbents' network ties, we regress the number of deals entrants lead-manage in year t in market m on the market's network density as of year $t-1$ and suitably lagged controls for the pool of qualified potential entrants and the aforementioned demand and supply proxies. We have two alternative network measures (asymmetric and symmetric density) and two alternative market definitions (using states and MSAs), resulting in four specifications. 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 effects.

Table II reports the estimates. The pseudo- R^2 exceeds 50% indicating good explanatory power. In each specification, we find a strongly negative and significant relation between the extent of networking and entry, consistent with our conjecture that networking can help reduce entry. As we control separately for whether deals are typically syndicated in the market, networking likely captures more than a simple refusal to syndicate a deal with an entrant.

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 geographic proximity to the market or

prior investment experience (especially having invested both in the area and the industry). A greater prevalence of past network ties between potential entrants and incumbents also makes entry more likely, giving a first indication that entry indeed involves a measure of reciprocity: By sharing its deal flow today, a VC firm may gain access to another market at a later date.

As for the market characteristics, entry increases in investment opportunities, variability of demand, flows of capital into the industry, and the size of the VC market. There is less entry in larger states and (using the MSA definition) in states with more qualified graduates. Entry is unrelated to a market's lagged exit performance, the number of incumbents, and GSP growth.

B. Omitted Variables and Causality

Table II hints at a link between the extent of entry in a VC market and the density of the incumbents' network ties, but the correlation could be spurious. A first-order concern is that some omitted variable simultaneously makes networking more advantageous and entry less desirable, making networking endogenous. An obvious example is cost variation. VCs might network to reduce cost; at the same time, high-cost markets may attract less entry. In this case, the results in Table II would overstate the effect of networking on entry. The reverse is also possible. Suppose we have inadequate controls for investment opportunities. In markets with poor investment opportunities, VCs may be less keen to share their deals, while entry is also less attractive. In this case, the results in Table II would understate the effect of networking on entry.

Table II includes market fixed effects to control for time-invariant market-specific omitted variables, but our results could still be biased due to time-varying omitted variables. While it is difficult to address omitted-variable concerns in the absence of a natural experiment, we adopt two approaches within the limitations of our data. The first uses two instrumental variables to deal directly with the potential endogeneity of networking; the second exploits the nested panel

structure of our data to construct proxies for two likely types of omitted variables.

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

C.1. Instruments

First, we argue that compared to traditional VCs, corporate VCs are more likely to syndicate for opportunistic reasons, rather than in order to deter entry. According to Gompers and Lerner (2000b), corporate VCs have different (often, strategic) objectives and shorter horizons (on average, they are closed down after four years). Also, they are typically staffed with managers seconded from the parent corporation (Gompers and Lerner (2001)) who are likely to be considerably less well networked (at the personal level) than are dedicated VC professionals. Thus, we expect the presence of corporate VCs in a market to be associated with lower levels of networking, a prediction 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, so this instrument should satisfy the exclusion restriction (i.e., it likely correlates with the extent of networking but is unlikely to affect entry directly).

Our second instrument is based on the idea that more frequent interaction helps VCs form ties, leading to denser networks. We link frequency of interaction, which is unobservable, to the geographic distribution of demand. Markets in which demand is spread uniformly 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. Anecdotally, VCs tend to meet while in town to attend board meetings of their portfolio companies (Kuemmerle et al. (2000)) and during “pitch events” for local startups seeking capital. The more clustered are start-ups, the greater the chances that any two VCs will meet and establish a tie. We capture this using the entropy of the number of investments per zip code area in the

market. The more unequal the geographic distribution, the lower the entropy.

C.2. First-stage Results

The first-stage regression in our IV models predicts the extent of networking in the market as a function of the two instruments, the second-stage control variables (as per Table II), and market and year fixed effects. Table III reports the estimates for each of the four specifications. Overall, the models appear to be well specified: The within-group R^2 in each exceeds 50%.

Consistent with our hypothesis that markets in which demand is concentrated geographically are more densely networked, we find that the entropy of demand is negatively and significantly related to both density measures under both market definitions. The same is true of the fraction of corporate VCs in a market (except when we model symmetric density in MSA markets).

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. The F -tests suggest our instruments are collectively strong in three of the four models, using Staiger and Stock’s (1997) recommended critical value of 10, and the instruments explain between 17.4% and 27.4% of the variation in density.

C.3. Determinants of Market Entry: Second-stage Results

Table IV presents the results of the instrumental-variables models. The dependent variables in Panels A through D are the *number of deals* in year t lead-managed by entrants or involving new entrants in any syndicate position and the *number of VCs* entering as lead-managers or in any syndicate position, 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 variables in Panels E and F are the fraction of deals lead-managed by, or simply involving, entrants. These have support on $[0,1]$ and positive mass at both 0 and 1, so we

estimate fractional logit models (Papke and Wooldridge (1996)). As fractional logits cannot accommodate fixed effects, Panels E and F pool 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. Standard errors are based on the Murphy-Topel (1985) adjustment for consistency.

As before, we find a negative and statistically significant relation between networking and entry. Comparing Table II to Panel A of Table IV, we see that failure to account for endogeneity causes us to underestimate the effect of network density. This suggests that the omitted variable simultaneously makes networking and entry more desirable. A plausible example of such a variable is omitted investment opportunities.

The economic effect of networking is large. Holding all other covariates at their sample means, a one-standard deviation increase in symmetric density, for instance, reduces the expected number of deals entrants win in state markets by 1.44. This is around two times larger than in the naïve models shown in Table II, and it is large compared to the median of five. The predicted difference in the number of deals won in the least and most networked markets is 7.8. (In general, the economic effects are somewhat smaller when we consider MSA markets, though as Table I shows, so is the extent of entry.) Networking has the third largest economic effect in this specification, after variation in investment opportunities and state GSP.

Similar results obtain for the other five entry measures. In Panel C, for instance, a one-standard deviation increase in asymmetric density is associated with a decrease of 1.3 in the number of lead-VC entrants in state markets (compared to a median of five). The corresponding effect in Panel D, which focuses on the number of VCs entering in any syndicate capacity, is 3.6 (compared to a median of nine). In Panels E and F, we find that entrants' combined market share is

significantly lower in more densely networked markets. To illustrate, a one-standard deviation increase in network density reduces the fraction of deals lead-managed by entrants by around 10% from the unconditional mean, depending on the specification.

Collectively, these results 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.

D. Correction for Omitted Variables

The nested structure of our panel allows us to investigate the effects of omitted variables without relying on instruments. Suppose the omitted variables, currently subsumed in the error terms of the networking and entry equations, are time-varying factors that are either location-specific or industry-specific. That is, they are of the form $\gamma C_{lt} + \delta C_{st}$, where l indexes locations and s indexes industries. Then, density can be expressed as:

$$D_{lst} = \beta X_{lst} + v_{lst} = \beta X_{lst} + \gamma C_{lt} + \delta C_{st} + \varpi_{lst}. \quad (1)$$

Under this quite general assumption, we can construct a proxy for C_{lt} using only observables.¹³ Specifically, we subtract from D_{lst} its mean across locations, holding industry constant, and solve for C_{lt} . Because C_{st} does not vary across locations, it cancels out and we obtain a proxy for C_{lt} that is a function of observables and a constant (mean C_{lt}) which is subsumed in the market fixed effects:

$$C_{lt}^* = \gamma C_{lt} + \varepsilon_{lst} = (D_{lst} - \frac{1}{N_{lt}} \sum_l D_{lst}) - (\beta X_{lst} - \frac{\beta}{N_{lt}} \sum_l X_{lst}) + \frac{\gamma}{N_{lt}} \sum_l C_{lt} + \varepsilon_{lst} \quad (2)$$

Estimates of β can be obtained from a regression of D_{lst} on observables X_{lst} . The proxy for C_{st} is constructed analogously. The two proxies are then included in the entry equation to reduce the

¹³ Bearing in mind that we include market fixed effects, the only type of omitted variable we cannot capture this way is one that varies simultaneously across time, location, and industry.

bias-inducing correlation between the networking variable and the disturbances.

