LSE RICAFE

Working Paper NO. 026

Whom You Know Matters: Venture Capital Networks and Investment Performance

Yael Hochberg
Kellogg School of Management, Northwestern University

Alexander Ljungqvist
Stern School of Business, New York University and CEPR

Yang Lu
Stern School of Business, New York University

April 2006

RICAFE - Risk Capital and the Financing of European Innovative Firms

A project financed by the European Commission, DG Research
Improving the Human Potential and the Socio- Economic Knowledge Base Programme.
Contract No : HPSE-CT-2002-00140

Financial Markets Group, London School of Economics and Political Sciences
Department of Economics and Finance, Turin University.
Centre for Financial Studies - CFS (Frankfurt)
Haute Etudes Commerciales - HEC (Paris)

Whom You Know Matters:
Venture Capital Networks and Investment Performance

YAEL HOCHBERG, ALEXANDER LJUNGQVIST,
and YANG LU *

ABSTRACT

Many financial markets are characterized by strong relationships and networks, rather than arm's-length, spot market transactions. We examine the performance consequences of this organizational structure in the context of relationships established when VCs syndicate portfolio company investments. We find that better-networked VC firms experience significantly better fund performance, as measured by the proportion of investments that are successfully exited through an IPO or a sale to another company. Similarly, the portfolio companies of better-networked VCs are significantly more likely to survive to subsequent financing and eventual exit. We also provide initial evidence on the evolution of VC networks.

* Hochberg is from the Northwestern University Kellogg School of Management, Ljungqvist is from the New York University Stern School of Business and the Centre for Economic Policy Research, London, and Lu is from the New York University Stern School of Business. Thanks for helpful comments and suggestions go to Viral Acharya, Steve Drucker, Jan Eberly, Eric Green, Yaniv Grinstein, David Hsu, Josh Lerner, Laura Lindsey, Max Maksimovic, Roni Michaely, Maureen O'Hara, Mitch Petersen, Ludo Phalippou, Jesper Sorensen, Morten Sorensen, Rob Stambaugh (the editor), Per Strömberg, an anonymous referee, and seminar participants at the University of Amsterdam, Bar Ilan University, Binghamton University, Cornell University, London Business School, Northwestern University, the Stockholm School of Economics, Tel Aviv University, the University of Texas at Austin, Tilburg University, the University of Utah, the Spring 2005 National Bureau of Economic Research (NBER) Entrepreneurship meeting, and the 2005 Western Finance Association meetings.

Networks are widespread in many financial markets. Bulge-bracket investment banks, for instance, make use of strong relationships with institutional investors when pricing and distributing corporate securities (Cornelli and Goldreich (2001)). In the corporate loan market, banks often prefer syndicating loans with other banks over being the sole lender. Similarly, in the primary equity and bond markets, banks tend to co-underwrite securities offerings with banks with which they have long-standing relationships with (Ljungqvist, Marston, and Wilhelm (2005)).

Networks also feature prominently in the venture capital (VC) industry. VCs tend to syndicate their investments with other VCs, rather than investing alone (Lerner (1994a)). They are thus bound by their current and past investments into webs of relationships with other VCs. Once they have invested in a company, VCs draw on their networks of service providers – head hunters, patent lawyers, investment bankers etc. – to help the company succeed (Gorman and Sahlman (1989), Sahlman (1990)). Indeed, one prominent VC goes as far as describing itself as a venture keiretsu (Lindsey (2005), Hsu (2004)). In short, many VCs show a preference for networks rather than arm's-length, spot-market transactions.

While the literature documents the prevalence of networks in many financial markets, the performance consequences of this organizational structure remain largely unknown. In the venture capital market, for instance, some VCs presumably have better-quality relationships and hence enjoy more influential network positions than others, implying differences in clout, investment opportunity sets, access to information, etc. across VCs. In this study, we ask whether these differences help explain the cross-section of VC investment performance.

We focus on the coinvestment networks that VC syndication gives rise to. Syndication relationships are a natural starting point not only because they are easy to observe, but also because there are good reasons to believe they affect the two main drivers of a VC's performance, namely, the ability to source high-quality deal flow (i.e., select promising companies) and the ability to nurture investments (i.e., add value to portfolio companies).[1] Our results suggest both factors are at play.

There are at least three reasons to expect that syndication networks improve the quality of deal flow. First, VCs invite others to coinvest in their promising deals in the expectation of future reciprocity (Lerner (1994a)). Second, by checking each other's willingness to invest in potentially promising deals, VCs can pool correlated signals and thereby select better investments in situations of often extreme uncertainty

about the viability and return potential of investment proposals (Wilson (1968), Sah and Stiglitz (1986)). Third, individual VCs tend to have investment expertise that is both sector-specific and location-specific. Syndication helps diffuse information across sector boundaries and expands the spatial radius of exchange, allowing VCs to diversify their portfolios (Stuart and Sorensen (2001)).