Table V presents the results of the augmented entry models. The effect of networking on entry is invariably negative, and it is statistically significant at the 5% level in 22 of the 24 models. The coefficient estimates are similar in magnitude to those in the IV models in Table IV. Though not reported, the coefficients estimated for C_{it}^* , the proxy for location-specific omitted factors, are consistently positive and statistically significant; the coefficients for C_{st}^* are never significant. The relevant omitted variable hence appears to be location-specific, and the sign suggests it captures something that makes both networking and entry more desirable (such as omitted investment opportunities). This mirrors our conclusion from the instrumental-variables models in Table IV.

In sum, both the IV approach and the omitted variables correction support the interpretation that more densely networked markets are associated with less entry, even after accounting for possible omitted variables that make networking endogenous to entry.

III. Firm-level Analysis

We now model an individual VC firm's entry decision to see how entrants can overcome networking-related entry barriers. In particular, we ask whether an entrant can soften the reaction it receives in a market by first giving an incumbent reciprocal access to deal flow in its home market. Preliminary univariate analysis (not tabulated) supports this: Such reciprocity increases the likelihood of successful entry threefold.

To control for other influences on the entry decision, we estimate multivariate firm-level probit models. The dependent variable equals one if VC firm i enters market m successfully and zero otherwise. The sample consists of all potential entrants for each market, defined as in Section I.B. The main variables of interest are the target market's network density and an indicator for i 's prior ties to an incumbent. Other controls include the VC firm's size, location, and experience, and our

proxies for demand and supply. Table VI reports the results. In each specification, we find that a VC firm is significantly less likely to enter the more densely networked the market. This mirrors the main result of the market-level models discussed in Section II. The pseudo R^2 are around 16%.

Who does enter? Prior ties to incumbents (positive outdegree) have a positive and significant effect on the likelihood of entry in all four models. Thus, successful entrants are those that have syndicated with target-market incumbents in other markets, consistent with the notion that entry involves an element of reciprocity. Interaction terms crossing outdegree with density are positive and statistically significant. Thus, for entrants with suitable connections, the extent of networking in the target market appears to be irrelevant.

Larger VC firms, measured by capital under management since inception, are significantly more likely to enter. While size might proxy for a range of relevant characteristics, entry by large VC firms may be more likely to be accommodated because big players can offer greater rewards in the form of syndication opportunities in their home markets.

The single most significant determinant of the entry decision in Table VI is location. Depending on specification, VC firms located within 100 miles of the center of the target market are between 126% and 144% more likely to enter than those located farther away. Previous related investment experience, whether in the area or the industry or both, is similarly helpful. Economically, these effects too are large. For instance, prior experience in the industry and state increases the likelihood of entry by around 86%. Prior industry experience in the absence of prior investments in the state has a smaller economic effect, increasing the likelihood of entry by around 27%, while experience in the state but not in the industry increases it by 22%.

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 $p < 0.0001$.

IV. Strategic vs. Efficient Networking

Networking appears to reduce entry, but is that why incumbents network? In this section, we test whether incumbents network simply because it is efficient to do so, or whether they also seek to deter entry. If networking is efficient, the entry-reducing effects we document are accidental. For instance, networking may reduce incumbents' cost and improve the quality of their investment screening, either of which would put entrants at a disadvantage. If networking is strategic, on the other hand, it should be part of a broader pattern of entry deterrence. We investigate this possibility by examining the response of incumbents to an increase in the threat of entry.

Suppose there are two markets. M1 has three incumbents (VC1, VC2, VC3) and M2 has two (VC4, VC5). Let x be the unconditional probability that VC5 enters M1. From Section III, we know that if VC5 invites VC3 into its home market, the probability that VC5 will later successfully enter M1 increases, say to $x+y$. If VCs network to deliberately reduce entry, an increased threat of entry should elicit a strategic response from VC1 and VC2, the other incumbents of M1. Specifically, they should reduce the attractiveness of entry by freezing out VC3 (informationally, etc.), so as to neutralize the link VC5 has made into their market.¹⁴

Empirically, we perform a difference-in-difference test, comparing the difference over time in each incumbent's participation in its home-market network as a function of whether or not the incumbent has done business with a potential entrant in another market. The unit of observation is

¹⁴ This test is biased against us. VC3 will only do business with VC5 in the first place if it expects the other incumbents' response to be relatively lenient – which will make it harder to detect such a response in the data.

thus an incumbent VC firm, i . The dependent variable is the change in the probability that firm i is invited to join a syndicate lead-managed by another incumbent operating in its market. The main variable of interest is an indicator set equal to one if firm i co-syndicated with a potential entrant in another market during year $t-1$. We test the hypothesis that the other incumbents in i 's home market react by excluding it from some or all of their syndicates for a period of time.

As strategic behavior invites free-riding, we expect the likelihood and severity of punishment to be greater the fewer incumbents. Hence we interact the variable of interest with an indicator set equal to one if there are five or fewer incumbents in the market. (Our results are not sensitive to other reasonable cut-offs.) To allow for flexibility in the duration of punishment, we compute the change in syndication probability from year t to each of the next five years. Note that VC firms entering after year t (i.e., future incumbents) are not included in this calculation, as they cannot plausibly punish VC firm i for causing entry to become easier before they themselves entered. We also screen out markets with a monopolist incumbent, as there can be no strategic response.

Table VII reports the results. With two market definitions (state and MSA) and a five-year window, we estimate ten OLS regressions. Each controls for year and industry effects as well as two VC firm characteristics: Size and “degree,” a measure of network centrality. We expect larger and better connected VCs to face more lenient reactions from their fellow incumbents.

As expected, in markets with few incumbents, doing business with a potential entrant reduces the probability of inclusion in home-market syndicates the next year in state markets with five or fewer incumbents by 1.1 percentage points ($= -0.313 - 0.806$) and by 2.2 percentage points in MSA markets. The unconditional probability in year t is 4.8% and 5.9%, respectively, so the reduction is large economically. In other words, incumbents appear to respond strategically to an increased threat of entry, consistent with networking deliberately rather than accidentally reducing entry.

The strategic response is not only large, it is persistent and increasing over time. In state markets, an incumbent that has done business with a potential entrant can expect to see its home-market syndication opportunities decrease by 1.1, 2.3, 3.5, 3.4, and 4.3 percentage points over the next five years. (For MSA markets, the response peaks after four years, at -4.6 percentage points.)

V. Valuation Effects

Our results support the hypothesis that strategic networking deters 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. Because we do not observe any qualitative funding terms (such as control rights, liquidation preferences, or anti-dilution protection), we focus on 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 tends to increase over a sequence of funding rounds and with its maturity. It also appears to be related to networking. Sorting state markets into quartiles based on asymmetric density, for instance, the average real valuation is \$10.6 million in the most densely networked markets versus \$20.4 million in the least densely networked ones.

These figures do not control for other reasons why valuations might differ. Table VIII reports OLS regression results where the unit of analysis is a funding round and the dependent variable is the log of the round valuation. The explanatory variables of interest are the density measures; the fraction of deals entrants won 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 may have to offer higher valuations to compete with incumbents.

Absent data on sales, earnings, or book values in the VE database, we have no company-specific value drivers 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, 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 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, such as local pricing anomalies, conditions in the managerial labor market, and so on.

As in Section II.D, we augment the regression with the omitted variable proxies C_{lt}^* and C_{st}^* , to allow for the possibility that time-varying factors that are either location-specific or industry-specific influence both the networking decision and valuations in a market. An example is cost: High-cost locations may be associated with more networking and lower valuations.

The adjusted R^2 of around 40% indicate good fit. Companies in more densely networked markets are valued significantly less highly, suggesting that incumbent VCs benefit from reduced entry by paying less for their deals. Economically, a one-standard deviation increase in density is associated with a more than 10% decrease in valuation from the unconditional mean of \$25.6 million, all else equal. On the other hand, valuations are higher the more market share entrants have gained in the recent past, suggesting that entry benefits entrepreneurs through higher prices. Also, perhaps not surprisingly, entrants pay significantly higher valuations than do incumbents, all

else equal. The controls account for a little under a third of the reported R^2 .

The *Venture Economics* valuation data have two shortcomings which could lead to spurious results. First, they are self-reported, and only one fifth of the funding rounds in the VE database disclose valuations. There is every reason to expect companies to disclose data strategically. For instance, a company may choose not to disclose a “down-round” (i.e., a discount to the previous round). To correct for strategic disclosure, we follow Hwang, Quigley, and Woodward (2005) who derive a Heckman selection-correction from an ordered probit model of seven events at which valuations could be disclosed.¹⁵ The explanatory variables are the company’s development status (as per its previous 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). Our replication yields results that are at least as strong as theirs (not shown).

When we include the inverse Mill’s ratio for each company and round from the Hwang et al. (2005) model in the Table VIII specifications, we continue to find that round valuations are lower in more densely networked markets and increase after entrants have won more market share and if an entrant leads a round. As Panel A of Table IX shows, all coefficients are highly statistically significant. Compared to the relevant coefficients from the Table VIII specifications, the selection-corrected model produces slightly smaller economic effects for the network measures.

The second shortcoming of the VE valuation data is the absence of company-level data on value drivers. No doubt our valuation models leave out many factors that influence valuations, such as the company’s track record, the quality of management, or the strength of intellectual property. However, we can exploit the panel structure of the data – companies receive multiple

Table IX

¹⁵ The events are: 1) Shutdown; 2) no funding at all; VC funding 3) with or 4) without disclosure; funding through acquisition 5) with or 6) without disclosure; or 7) funding and revelation of value through an IPO.

funding rounds – to remove the effect of unobserved company-specific factors. We do so while continuing to control for unobserved market-specific factors that might bear on valuation. 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 B of Table IX. 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). While some coefficients are somewhat smaller than in Table VIII, we continue to find, as before, that networking significantly reduces valuations while entry increases them. As Panel C shows, this finding is robust to simultaneously adjusting for selective disclosure and unobserved company-level heterogeneity.

In conclusion, networking and reduced entry affect company valuations adversely and these effects do not appear to be an artifact of well-known problems with the VE valuation data.

VI. Discussion of Alternative Explanations

There are two main alternative explanations for our findings that are hard to rule out within the limitations of the data on hand. First, entrants are likely at a competitive disadvantage in sourcing deal flow, as companies raising capital are unlikely to broadcast their intentions to every potential entrant. This competitive disadvantage likely increases in the number of incumbents, as companies seeking capital already have many funding options. This could drive our results if our controls for the number of incumbents (and other measures of market size) are inadequate or if the degree of networking and the number of incumbents correlate positively. However, the data do not appear to support such a positive correlation. In state and MSA markets, the correlation between the number of incumbents and density is in fact negative, at -29% and -36%, respectively.

Second, we observe only a start-up's actual choice of VC backer, as opposed to its choice set.

Thus, we cannot know which entrants it considered raising funding from, and on what terms. If entrants' terms are systematically less attractive, then in a competitive market, one would expect to see less entry. If more densely networked markets are actually more competitive, in the sense that start-ups receive more funding offers, there may be less entry simply because entrants are at a cost disadvantage. While this story is plausible, and we cannot rule it out, it appears hard to reconcile with our findings on valuations. If more densely networked markets were also more competitive, we would expect to see higher valuations in such markets, but Table IX suggests the opposite is the case. This is more nearly consistent with such markets being less competitive, though we note that valuations could be higher in less networked markets for other reasons. For instance, more densely networked markets could be more efficient at avoiding allocating capital to bad projects. As we do not observe valuations for unfunded projects, we cannot rule out this alternative.

VII. Conclusions

We examine whether networking among U.S. VC firms restricts entry into local VC markets, thereby improving their bargaining power over entrepreneurs. We expect more densely networked markets to be harder to enter, not only because of the relatively greater network externalities that incumbents enjoy in such markets, but also because withdrawal of network access may provide an effective threat of punishment against incumbents who cooperate with new entrants.

We find 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 giving incumbents reciprocal access to the entrant’s deal flow in its home market.

Having established a link between syndication networks and reduced entry, 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. This is consistent with an increase in incumbents’ bargaining power.

While networking is no doubt motivated by efficiency considerations, its entry-reducing effects do not appear entirely accidental. Our evidence suggests that incumbents react strategically to an increased threat of entry – such as when a fellow incumbent does business with a potential entrant elsewhere – by excluding the offending VC from their deals for a number of years.

If networking reduces entry, it may lead to a more restricted supply of capital to entrepreneurial ventures and to harsher funding terms. An unanswered question is whether networks provide offsetting benefits to entrepreneurs. For instance, raising money in a more densely networked market may take less time. We leave an examination of the overall welfare effects of networking to future work.

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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. See Wasserman and Faust (1997) for further details.

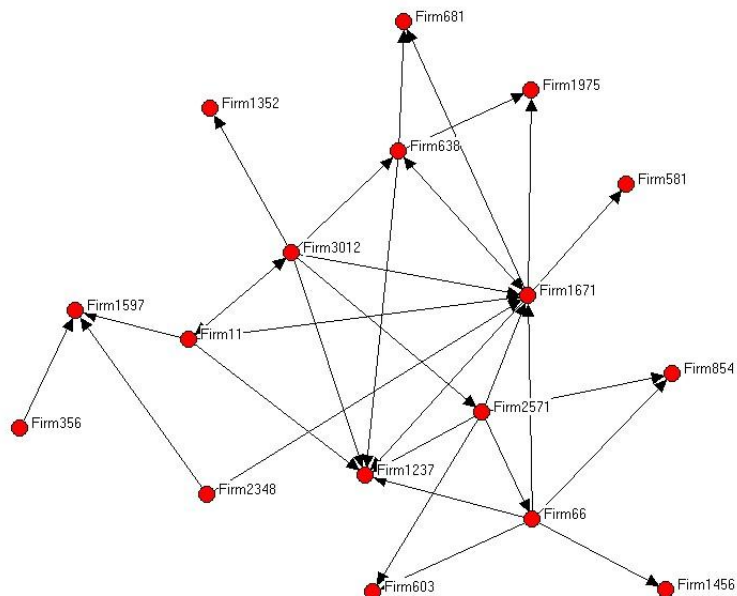


Figure 2. Example of a Sparsely Networked Market

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.

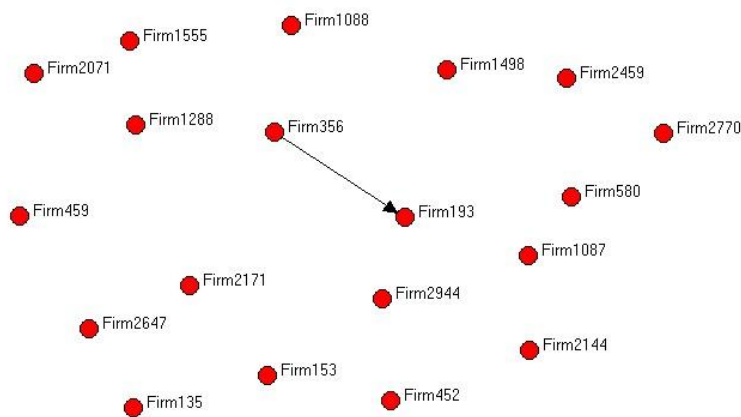


Table I. Descriptive Sample Statistics.