In addition to improving deal flow, syndication networks may also help VCs add value to their portfolio companies. Syndication networks facilitate the sharing of information, contacts, and resources among VCs (Bygrave (1988)), for instance by expanding the range of launch customers or strategic alliance partners for their portfolio companies. No less importantly, strong relationships with other VCs likely improve the chances of securing follow-on VC funding for portfolio companies, and may indirectly provide access to other VCs' relationships with service providers such as headhunters and prestigious investment banks.

An examination of the performance consequences of VC networks requires measures of how well networked a VC is. We borrow these measures from graph theory, a mathematical discipline widely used in economic sociology.[2] Graph theory provides us with tools for measuring the relative importance, or "centrality," of each actor in a network. These tools capture five different aspects of a VC firm's influence: The number of VCs with which it has a relationship, as a proxy for the information, deal flow, expertise, contacts, and pools of capital it has access to; the frequency with which it is invited to coinvest in other VCs' deals, thereby expanding its investment opportunity set; its ability to generate such coinvestment opportunities in the future by syndicating its own deals today in the hope of future payback from its syndication partners; its access to the best-connected VCs; and its ability to act as an intermediary, bringing together VCs with complementary skills or investment opportunities that lack a direct relationship between them.

We also require data on the performance of VC investments. We examine the performance of both the VC fund and the fund's portfolio companies. At the fund level, in the absence of publicly available data on VC fund returns, we examine "exit rates," defined as the fraction of portfolio companies that are successfully exited via an initial public offering (IPO) or a sale to another company. At the portfolio company level, we examine not only whether the portfolio company achieves a successful exit, but also whether it survives to obtain an additional round of funding.

Controlling for other known determinants of VC fund performance such as fund size (Kaplan and

Schoar (2005)) as well as the competitive funding environment and the investment opportunities available to the VC (Gompers and Lerner (2000)), we find that VCs that are better-networked at the time a fund is raised subsequently enjoy significantly better fund performance, as measured by the rate of successful portfolio exits over the next ten years. Comparing our five centrality measures suggests that the size of a VC firm's network, its tendency to be invited into other VCs' syndicates, and its access to the best-networked VCs have the largest effect economically, while an ability to act as an intermediary in bringing other VCs together plays less of a role. The economic magnitude of these effects is meaningful: Depending on the specification, a one-standard deviation increase in network centrality increases exit rates by around 2.5 percentage points from the 34.2% sample average. Using limited data on fund internal rates of returns (IRRs) disclosed following recent Freedom of Information Act lawsuits, we estimate that this is roughly equivalent to a 2.5 percentage point increase in fund IRR from the 15% sample average.

When we examine performance at the portfolio company level, we find that a VC's network centrality has a positive and significant effect on the probability that a portfolio company survives to a subsequent funding round or exits successfully. This effect is economically large. For instance, the survival probability in the first funding round increases from the unconditional expectation of 66.8% to 72.4% for a one-standard deviation increase in the lead VC's network centrality.

Our tests suggest that network centrality does not merely proxy for privileged access to better deal flow. While access to deal flow is important, well-networked VCs appear to perform better because they are able to provide better value-added services to their portfolio companies.

Perhaps the leading alternative explanation for the performance-enhancing role of VC networking is simply experience (e.g., Kaplan, Martel, and Strömberg (2003)). It seems plausible that the better-networked VCs are also the older and more experienced VCs. To rule out the possibility that our measures of network centrality merely proxy for experience, our models explicitly control for a variety of dimensions of VC experience. Interestingly, once we control for VC networks, the beneficial effect of experience on performance is reduced, and in some specifications, even eliminated. It is also not the case that the better-networked VCs are simply the VCs with better past performance records: While we do find evidence of performance persistence from one fund to the next, our measures of network centrality continue to have a positive and significant effect on fund exit rates when we control for persistence.

The way we construct the centrality measures makes it unlikely that our results are driven simply by reverse causality (that is, the argument that superior performance enables VCs to improve their network positions, rather than the other way around). For a fund of a given vintage year, measures of network centrality are constructed from syndication data for the five preceding years. Performance is then taken as the exit rate over the life of the fund, which lasts 10 to 12 years. Thus, we relate a VC firm's past network position to its future performance. Moreover, we find little evidence that past exits drive future network position. Instead, what appears to be key in improving a VC firm's network position is demonstrating skill in selecting, and adding value to, investments.