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 either a U.S. state or a Metropolitan Statistical Area (MSA). *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 state markets and 130 distinct MSA markets. Under each definition, there are between one and 24 annual observations for each market, resulting in 1,375 state-market-years and 1,292 MSA-market-years. 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 network densities, shown in Panel B. Density is defined as the proportion of all logically possible ties among incumbents that are present in the 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. 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. The coefficient of variation of monthly number of deals is computed over the prior five years. State GSP data come from the U.S. Department of Commerce's Bureau of Economic Analysis (BEA). For MSAs, we use data for the state or states the MSA is located in. Since our sample covers more than 20 years of data, we use the BEA's implicit GNP deflator to adjust for inflation. 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 real 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. We obtain data on annual state-level science and engineering degree completions from the National Science Foundation (NSF). Science and engineering includes the following subjects: Engineering, physical sciences, geosciences, mathematics and computer sciences, life sciences, and science and engineering technologies. 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 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).

	State markets			MSA markets		
	Mean	Std. Dev.	Median	Mean	Std. Dev.	Median
Panel A: Entry measures						
# incumbents	28.3	41.0	15	24.3	28.4	16
# deals lead-managed by incumbents	24.1	57.5	10	16.8	27.4	9
# deals lead-managed by entrants	8.5	12.2	5	6.7	9.6	4
# deals involving entrants	12.8	21.6	7	10.3	15.6	6
fraction of deals by # lead-managed by entrants	0.301	0.182	0.286	0.274	0.171	0.250
fraction of deals by # involving entrants	0.413	0.197	0.400	0.403	0.190	0.389
# entrants that lead syndicates	7.2	9.6	5	5.8	7.8	4
# entrants	14.7	19.9	9	12.7	17.0	8
Panel B: Network measures						
asymmetric density	0.021	0.013	0.018	0.024	0.014	0.021
symmetric density	0.078	0.052	0.067	0.092	0.053	0.081
Panel C: Market, state, and industry characteristics ($t-1$)						
excess investment performance in market	0.047	0.095	0.038	0.151	0.108	0.140
coefficient of variation of monthly # deals	1.161	0.346	1.171	1.173	0.326	1.175
# deals in market	37.9	78.0	18	28.6	42.2	17
real GSP (\$billion)	323.8	262.1	237.2	547.6	413.9	450.1
real GSP growth rate	0.033	0.026	0.032	0.036	0.029	0.036
fraction of deals that are syndicated, $t-5$ to $t-1$	0.425	0.131	0.429	0.472	0.144	0.483
value-weighted mean industry B/M ratio	0.524	0.225	0.489	0.501	0.217	0.473
inflow into VC funds in industry (\$m)	6,954.6	12,309.6	2,247.0	7,415.4	13,003.4	2,247.0
# science & eng. degrees awarded in state per 1000 inhabitants	2.6	0.8	2.5	2.5	0.5	2.4
Panel D: Potential entrants						
fraction located within 100 miles of market	0.065	0.073	0.025	0.086	0.074	0.059
fraction investing in same industry and same area	0.068	0.028	0.064	0.066	0.033	0.062
fraction investing in same industry but not same area	0.310	0.157	0.291	0.318	0.153	0.298
fraction investing in same area but not same industry	0.059	0.081	0.028	0.044	0.046	0.025
fraction w/ positive outdegree	0.131	0.054	0.132	0.137	0.053	0.137

Table II. Number of Deals Entrants Lead.

The dependent variable is the number of deals won by 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 parentheses. We use ***, **, and * to denote significance at the 0.1%, 1%, and 5% level, respectively. In the two specifications where markets are defined as state/industry pairs, the number of distinct markets is 129 and the number of observations (market-years) is 1,375. In the two specifications where markets are defined as MSA/industry pairs, the number of markets is 130 and the number of observations is 1,292.

Network measure used:	State markets		MSA markets	
	asymmetric density	symmetric density	asymmetric density	symmetric density
network measure	-6.413*** (1.942)	-2.261*** (0.469)	-8.216*** 1.931	-2.327*** 0.417
Potential entrants				
fraction headquartered within 100 miles	1.601*** (0.337)	1.563*** (0.337)	0.651** 0.212	0.638** 0.212
fraction investing in same industry and same area	1.820* (0.838)	1.885* (0.835)	2.913*** 0.601	3.055*** 0.601
fraction investing in same industry but not in area	0.689** (0.265)	0.642* (0.265)	-0.563*** 0.171	-0.562*** 0.171
fraction investing in same area but not in industry	-2.091*** (0.536)	-2.113*** (0.536)	-1.765*** 0.539	-1.733*** 0.538
fraction w/ positive outdegree	2.263*** (0.385)	2.288*** (0.385)	3.262*** 0.394	3.141*** 0.395
Market, state, and industry characteristics ($t-1$)				
fraction of deals syndicated, $t-5$ to $t-1$	0.302 (0.177)	0.290 (0.174)	-0.587*** 0.149	-0.592*** 0.140
1/(# distinct VC firms incumbent in the market)	0.837 (1.508)	-0.146 (1.377)	0.966 1.976	-1.109 1.683
excess investment performance in market	0.177 (0.162)	0.187 (0.163)	-0.129 0.138	-0.127 0.138
value-weighted mean industry book/market ratio	-2.150*** (0.179)	-2.133*** (0.179)	-0.784*** 0.114	-0.874*** 0.117
coeff. variation of monthly no. of deals in market	0.136* (0.060)	0.137* (0.060)	0.070 0.061	0.070 0.061
log inflow into VC funds in industry (\$m)	0.147*** (0.025)	0.147*** (0.025)	0.245*** 0.017	0.240*** 0.017
log no. deals in market	0.059 (0.037)	0.046 (0.037)	0.407*** 0.024	0.392*** 0.024
# science & engineering degrees awarded/1000 inhabitants	0.052 (0.047)	0.057 (0.047)	-0.091** 0.034	-0.085* 0.034
log real GSP (\$m)	-0.996*** (0.254)	-1.032*** (0.255)	-0.037* 0.017	-0.037* 0.017
real GSP growth rate (%)	0.863 (0.632)	0.846 (0.631)	-0.179 0.614	-0.222 0.614
Diagnostics				
Pseudo- R^2	59.1 %	59.2 %	53.2 %	53.3 %

Table III. First-stage Models.

The models are estimated using OLS with fixed (market) effects. The motivation for our two instruments can be found in the text. The entropy of distribution of demand for capital in a given local market is measured as follows. Denote by N the number of investments in a market in the prior five years, and by n_i the number of such investments in zip code area i . Then the market's entropy equals $-\sum_i n_i / N \ln(n_i / N)$. Entropy is lower, the more unequal the geographic distribution of demand. All covariates from the second-stage models are included in the regressions but, to conserve space, their coefficients are not shown. Heteroskedasticity-consistent standard errors (clustered on market) are shown in parentheses. We use $***$, $**$, and $*$ to denote significance at the 0.1%, 1%, and 5% level (two-sided), respectively. In the two specifications where markets are defined as state/industry pairs, the number of distinct markets is 129 and the number of observations (market-years) is 1,375. In the two specifications where markets are defined as MSA/industry pairs, the number of markets is 130 and the number of observations is 1,292.

Dependent variable:	State markets		MSA markets	
	asymmetric density	symmetric density	asymmetric density	symmetric density
Instruments				
entropy of demand distribution	-0.002 [*] (0.001)	-0.017 ^{***} (0.004)	-0.002 ^{***} (0.001)	-0.021 ^{***} (0.003)
fraction of \$ invested by corporate VCs in market	-0.020 ^{***} (0.004)	-0.086 ^{***} (0.015)	-0.007 [*] (0.003)	-0.020 (0.014)
Covariates from 2nd stage				
included but not shown
Diagnostics				
Within-group R^2	60.3 %	54.3 %	68.6 %	60.7 %
F -test: all FE = 0	5.5 ^{***}	5.8 ^{***}	7.2 ^{***}	7.3 ^{***}
Instrument strength test (F -test with critical value of 10)	18.0 ^{***}	24.5 ^{***}	6.4 ^{***}	19.9 ^{***}
Adjusted R^2 from regression of density on instruments only	27.4 %	17.4 %	23.5 %	21.8 %

Table IV. Entry Models using Two-stage Estimators.