Our main results are based on centrality measures derived from syndication networks that span all industries and the entire United States. To the extent that VC networks are geographically concentrated or industry-specific, this may underestimate a VC's network centrality. We therefore repeat our analysis using industry-specific networks and a separate network of VC firms in California, the largest VC market in the U.S. Not only are our results robust to these modifications, but their economic significance increases substantially. In the California network, for instance, the economic effect of better network positioning is twice as large as in the country-wide network.

Our contribution is fivefold. First, this is the first paper to examine the performance consequences of the VC industry's predominant choice of organizational form: Networks. Previous work focuses on describing the structure of syndication networks (Bygrave (1988), Stuart and Sorensen (2001)) and motivating the use of syndication (Lerner (1994a), Podolny (2001), Brander, Amit, and Antweiler (2002)). Second, our findings shed light on the industrial organization of the VC market. Like many financial markets, the VC market differs from the traditional arm's-length spot markets of classical microeconomics. The high network returns we document suggest that enhancing one's network position should be an important strategic consideration for an incumbent VC, while presenting a potential barrier to entry for new VCs. Our results add nuance to Hsu's (2004) finding that portfolio companies are willing to pay to be backed by brand-name VCs and suggest that there are real performance consequences to the contractual differences illustrated in Robinson and Stuart's (2004) work on strategic alliances. Third, our findings have ramifications for institutional investors choosing VC funds which to invest in, as better-networked VCs appear to perform better. Fourth, our analysis provides a deeper understanding of the possible drivers of

cross-sectional performance of VC funds, and points to the importance of additional fundamentals beyond those previously documented in the academic literature. Finally, we provide preliminary evidence regarding the evolution of a VC firm's network position.

The remainder of the paper is organized as follows. Section I provides an overview of network analysis techniques. We present a simple example illustrating network analysis in the Appendix. Section II describes our data. Sections III and IV analyze the effect of VC networking on fund performance and portfolio company survival, respectively. Section V explores whether networking boosts performance by enabling the VC to provide better value-added services. Section VI presents robustness checks. Section VII investigates how a VC becomes influential in the VC network. Finally, Section VIII concludes.

I. Network Analysis Methodology

Network analysis aims to describe the structure of networks by focusing on the relationships that exist among a set of economic actors. A key aim is to identify influential actors. Influence is measured by how "central" an actor's network position is, based on the extent of his involvement in relationships with others. Network analysis uses graph theory to make the concept of centrality more precise.[3] Consider the network illustrated in Figure 1, which graphs the syndication relationships among U.S. biotech-focused VCs over the period 1990 through 1994.[4] VC firms are represented as nodes and arrows represent the ties among them. Arrows point from the originator of the tie (the VC leading the syndicate in question) to the receiver (the VC invited to coinvest in the portfolio company). Visually, it appears that two firms – 826 and 2584 – are the most "central" in this network, in the sense that they are connected to the most VC firms, and that firm 826 is invited to join other VCs' syndicates most often.

FIGURE I APPROXIMATELY HERE

In graph theory, a network such as the one illustrated in Figure 1 is represented by a square "adjacency" matrix, the cells of which reflect the ties among the actors in the network. In our setting, we code two VCs coinvesting in the same portfolio company as having a tie.[5] Adjacency matrices can be "directed" or "undirected." Only directed matrices differentiate between the originator and the receiver of a tie. (Figure 1 illustrates a directed network.) In our setting, an undirected adjacency matrix records as a tie any participation by both VC firm i and VC firm j in a syndicate. The directed adjacency matrix differentiates between syndicates led by VC i versus those led by VC j.[6]

Networks are not static. Relationships may change, and entry to and exit from the network may change each VC's centrality. We therefore construct our adjacency matrices over trailing five-year windows. Using these matrices, we construct five centrality measures based on three popular concepts of centrality, specifically, degree, closeness, and betweenness. Using a numerical example, the Appendix shows in detail how these centrality measures are constructed. Here, we focus on how each measure captures a slightly different aspect of a VC's economic role in the network.

A. Degree Centrality

Degree centrality measures the number of relationships an actor in the network has. The more ties, the more opportunities for exchange and so the more influential, or central, the actor. VCs that have ties to many other VCs may be in an advantaged position. Since they have many ties, they are less dependent on any one VC for information or deal flow. In addition, they may have access to a wider range of expertise, contacts, and pools of capital. Formally, degree counts the number of unique ties each VC has, that is, the number of unique VCs with which a VC has coinvested. Let $p_{ij} = 1$ if at least one syndication relationship exists between VCs i and j, and zero otherwise. VC i's *degree* then equals $\Sigma_j p_{ij}$.

In undirected data, VCs' degrees differ merely as a result of the number of ties they have. In directed data, we can distinguish between VCs who receive many ties (i.e., are invited to be syndicate members by many lead VCs) and those who originate many ties (i.e., lead syndicates with many other VC members). This gives rise to the following two directed measures of degree centrality.

The first, *indegree*, measures the frequency with which a VC firm is invited to coinvest in other VCs' deals, thereby expanding its investment opportunity set and providing it access to information and resources it otherwise may not have had access to. Formally, let $q_{ji} = 1$ if at least one syndication relationship exists in which VC j is the lead investor and VC i is a syndicate member, and zero otherwise. VC i's *indegree* then equals $\Sigma_j q_{ji}$.

The second, *outdegree*, measures a VC's ability to generate future coinvestment opportunities by inviting others into its syndicates today (i.e., reciprocity). Outdegree counts the number of other VCs a VC firm has invited into its own syndicates. Formally, VC i's *outdegree* equals $\Sigma_j q_{ij}$.

Clearly, all three degree centrality measures are a function of network size, which in our data set varies over time due to entry and exit by VCs. To ensure comparability over time, we normalize each measure by

dividing by the maximum possible degree in an n-actor network (i.e., n–1).[7]

B. Closeness

While degree counts the number of relationships an actor has, closeness takes into account their "quality." A particularly useful measure of closeness is "eigenvector centrality" (Bonacich (1972, 1987)), which weights an actor's ties to others by the importance of the actors he is tied to. In essence, eigenvector centrality is a recursive measure of degree, whereby the actor's centrality is defined as the sum of his ties to other actors weighted by their respective centralities. In our setting, eigenvector centrality measures the extent to which a VC is connected to other well-connected VCs. Formally, VC i's eigenvector centrality is given by $ev_i = \Sigma_j\, p_{ij}\, ev_j$.[8] This is normalized by the highest possible *eigenvector* centrality measure in a network of n actors.

C. Betweenness

Betweenness attributes influence to actors on whom many others must rely to make connections within the network. In our setting, betweenness proxies for the extent to which a VC may act as an intermediary by bringing together VCs with complementary skills or investment opportunities that lack a direct relationship between them. Formally, let b_{jk} be the proportion of all paths linking actors j and k that pass through actor i. Actor i's *betweenness* is defined as $\Sigma\, b_{jk}\ \forall\ i \neq j \neq k$. Again, we normalize by dividing by the maximum *betweenness* in an n-actor network.

II. Sample and Data

The data for our analysis come from Thomson Financial's Venture Economics database. Venture Economics began compiling data on venture capital investments in 1977, backfilling to the early 1960s. Most VC funds are structured as closed-end, often ten-year, limited partnerships. They are not usually traded, nor do they disclose fund valuations. The typical fund spends its first three or so years selecting companies to invest in, and then nurtures them over the next few years (Ljungqvist, Richardson, and Wolfenzon (2005)). In the second half of the fund's life, successful portfolio companies are exited via IPOs or sales to other companies generating capital inflows that are distributed to the fund's investors. At the end of the fund's life, any remaining portfolio holdings are sold or liquidated and the proceeds distributed to investors.

Owing to this investment cycle, relatively recent funds have not yet operated for sufficiently long to

measure their lifetime performance. Simply excluding such funds is sometimes felt to result in performance measures that do not reflect the changes in, and current state of, the VC industry. As a compromise, Kaplan and Schoar (2005) and Jones and Rhodes-Kropf (2003) consider all funds raised up to and including 1999, but also show robustness to excluding funds that have not yet completed their ten-year runs as of the end of their sample period. In the same spirit, we consider all investments made by VC funds raised between 1980 and 1999 that are included in the Venture Economics database. We begin in 1980 because venture capital as an asset class that attracts institutional investors has only existed since then.[9] Closing the sample period at year-end 1999 provides at least four years of operation for the youngest funds, using November 2003 as the latest date for measuring fund performance. Our results are robust to excluding funds that have not yet completed their ten-year lives.

We concentrate solely on investments by U.S.-based VC funds, and exclude those by angels and buyout funds. We distinguish between *funds* and *firms*. While VC funds have a limited (usually ten-year) life, the VC firms that manage the funds have no pre-determined lifespan. Success in a first-time fund often enables the VC firm to raise a follow-on fund (Kaplan and Schoar (2005)), resulting in a sequence of funds raised a few years apart. We assume that experience and contacts acquired in the running of one fund carry over to the firm's next fund and thus we measure VC experience and networks at the parent firm rather than the fund level. The estimation data sets contain 3,469 VC funds managed by 1,974 VC firms that participate in 47,705 investment rounds involving 16,315 portfolio companies; 44.7% of investment rounds and 50.3% of sample companies involve syndicated funding.