The table reports the results of two-stage (instrumental variables) entry models similar to the single-stage entry models shown in Table II. We treat the network measures as endogenous and replace them with the predicted values generated from the regressions shown in Table III. The dependent variables in Panels A through D are the number of deals won by VC firms entering a market in year t , the number of deals entrants were involved as lead VC or syndicate member in the target market in year t , the number of VC firms entering a market that lead-manage syndicates in year t , and the number of VC firms entering in any syndicated position 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-D are estimated using conditional fixed-effects Poisson. The dependent variables in Panels E and F are the fraction of deals by number lead-managed by, or simply involving, entrants in a market in year t . (We obtain qualitatively similar results when we instead use the fraction of deals by *value* won by entrants.) These dependent variables have 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 Panels E and F. 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 parentheses, are based on the Murphy-Topel (1985) adjustment for consistency. We use ***, **, and * to denote significance at the 0.1%, 1%, and 5% level (two-sided), respectively. The number of distinct markets is 129 (state/industry) and 130 (MSA/industry). The number of observations is 1,375 (state/industry) and 1,292 (MSA/industry).

Network measure used:	State markets		MSA markets	
	asymmetric density	symmetric density	asymmetric density	symmetric density
Panel A: Number of deals entrants lead				
instrumented network measure	-29.86*** (8.61)	-4.13* (1.99)	-8.25* (3.31)	-3.21*** (0.73)
Pseudo- R^2	59.4 %	59.3 %	52.7 %	52.9 %
Panel B: Number of deals entrants involved in				
instrumented network measure	-24.20** (7.25)	-4.42*** (1.49)	-11.32*** (3.25)	-2.34*** (0.65)
Pseudo- R^2	71.2 %	71.2 %	63.6 %	63.6 %
Panel C: Number of entrants leading syndicates				
instrumented network measure	-23.04* (9.32)	-4.12* (1.99)	-6.91* (3.41)	-2.71*** (0.69)
Pseudo- R^2	55.7 %	55.7 %	49.8 %	49.9 %
Panel D: Number of entrants				
instrumented network measure	-32.62*** (6.33)	-5.34** (2.00)	-12.22*** (2.92)	-1.86*** (0.51)
Pseudo- R^2	69.2 %	69.2 %	63.5 %	63.4 %
Panel E: Fraction of deals entrants lead				
instrumented network measure	-13.42*** (3.77)	-3.49*** (0.89)	-10.96** (4.25)	-2.80*** (0.89)
R^2	49.0 %	49.1 %	35.2 %	35.4 %
Panel F: Fraction of deals entrants involved in				
instrumented network measure	-14.68*** (3.98)	-2.94*** (0.90)	-13.09*** (4.11)	-2.13** (0.83)
R^2	50.4 %	50.1 %	35.3 %	35.0 %

Table V. Entry Models with Correction for Omitted Variables.

The table reports the results of entry models purged of the effects of omitted variables that are time-varying and either location-specific (C_{lt}) or industry-specific (C_{st}) and that simultaneously affect networking decisions and entry. The omitted variable correction exploits the nested panel structure of our data. This obviates the need for instruments. It consists of augmenting the entry models with proxies for C_{lt} and C_{st} , constructed as $\text{density}_{lst} - \text{mean}(\text{density}_{lst}) - [\text{predicted density}_{lst} - \text{mean}(\text{predicted density}_{lst})]$. To obtain a proxy for C_{lt} , means are computed across locations l and within year t and industry s ; for C_{st} , means are computed across industries s and within year t and location l . Predicted densities are obtained from the models shown in Table III, without instruments. The inclusion of C_{lt} and C_{st} in the entry model removes the effect of the omitted variables from the coefficients estimated for the networking variables, our primary variables of interest. The dependent variables and econometric specifications are the same as for the entry models shown in Table IV. 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 are shown in parentheses. We use ***, **, and * to denote significance at the 0.1%, 1%, and 5% level (two-sided), respectively. The number of distinct markets is 129 (state/industry) and 130 (MSA/industry). The number of observations is 1,375 (state/industry) and 1,292 (MSA/industry).

Network measure used:	State markets		MSA markets	
	asymmetric density	symmetric density	asymmetric density	symmetric density
Panel A: Number of deals entrants lead				
network measure	-25.53*** (5.71)	-9.10*** (1.32)	-19.25* (9.65)	-8.41*** (1.81)
Pseudo- R^2	59.3 %	59.7 %	52.7 %	53.1 %
Panel B: Number of deals entrants involved in				
network measure	-23.23*** (4.70)	-7.43*** (1.11)	-18.71** (7.14)	-6.83*** (1.36)
Pseudo- R^2	71.3 %	71.5 %	63.7 %	63.9 %
Panel C: Number of entrants leading syndicates				
network measure	-21.98*** (5.45)	-8.39*** (1.27)	-19.35** (8.62)	-8.10*** (1.66)
Pseudo- R^2	55.6 %	55.9 %	49.7 %	50.1 %
Panel D: Number of entrants				
network measure	-15.97*** (4.60)	-5.89*** (1.13)	-11.51** (4.44)	-4.20** (1.48)
Pseudo- R^2	69.1 %	69.3 %	63.3 %	63.5 %
Panel E: Fraction of deals entrants lead				
network measure	-10.21* (4.73)	-5.85*** (1.48)	-11.05 (10.63)	-4.76* (2.05)
R^2	48.2 %	49.1 %	35.2 %	35.6 %
Panel F: Fraction of deals entrants involved in				
network measure	-2.25 (5.91)	-3.27** (1.28)	-10.99* (5.04)	-3.49** (1.15)
R^2	49.6 %	50.0 %	35.1 %	35.0 %

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

The dependent variable equals one if the potential entrant enters, and zero otherwise. Where markets are defined as state/industry pairs, there are 1,131 market-years and 3,024 distinct potential entrants. Where markets are defined as MSA/industry pairs, there are 970 market-years and 2,993 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 parentheses. We use ^{***}, ^{**}, and ^{*} to denote significance at the 0.1%, 1%, and 5% level (two-sided), respectively.