We define what constitutes a syndicate in two different ways. For the two directed centrality measures, *indegree* and *outdegree*, we need to distinguish between VCs that lead syndicates and those that are coinvestors. To do so, we examine syndicates at the investment-round level. We define the syndicate as the collection of VC firms that invest in a given portfolio company investment round. As per convention, we identify the lead investor as the syndicate member making the largest investment in the round.[10]

For the undirected centrality measures, we are primarily interested in the ties among VCs instanced by coinvestment in the same portfolio company. Here, we are less concerned about whether the coinvestment occurred in the same financing round or in different rounds, because we assume VC relationships are built by interacting with one another in board meetings and other activities that help the portfolio company

succeed. Thus, a VC that invested in the company's first round may interact with a VC that joined in the second round. To capture this, we examine syndicates at the company level and define the syndicate as the collection of VC firms that invested in a given portfolio company.[11]

A. Fund Characteristics

Table I describes our sample funds. The average sample fund had $64 million of committed capital, with a range from $0.1 million to $5 billion. (Fund size is unavailable for 364 of the 3,469 sample funds.) Fund sequence numbers denote whether a fund is the first, second and so forth fund raised by a particular VC management firm. The average sample fund is a third fund, though sequence numbers are missing in Venture Economics for one-third of the funds. One-quarter of the funds are identified as first-time funds. Around one-third (36.5%) focus on seed or early-stage investment opportunities. Corporate VCs account for 15.9% of sample funds.

Many VCs specialize in a particular industry, and important performance drivers such as investment opportunities and competition for deal flow likely vary across industries. Venture Economics classifies a fund's portfolio companies into six broad industry groups. We take a sample fund's industry specialization to be the broad Venture Economics industry group that accounts for most of its invested capital. On this basis, 46.2% of funds specialize in "Computer related" companies, 18.9% in "Nonhigh-technology," 15.5% in "Communications and media," 9.2% in "Medical, health, life sciences," 6% in "Biotechnology," and 4.3% in "Semiconductors, other electronics."

TABLE I APPROXIMATELY HERE

B. Measuring Fund Performance

Ideally, we would measure fund performance directly, using the return a fund achieved over its ten-year life. However, returns for individual funds are not systematically available to researchers as VC funds generally disclose their performance only to their investors and Venture Economics only makes fund returns publicly available in aggregate form. Some researchers have recently had access to disaggregated performance data from Venture Economics, but only in anonymized format (see Kaplan and Schoar (2005), Jones and Rhodes-Kropf (2003)). Absent a facility for identifying individual funds and thus matching their returns to their network characteristics and other cross-sectional variables, such anonymized data would not help us examine the effect of VC networking on investment performance.

Instead, we measure fund performance indirectly. According to Ljungqvist, Richardson, and Wolfenzon (2005), the average VC fund writes off 75.3% of its investments. This implies that VC funds earn their capital gains from a small subset of their portfolio companies, namely, those they exit via an IPO or a sale to another company (M&A).[12] All else equal, the more successful exits a fund has, the larger will be its IRR. Thus, we take as our main proxy for VC fund performance the fraction of the fund's portfolio companies that have been successfully exited via an IPO or M&A transaction, as identified in the Venture Economics database as of November 2003. In Section III.D, we show that this is a reasonable proxy for fund returns.

Table I reports descriptive statistics. In the sample of 3,469 funds raised between 1980 and 1999, exit rates average 34.2%, with IPOs outnumbering M&A transactions three-to-two (with exit rates of 20.7% and 13.6%, respectively).[13] These exit rates are comparable to those reported in Gompers and Lerner (2000) for the 1987 to 1991 period. Though not shown in the table, exit rates peaked among funds raised in 1988, with a mild upward trend in exit rates among funds raised before 1988 and a more pronounced downward trend among funds raised since. The youngest funds – those raised in 1998 and 1999 – had markedly lower exit rates, either because they have yet to complete their ten-year investment lives or due to the deterioration in the investment climate and, especially, in the IPO market since the ending of the dot-com and technology booms of the late 1990s. Whatever the reason, to capture this pronounced time pattern we include year dummies throughout our fund-level analysis.

C. Company-level Performance Measures

Data limitations prevent us from computing company-level rates of return: The Venture Economics database does not include details on the fraction of equity acquired by the VCs or the securities they hold, and occasionally lacks information even on the amount invested.[14] Instead, we use two indirect measures of company-level performance. Most venture-backed investments are "staged" in the sense that portfolio companies are periodically reevaluated and receive follow-on funding only if their prospects remain promising (Gompers (1995)). Thus, we view survival to another funding round as an interim signal of success. Eventually, successful portfolio companies are taken public or sold. Absent return data, we follow Gompers and Lerner (1998, 2000), Brander, Amit, and Antweiler (2002), and Sorensen (2005) in viewing a successful exit as a final signal of the investment's success.[15]

We restrict the data set to companies that received their *first* institutional funding round between 1980 and 1999, and record their subsequent funding rounds and, if applicable, exit events through November 2003.[16] Figure 2 shows what happened to these 16,315 companies. Around one-third of the companies do not survive beyond the first funding round and thus are written off, 1,020 companies (6.3%) proceed to an IPO or M&A transaction after the first round, and the remaining 9,875 companies (60.5%) receive follow-on funding. Conditional on surviving to round 2, the survival probability increases: Of the 9,875 companies that survive round 1, 7.7% exit and 70% survive to round 3. Conditional on surviving to round 3, 10.1% exit and 69.2% survive to round 4. And so forth. Overall, 4,235 of the 16,315 portfolio companies (26%) successfully exited by November 2003. The median company receives two funding rounds.

FIGURE 2 APPROXIMATELY HERE

It is important to realize that Venture Economics provides virtually no information about the portfolio companies beyond the dates of the funding rounds, the identity of the investors, subsequent exits, and the companies' Venture Economics industry classification. Of the 16,315 companies with first rounds in the data set, 32.7% are classified by Venture Economics as "Computer related," 30.9% as "Nonhigh-technology," 14.1% as "Communications and media," 10.9% as "Medical, health, life sciences," 6.4% as "Semiconductors, other electronics," and 4.9% as "Biotechnology."

D. VC Firm Experience

Kaplan and Schoar (2005) show that returns are persistent across a sequence of funds managed by the same VC firm. Persistence could result from investment skill and experience. We derive four proxies for experience, measuring the age of the VC firm (the number of days since the VC firm's first-ever investment), the number of rounds the firm has participated in, the cumulative total amount it has invested, and the number of portfolio companies it has backed. Each is calculated using data from the VC firm's creation to year t.[17] To illustrate, by the time Sequoia Capital raised Fund IX in 1999, it had been active for 24 years and had participated in 888 rounds, investing a total of $1,275 million in 379 separate portfolio companies. In the interest of brevity, we only present regression results using the cumulative total investment amount, though we obtain similar results using any of the other three measures.

E. Network Measures

Over our sample period, the VC industry experienced substantial entry and exit and thus a considerable

reordering of relationships. To capture the dynamics of these processes, we construct a new network for each year *t*, using data on syndications from the five years ending in *t*.[18] Within each of these five-year windows, we make no distinction between relationships reflected in earlier or later syndicates. We then use the resulting adjacency matrices to construct the five centrality measures described in Section I.

The parent of the average sample fund has normalized *outdegree* of 1.203%, *indegree* of 1.003%, and *degree* of 4.237% (see Table I). This means that the average VC, when acting as lead, involves a little over 1% of all VCs active in the market at the time as coinvestors, has been invited to become a syndicate member by around 1% of all VCs, and has coinvestment relationships with a little over 4% of the other VCs (ignoring its and their roles in the syndicate). Together with the fact that more than half of all investments are syndicated, these low degree centrality scores suggest that VCs repeatedly coinvest with a small set of other VCs, that is, that relationships are relatively exclusive and stable. In addition, they also reflect the tendency of some VCs to never syndicate their investments.[19]

To illustrate the variation in the *degree* measures, consider the extremes. Over the five years ending in 1999, New Enterprise Associates syndicated with the largest number of VCs (369). By contrast, 186 (10.3%) of the 1,812 VC firms active in the market during the 1995 to 1999 window never syndicated any investments, preferring instead to invest on their own.

Betweenness and *eigenvector* centrality average 0.29% and 3.74% of their respective theoretical maximum. Throughout most of the 1990s, New Enterprise Associates had the highest *betweenness* centrality scores (standing “between” approximately 6% of all possible VC pairs).

All five network measures exhibit a fair degree of variation, suggesting that the influence of individual VCs varies substantially. Thus, positional advantage is quite unequally distributed in our networks.

F. Competition for Deal Flow and Investment Opportunities

Our models include a range of control variables. Gompers and Lerner (2000) show that the prices VCs pay when investing in portfolio companies increase as more money flows into the VC industry, holding investment opportunities constant. They interpret this pattern as evidence that competition for scarce investment opportunities drives valuations up. If so, it seems plausible that competition for deal flow also affects the quality of VCs’ investments and thus their performance. We therefore include in our fund-level and company-level models the aggregate VC fund inflows in the year a sample fund was raised and the

year a portfolio company completed a funding round, respectively. Table I shows that the average sample fund was raised in a year in which $23.8 billion flowed into the VC industry.