Network measure used:	State markets		MSA markets	
	asymmetric density	symmetric density	asymmetric density	symmetric density
network measure	-1.144 [*] (0.454)	-0.406 ^{***} (0.120)	-0.861 [*] (0.425)	-0.340 ^{**} (0.119)
Potential entrants				
=1 if positive outdegree	0.048 ^{***} (0.013)	0.066 ^{***} (0.012)	0.120 ^{***} (0.015)	0.097 ^{***} (0.014)
... x network measure	5.099 ^{***} (0.600)	1.232 ^{***} (0.143)	3.157 ^{***} (0.597)	1.109 ^{***} (0.143)
$\ln(1+\text{assets under management since VC firm's inception})$	0.072 ^{***} (0.002)	0.073 ^{***} (0.002)	0.054 ^{***} (0.002)	0.057 ^{***} (0.002)
=1 if located within 100 miles of center of market	0.528 ^{***} (0.009)	0.530 ^{***} (0.009)	0.583 ^{***} (0.009)	0.580 ^{***} (0.009)
=1 if has invested in same industry and same area (-5 yrs)	0.434 ^{***} (0.011)	0.413 ^{***} (0.011)	0.544 ^{***} (0.012)	0.522 ^{***} (0.012)
=1 if has invested in same industry but not in area (-5 yrs)	0.208 ^{***} (0.008)	0.190 ^{***} (0.008)	0.261 ^{***} (0.008)	0.241 ^{***} (0.009)
=1 if has invested in same area but not in industry (-5 yrs)	0.162 ^{***} (0.012)	0.140 ^{***} (0.013)	0.157 ^{***} (0.016)	0.135 ^{***} (0.016)
Market, state, and industry characteristics ($t-1$)				
excess investment performance in market	0.059 (0.039)	0.062 (0.039)	0.062 (0.039)	0.065 (0.039)
value-weighted mean industry book/market ratio	-0.341 ^{***} (0.023)	-0.337 ^{***} (0.024)	-0.327 ^{***} (0.027)	-0.312 ^{***} (0.028)
coeff. variation of monthly no. of deals in market	0.149 ^{***} (0.015)	0.156 ^{***} (0.015)	0.129 ^{***} (0.016)	0.136 ^{***} (0.015)
log inflow into VC funds in industry (\$m)	0.036 ^{***} (0.004)	0.037 ^{***} (0.004)	0.028 ^{***} (0.004)	0.030 ^{***} (0.004)
log no. deals in market	0.352 ^{***} (0.006)	0.349 ^{***} (0.006)	0.347 ^{***} (0.006)	0.345 ^{***} (0.007)
log real GSP (\$m)	-0.003 (0.005)	-0.003 (0.005)	0.003 (0.003)	0.002 (0.003)
real GSP growth rate	0.529 ^{**} (0.181)	0.543 ^{**} (0.181)	0.425 [*] (0.174)	0.421 [*] (0.174)
Diagnostics				
Pseudo- R^2	15.7 %	15.8 %	16.0 %	16.0 %

Table VII. Incumbents' Reaction to an Increased Threat of Entry.

The unit of observation is an incumbent VC firm, i . The dependent variable is the change in the probability that an incumbent VC firm i is invited to join a syndicate lead-managed by another incumbent operating in the same market. The main variable of interest is an indicator set equal to one if VC firm i co-syndicated with a potential entrant in another market during year $t-1$. This raises the probability of entry in the home market. The table tests the hypothesis that the other incumbents in the home market react by punishing VC firm i by excluding it from some or all of their syndicates for a period of time. We expect the likelihood and severity of punishment to be greater the fewer incumbents are active in the market. We compute the change in syndication probability from year t to each of the next five years as the fraction of rounds lead-managed by the other incumbents that the incumbent VC firm i participates in. Note that VC firms entering after year t (i.e., future incumbents) are not included in this calculation, as they cannot plausibly punish VC firm i . We screen out markets with a monopolist incumbent. The estimation sample size drops over the five years due to attrition as some of the original incumbents reach the end of their economic lives. All regressions are estimated using OLS. Intercepts, year effects, and industry effects are included but not reported. Heteroskedasticity-consistent standard errors are shown in parentheses. We use ***, **, and * to denote significance at the 0.1%, 1%, and 5% level (two-sided), respectively.

	Change in $Pr(\text{invited into syndicate})$, in %, through				
	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
Panel A: State markets					
=1 if syndicated with potential entrant	-0.313 (0.275)	-0.455 (0.258)	-0.253 (0.309)	-0.504 (0.323)	-0.058 (0.346)
... x (5 or fewer incumbents)	-0.806 (0.744)	-1.843** (0.724)	-3.263*** (0.853)	-2.864** (0.910)	-4.283*** (1.004)
VC firm's size (\$ under mgmt.)	0.283** (0.101)	0.461*** (0.098)	0.550*** (0.119)	0.631*** (0.137)	0.728*** (0.133)
VC firm's <i>degree</i>	-0.015 (0.022)	-0.071** (0.021)	-0.076** (0.024)	-0.097*** (0.025)	-0.128*** (0.023)
Adjusted R^2	0.5 %	1.2 %	1.4 %	1.5 %	2.5 %
No. of observations	12,619	11,361	9,913	8,293	7,228
Panel B: MSA markets					
=1 if syndicated with potential entrant	-0.481 (0.400)	-0.360 (0.450)	-0.617 (0.435)	-0.735 (0.543)	0.013 (0.592)
... x (5 or fewer incumbents)	-1.747* (0.722)	-0.502 (0.796)	-2.942*** (0.859)	-3.816*** (0.928)	-2.912** (0.944)
VC firm's size (\$ under mgmt.)	0.698*** (0.122)	0.679*** (0.136)	0.932*** (0.145)	1.111*** (0.170)	1.200*** (0.181)
VC firm's <i>degree</i>	-0.093*** (0.026)	-0.086** (0.028)	-0.120*** (0.028)	-0.157*** (0.031)	-0.206*** (0.031)
Adjusted R^2	1.0 %	1.0 %	2.2 %	2.5 %	2.4 %
No. of observations	11,348	10,053	8,475	6,960	5,878

Table VIII. 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. Markets are defined either as state/industry pairs or as MSA/industry pairs. In the latter definition, we lose some observations due to missing zip codes. Year effects are jointly and individually insignificant and so excluded. Intercepts are not shown. Standard errors are shown in parentheses. We use ^{***}, ^{**}, and ^{*} to denote significance at the 0.1%, 1%, and 5% level (two-sided), respectively.

Network measure used:	Dependent variable: log valuation			
	State markets		MSA markets	
	asymmetric density	symmetric density	asymmetric density	symmetric density
network measure	-12.503 ^{***} (2.361)	-3.898 ^{***} (0.685)	-10.657 ^{***} (2.135)	-4.227 ^{***} (0.682)
fraction of deals won by entrants in previous year	0.616 ^{***} (0.122)	0.648 ^{***} (0.123)	0.353 ^{**} (0.112)	0.385 ^{***} (0.112)
Lead investor characteristics				
=1 if lead investor in current round is entrant	0.283 ^{***} (0.027)	0.282 ^{***} (0.027)	0.262 ^{***} (0.027)	0.259 ^{***} (0.027)
investment experience (log dollars under management)	0.076 ^{***} (0.004)	0.075 ^{***} (0.004)	0.069 ^{***} (0.004)	0.068 ^{***} (0.004)
Market, state, and industry characteristics				
value-weighted mean industry book/market ratio	-0.392 ^{**} (0.141)	-0.349 [*] (0.141)	-0.550 ^{***} (0.146)	-0.432 ^{**} (0.146)
price index of publicly traded equity in same industry	0.286 ^{***} (0.025)	0.288 ^{***} (0.025)	0.308 ^{***} (0.026)	0.310 ^{***} (0.026)
log inflow into VC funds in industry (\$m)	0.140 ^{***} (0.012)	0.142 ^{***} (0.012)	0.135 ^{***} (0.013)	0.136 ^{***} (0.013)
log no. deals in market	0.030 (0.039)	0.004 (0.040)	0.032 (0.038)	0.004 (0.039)
proxy for omitted location-specific variable	9.048 (4.894)	3.197 ^{**} (1.134)	4.417 (4.335)	1.299 (0.924)
proxy for omitted industry-specific variable	1.909 (2.948)	0.554 (0.673)	7.310 (3.855)	3.911 ^{***} (0.990)
Company characteristics				
=1 if seed or early-stage	-0.658 ^{***} (0.023)	-0.656 ^{***} (0.023)	-0.644 ^{***} (0.026)	-0.642 ^{***} (0.026)
=1 if second funding round	0.460 ^{***} (0.027)	0.460 ^{***} (0.027)	0.487 ^{***} (0.030)	0.488 ^{***} (0.030)
=1 if third funding round	0.800 ^{***} (0.031)	0.799 ^{***} (0.031)	0.848 ^{***} (0.035)	0.847 ^{***} (0.035)
=1 if fourth or later funding round	0.964 ^{***} (0.030)	0.963 ^{***} (0.030)	1.035 ^{***} (0.033)	1.034 ^{***} (0.033)
Diagnostics				
Adjusted R^2	40.1 %	40.1 %	41.5 %	41.6 %
No. of rounds	11,106	11,106	9,003	9,003

Table IX. 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 VIII. Panel A corrects the OLS-with-market-fixed-effects specification shown in Table VIII 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 B 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 C combines the selection correction of Panel B with the two-level model of Panel C. Standard errors are shown in parentheses. We use ^{***}, ^{**}, and ^{*} to denote significance at the 0.1%, 1%, and 5% level (two-sided), respectively.