Controlling for the investment opportunities open to a VC is harder. Gompers and Lerner (2000) propose public-market pricing multiples as indirect measures of the investment climate in the private markets. There is a long tradition in corporate finance, based on Tobin (1969), that views low book-to-market (B/M) ratios in an industry as an indication of favorable investment opportunities. Price-earnings (P/E) ratios are sometimes used for the same purpose. By definition, private companies lack market value data, so we must rely on multiples from publicly traded companies. To allow for interindustry differences in investment opportunities, we map all COMPUSTAT companies into the six broad Venture Economics industries. We begin with VC-backed companies that Venture Economics identifies as having gone public, and for which SIC codes are therefore available. We then identify which Venture Economics industry each available four-digit SIC code is linked to most often,[20] and compute the pricing multiple for each of the six Venture Economics industries in year *t* as the value-weighted average multiple of all COMPUSTAT companies in the relevant four-digit SIC industries.[21]

VC funds take a number of years to invest their available capital, during which time investment opportunities may change. For the purpose of the fund-level analyses in Section III, we average B/M and P/E ratios over each fund's first three years of existence to approximate its active investment period. Results are robust to using longer or shorter windows. Table I reveals that the average fund faces a P/E ratio of 16.4 and a B/M ratio of 0.514 in its industry of specialization over the first three years of its life.

III. Fund-level Analysis

A. Benchmark Determinants of Fund Performance

To validate our use of exit rates instead of fund returns, we replicate Kaplan and Schoar's (2005) VC fund performance model, which relates performance to log fund size and log fund sequence number (each included in levels and squares) and a set of vintage year dummies. Table II reports the results. When both size and sequence number are included, only the year dummies are significant (see column (1)).[22] Like Kaplan and Schoar, we find only weak evidence that more mature funds perform better (p=0.099) once we exclude fund size in column (2), and strong evidence that larger funds perform significantly better (p<0.001) once we exclude fund sequence number in column (3). As in Kaplan and Schoar (whose data set

is a subset of ours), the relation between fund performance and fund size is increasing and concave, consistent with diminishing returns to scale. The adjusted R^2 in model (3) is 13.6%.

TABLE II APPROXIMATELY HERE

In column (4), we replace sequence number with a dummy that equals one for first-time funds. We also control for funds that Venture Economics classifies as seed or early-stage funds, on the assumption that such funds invest in riskier companies and thus have relatively fewer successful exits, and for corporate VCs. First-time funds perform significantly worse, mirroring Kaplan and Schoar's (2005) results: All else equal, first-time funds have exit rates that are 3.7 percentage points below average (that is, 30.8% rather than 34.5%). In this specification, seed and early-stage funds do not perform differently from other funds, while corporate VCs perform marginally better.

The model shown in column (5) adds the log of vintage-year VC fund inflows in an attempt to control for Gompers and Lerner's (2000) "money chasing deals" result, whereby inflows of capital into VC funds increase the competition for a limited number of attractive investment opportunities. Consistent with the spirit of their results, we find that funds subsequently perform significantly worse the more money flowed into the VC industry in the year they were raised. The effect is large economically: A one-standard deviation increase in vintage-year fund inflows reduces exit rates by seven percentage points from the 34.5% estimation sample average, holding all other covariates at their sample means. Columns (6) and (7) add to this specification our two proxies for the investment opportunities available to funds when deploying their committed capital. Whether we use P/E or B/M ratios, the results indicate that a more favorable investment climate at the time a fund invested its capital is followed by significantly higher exit rates. Of the two, B/M ratios have the larger economic effect, with a one-standard deviation decrease in the B/M ratio among publicly traded companies in the fund's industry of specialization being associated with a 7.6 percentage point increase in subsequent exit rates. The models that follow include industry B/M ratios, though we note that all results are robust to using industry P/E ratios instead.

Before we turn to investigating the effect of network position on fund performance, we control for the investment experience of the fund's parent firm. This improves the explanatory power of the model, shown in column (8), substantially. As expected, funds with more experienced parents perform significantly better. A one-standard deviation increase in the log aggregate amount the parent has invested, measured up to the

year the VC fund was raised, increases exit rates by 4.3 percentage points. Note that the first-fund dummy loses significance in this model, indicating that it is a poor proxy for experience.