Network measure used:	Dependent variable: log valuation			
	State markets		MSA markets	
	asymmetric density	symmetric density	asymmetric density	symmetric density
Panel A: Heckman-selection corrected model				
Network measure	-10.983 ^{***} (2.377)	-3.449 ^{***} (0.690)	-9.014 ^{***} (2.151)	-3.671 ^{***} (0.688)
fraction of deals won by entrants in previous year	0.631 ^{***} (0.122)	0.659 ^{***} (0.122)	0.380 ^{***} (0.112)	0.408 ^{***} (0.112)
=1 if lead investor in current round is entrant	0.292 ^{***} (0.027)	0.291 ^{***} (0.027)	0.271 ^{***} (0.027)	0.269 ^{***} (0.027)
inverse Mill's ratio	0.118 ^{***} (0.021)	0.115 ^{***} (0.023)	0.146 ^{***} (0.025)	0.140 ^{***} (0.026)
Panel B: Two-level mixed effects model				
network measure	-9.094 ^{***} (2.116)	-2.721 ^{***} (0.610)	-9.934 ^{***} (1.929)	-3.521 ^{***} (0.612)
fraction of deals won by entrants in previous year	0.478 ^{***} (0.104)	0.492 ^{***} (0.104)	0.347 ^{***} (0.096)	0.364 ^{***} (0.096)
=1 if lead investor in current round is entrant	0.221 ^{***} (0.024)	0.220 ^{***} (0.024)	0.211 ^{***} (0.024)	0.210 ^{***} (0.024)
LR test vs. linear model (χ^2)	2,391.0 ^{***}	2,425.6 ^{***}	1,979.6 ^{***}	1,977.0 ^{***}
Panel C: Heckman-correct mixed effects model				
network measure	-7.245 ^{***} (2.135)	-2.165 ^{***} (0.617)	-8.127 ^{***} (1.944)	-2.902 ^{***} (0.619)
fraction of deals won by entrants in previous year	0.487 ^{***} (0.104)	0.499 ^{***} (0.104)	0.373 ^{***} (0.096)	0.388 ^{***} (0.096)
=1 if lead investor in current round is entrant	0.229 ^{***} (0.024)	0.227 ^{***} (0.024)	0.219 ^{***} (0.024)	0.219 ^{***} (0.024)
inverse Mill's ratio	0.127 ^{***} (0.021)	0.124 ^{***} (0.021)	0.152 ^{***} (0.023)	0.149 ^{***} (0.023)
LR test vs. linear model (χ^2)	2,424.8 ^{***}	2,456.5 ^{***}	2,019.1 ^{***}	2,013.0 ^{***}

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Internet Appendix to
Networking as a Barrier to Entry
and the Competitive Supply of Venture Capital*

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This Internet Appendix contains three supplemental tables augmenting the empirical evidence provided in the main body of the paper.

Supplemental Table I below breaks down our six entry measures by quintile of network density. In the case of the number of entrants or the number of deals, more densely networked markets are associated with less entry. This holds for the full sample, in the most active VC markets (Silicon Valley and Route 128, or California and Massachusetts), and when we partition the sample in 1993. In the case of the fraction of deals entrants lead or are involved in, we do not find a monotonic relation in this simple cut. As we show in the paper, the raw correlation appears to cover up the evidence of strategic behavior among VCs we find in our multivariate specifications.

Supplemental Tables II and III demonstrate the robustness of our empirical results to ignoring potential entrants located more than 100 miles away. As shown in the tables, we continue to find a negative relation between entry and network density in every specification, and while some coefficients are more noisily estimated, their economic magnitudes are similar to those reported in the paper. The results are statistically weakest for the fraction of deals proximate entrants lead.

Supplemental Table AI. Descriptive Analysis of Network Density and Market Entry.

The table presents a breakdown of various measures of entry across markets, from the least densely-networked quintile of markets to the most densely-networked, based on symmetric density. We present breakdowns over sub-periods as well as separately for the major VC markets of Silicon Valley in California and Route 128 in Massachusetts.

	State markets					MSA markets				
	Q1 (least dense)	Q2	Q3	Q4 (most dense)	Q5	Q1 (least dense)	Q2	Q3	Q4 (most dense)	Q5
All markets, 1980-2003										
Number of deals entrants lead	15.8	9.6	7.1	5.6	4.1	13.3	6.6	5.2	4.3	3.7
Number of deals entrants involved in	24.2	13.7	10.8	9.1	6.3	20.6	10.0	8.1	7.1	5.9
Number of entrants leading syndicates	13.1	8.2	6.2	4.9	3.6	11.2	5.7	4.5	3.8	3.3
Number of entrants	25.0	16.0	13.0	11.5	8.0	23.1	11.9	10.1	9.6	7.8
Fraction of deals entrants lead	31.6	32.8	29.3	26.9	30.8	28.9	27.7	25.9	26.7	27.2
Fraction of deals entrants involved in	40.8	43.1	40.1	39.5	42.8	39.5	40.0	38.7	42.3	40.7
All markets, 1980-1992										
Number of deals entrants lead	5.6	6.5	5.2	5.4	3.2	4.9	3.9	3.6	4.1	3.4
Number of deals entrants involved in	8.9	11.2	9.2	10.1	4.6	7.3	6.7	6.8	7.7	5.3
Number of entrants leading syndicates	4.9	5.7	4.7	4.8	2.8	4.4	3.5	3.3	3.7	3.0
Number of entrants	10.7	13.6	12.5	12.1	6.6	9.2	8.8	9.6	10.8	7.1
Fraction of deals entrants lead	21.3	23.6	25.1	24.9	28.9	23.8	23.2	21.8	22.5	27.7
Fraction of deals entrants involved in	29.8	34.9	38.6	38.3	40.4	34.0	36.3	37.5	39.5	40.3
All markets, 1993-2003										
Number of deals entrants lead	16.8	13.7	9.9	7.1	4.6	13.4	11.1	6.7	5.6	4.1
Number of deals entrants involved in	25.2	20.9	13.9	10.0	6.5	21.2	16.8	10.1	8.3	5.8
Number of entrants leading syndicates	13.9	11.5	8.5	6.2	4.1	11.3	9.4	5.7	4.8	3.6
Number of entrants	25.5	22.8	16.5	11.8	7.9	23.0	19.6	11.9	10.4	7.4
Fraction of deals entrants lead	30.7	35.6	37.1	32.2	32.8	27.7	31.8	26.7	29.9	30.6
Fraction of deals entrants involved in	39.4	46.0	48.3	42.8	44.5	38.3	44.0	39.8	43.7	43.4
CA and MA (or SV/128), 1980-2003										
Number of deals entrants lead	31.8	10.9	8.8	7.3	11.2	17.3	7.0	5.5	4.0	5.2
Number of deals entrants involved in	60.0	20.1	15.8	15.5	22.6	31.0	11.8	9.7	7.9	9.3
Number of entrants leading syndicates	25.5	9.4	7.6	6.5	9.4	14.7	6.0	4.8	3.6	4.4
Number of entrants	55.0	22.0	17.9	18.3	25.1	34.2	13.8	12.0	10.2	12.5
Fraction of deals entrants lead	15.7	14.7	16.4	14.8	23.4	21.8	21.5	21.9	20.6	28.8
Fraction of deals entrants involved in	26.9	26.7	28.6	28.4	41.6	34.2	36.3	37.6	37.1	47.2
Other markets, 1980-2003										
Number of deals entrants lead	12.6	8.7	6.6	4.5	3.4	11.4	6.1	5.2	4.2	3.1
Number of deals entrants involved in	17.0	11.3	8.6	6.2	4.7	15.6	8.4	7.2	6.2	4.4
Number of entrants leading syndicates	10.7	7.5	5.7	4.0	3.0	9.6	5.2	4.4	3.7	2.8
Number of entrants	19.0	13.9	10.9	8.1	6.5	17.6	10.2	9.1	8.5	5.9
Fraction of deals entrants lead	34.1	37.3	35.7	29.4	30.5	32.5	30.8	29.9	28.7	26.5
Fraction of deals entrants involved in	43.0	47.0	46.1	40.6	42.4	42.3	42.0	40.8	42.9	38.1

Supplemental Table AII. Entry Models using Two-stage Estimators (Nearby Entrants Only).

The table reports a variant of the Table IV two-stage (instrumental variables) entry models. Unlike in Table IV, the dependent variables measure entry only by VC firms that are located within 100 miles of the center of the target market. We treat the network measures as endogenous and replace them with the predicted values generated from the regressions shown in Table III in the paper. The dependent variables in Panels A through D are the number of deals won by nearby VC firms entering a market in year t , the number of deals nearby entrants were involved as lead VC or syndicate member in the target market in year t , the number of nearby VC firms entering a market that lead-manage syndicates in year t , and the number of nearby VC firms entering in any syndicated position 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-D are estimated using conditional fixed-effects Poisson. The dependent variables in Panels E and F are the fraction of deals by number lead-managed by, or simply involving, nearby entrants in a market in year t . (We obtain qualitatively similar results when we instead use the fraction of deals by *value* won by nearby entrants.) These dependent variables have 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 Panels E and F. 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 for consistency. We use ^{***}, ^{**}, ^{*}, and ⁺ to denote significance at the 0.1%, 1%, 5%, and 10% level (two-sided), respectively. The number of distinct markets is 129 (state/industry) and 130 (MSA/industry). The number of observations is 1,375 (state/industry) and 1,292 (MSA/industry).

Network measure used:	State markets		MSA markets	
	asymmetric density	symmetric density	asymmetric density	symmetric density
Panel A: Number of deals entrants lead				
instrumented network measure	-22.847 ^{***} <i>(7.042)</i>	-4.927 ^{**} <i>(1.632)</i>	-5.685 <i>(7.009)</i>	-1.586 <i>(1.456)</i>
Pseudo- R^2	51.3 %	51.3 %	47.4 %	47.4 %
Panel B: Number of deals entrants involved in				
instrumented network measure	-29.528 ^{***} <i>(5.352)</i>	-5.557 ^{***} <i>(1.222)</i>	-11.676 [*] <i>(5.583)</i>	-2.079 ⁺ <i>(1.133)</i>
Pseudo- R^2	65.0 %	64.9 %	59.9 %	59.9 %
Panel C: Number of entrants leading syndicates				
instrumented network measure	-26.905 ^{***} <i>(7.677)</i>	-5.583 ^{**} <i>(1.787)</i>	-8.793 [*] <i>(4.147)</i>	-1.626 <i>(1.577)</i>
Pseudo- R^2	48.3 %	48.3 %	44.6 %	44.6 %
Panel D: Number of entrants				
instrumented network measure	-29.798 ^{***} <i>(5.423)</i>	-5.422 ^{***} <i>(1.239)</i>	-15.472 ^{**} <i>(5.644)</i>	-2.252 [*] <i>(1.142)</i>
Pseudo- R^2	60.9 %	60.8 %	58.1 %	58.0 %
Panel E: Fraction of deals entrants lead				
instrumented network measure	-11.946 ⁺ <i>(6.822)</i>	-2.087 <i>(1.404)</i>	-9.983 ⁺ <i>(5.943)</i>	-1.498 <i>(1.614)</i>
R^2	24.0 %	23.9 %	24.0 %	24.2 %

Panel F: Fraction of deals entrants involved in

instrumented network measure

-13.346*	-1.600*	-13.472*	-1.490
(5.832)	(0.731)	(5.768)	(1.264)
R^2	29.9 %	38.6 %	34.7 %
			34.5 %

Supplemental Table AIII.**Entry Models with Correction for Omitted Variables (Nearby Entrants Only).**

The table reports the results of entry models purged of the effects of omitted variables that are time-varying and either location-specific (C_{lt}) or industry-specific (C_{st}) and that simultaneously affect networking decisions and entry. The omitted variable correction exploits the nested panel structure of our data. This obviates the need for instruments. It consists of augmenting the entry models with proxies for C_{lt} and C_{st} , constructed as $\text{density}_{lst} - \text{mean}(\text{density}_{lst}) - [\text{predicted density}_{lst} - \text{mean}(\text{predicted density}_{lst})]$. To obtain a proxy for C_{lt} , means are computed across locations l and within year t and industry s ; for C_{st} , means are computed across industries s and within year t and location l . Predicted densities are obtained from the models shown in Table III, without instruments. The inclusion of C_{lt} and C_{st} in the entry model removes the effect of the omitted variables from the coefficients estimated for the networking variables, our primary variables of interest. The dependent variables and econometric specifications are the same as for the entry models shown in Supplemental Table 2 above. 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 are shown in italics. We use ^{***}, ^{**}, ^{*}, and ⁺ to denote significance at the 0.1%, 1%, 5%, and 10% level (two-sided), respectively. The number of distinct markets is 129 (state/industry) and 130 (MSA/industry). The number of observations is 1,375 (state/industry) and 1,292 (MSA/industry).

Network measure used:	State markets		MSA markets	
	asymmetric density	symmetric density	asymmetric density	symmetric density
Panel A: Number of deals entrants lead				
network measure	-28.629 ^{**} <i>(10.592)</i>	-8.951 ^{***} <i>(2.409)</i>	-26.770 [*] <i>(11.895)</i>	-8.464 ^{**} <i>(3.052)</i>
Pseudo- R^2	51.6 %	51.8 %	47.5 %	47.7 %
Panel B: Number of deals entrants involved in				
network measure	-21.227 ^{**} <i>(7.885)</i>	-5.819 ^{***} <i>(1.705)</i>	-17.222 [*] <i>(8.619)</i>	-6.685 ^{**} <i>(2.237)</i>
Pseudo- R^2	65.3 %	65.5 %	60.0 %	59.1 %
Panel C: Number of entrants leading syndicates				
network measure	-24.865 ^{**} <i>(9.472)</i>	-8.676 ^{***} <i>(2.184)</i>	-26.310 [*] <i>(13.717)</i>	-8.366 ^{**} <i>(2.760)</i>
Pseudo- R^2	48.5 %	48.6 %	44.6 %	44.7 %
Panel D: Number of entrants				
network measure	-29.500 ^{***} <i>(9.237)</i>	-5.344 ^{**} <i>(1.854)</i>	-21.236 [*] <i>(10.767)</i>	-4.578 [*] <i>(2.267)</i>
Pseudo- R^2	56.5 %	56.5 %	56.4 %	56.5 %
Panel E: Fraction of deals entrants lead				
network measure	-22.433 [*] <i>(10.957)</i>	-3.513 ^{**} <i>(1.284)</i>	-23.864 ⁺ <i>(14.088)</i>	-5.426 ⁺ <i>(3.059)</i>
R^2	23.9 %	23.7 %	24.1 %	24.6 %
Panel F: Fraction of deals entrants involved in				
network measure	-7.504 <i>(9.383)</i>	-1.334 <i>(1.853)</i>	-13.452 <i>(13.069)</i>	-3.205 <i>(2.543)</i>
R^2	29.6 %	29.5 %	34.9 %	35.5 %