B. The Effect of Firm Networks on Fund Performance

Having controlled for fund characteristics, competition for deal flow, investment opportunities, and parent firm experience, does a VC's network centrality (measured over the prior five years) improve the performance of its fund (over the next ten years)? The results, shown in Table III, indicate that it is does. We estimate five separate regression models, adding our five centrality measures to the specification shown in column (8) of Table II. We add them one at a time given the relatively high degree of correlation among them.[23] Each specification in Table III suggests that better-networked VC firms are associated with significantly better fund performance, and the adjusted-R^2 increases to around 19%.[24]

TABLE III APPROXIMATELY HERE

Of the five network measures, *eigenvector* has the largest economic effect, closely followed by *degree* and *indegree*. To illustrate, a one-standard deviation increase in these measures is associated with 2.4 to 2.5 percentage point increases in exit rates, all else equal. Thus, a VC benefits from having many ties (*degree*), especially when the ties involve other well-connected VCs (*eigenvector*), and from being invited into many syndicates (*indegree*). Having the ability to act as a broker between other VCs (*betweenness*) has a smaller effect, with a one-standard deviation increase in this centrality measure being associated with only a one percentage point increase in fund performance. This will prove to be the case throughout our analysis, suggesting that indirect relationships (those requiring intermediation) play a lesser role in the venture capital market. Similarly, *outdegree* has a relatively small effect economically, consistent with the view that this measure captures a VC firm's investment in *future* reciprocity, which takes some time to pay off. In other words, inviting many VCs into one's syndicates today (i.e., high *outdegree*) will hopefully result in many coinvestment opportunities for one's future funds (i.e., high future *indegree*). We explore this dynamic relation between *indegree* and *outdegree* in Section VII.

C. Reverse Causality and Performance Persistence

We do not believe that our results are driven simply by reverse causality, that is, that a higher fund exit rate enables a VC to improve its network position, rather than the other way around. Recall that we construct the network centrality measures from syndication data for the five years *before* a fund is created.

The fact that these data can help explain fund performance over the next ten years suggests that networking truly affects performance.

To rule out that the network measures are simply proxying for omitted performance persistence, we reestimate our fund-level models including among the regressors the exit rate of the VC firm's most recent past fund. Note that this restricts our sample to VC firms that have raised at least two funds between 1980 and 1999; first-time funds and VC firms that do not raise follow-on funds are necessarily excluded.

Table IV presents the results. While we do find evidence of performance persistence, we continue to find that better-networked VC firms enjoy better fund performance, all else equal. The economic magnitude of the performance persistence is large. A one-standard deviation increase in the exit rate of the VC firm's most recent past fund is associated with a 6.3 to 6.5 percentage point increase in the current fund's exit rate. As before, the five network centrality measures affect exit rates positively, and three of them do so significantly. The economic magnitudes remain similar: All else equal, a one-standard deviation increase in network centrality is associated with a 2.4, 2.0, and 2.2 percentage point increase in fund performance for *indegree*, *degree*, and *eigenvectors*, respectively. As in Table III, *outdegree* and *betweenness* have a smaller effect on performance.

TABLE IV APPROXIMATELY HERE

D. Exit Rates and Internal Rates of Return

To ascertain the extent to which our measure of fund performance, exit rates, relates to fund returns, we use a sample of fund IRRs recently disclosed by public pension plans and state universities following Freedom of Information Act suits. Such data are available for 188 of the 3,469 funds in our sample. While this sample is small and not necessarily representative, it provides us with an opportunity to partially examine the relation between exit rates and IRRs and thus the robustness of our fund performance results.

The correlation between exit rates and IRRs is 0.42 ($p<0.001$), suggesting that exit rates are a useful but noisy proxy for IRRs. We reestimate our fund-level performance models on the subsample of funds for which IRRs are available. (To conserve space, the results are not reported in tables.) This both weakens and strengthens our results. On the one hand, the coefficients estimated for *outdegree*, *degree*, and *betweenness* are no longer statistically significant. On the other, the coefficient estimates for *indegree* and *eigenvector* are not only statistically significant, they are also very large economically: IRRs increase by between 11

and 14 percentage points from the 15% sample average for one-standard deviation increases in *indegree* and *eigenvector*. The adjusted-R^2s in all five models are high, ranging from 27.8% for the *outdegree* specification to 30% for the *eigenvector* specification.

Finally, we regress IRRs on exit rates to help interpret economic significance in our exit rate models (results not shown). On average, funds break even (i.e., IRR=0) at an exit rate of 18.8%. Beyond 18.8%, each 1% increase in exit rates is associated with a 1.046% increase in IRRs ($p<0.001$). If we are willing to assume that the relation between IRRs and exit rates remains roughly one-to-one in the overall sample (for which we do not have IRR data), this suggests that we can translate the economic significance exercises in the previous sections into IRR gains on nearly a one-for-one basis. In other words, a 2.5 percentage point increase in exit rates (from the mean of around 35%) is roughly equivalent to a 2.5 percentage point increase in IRR (from a mean of around 15%).

IV. Company-level Analysis

We now turn to estimating the effect of VC networking on portfolio company performance. In the absence of company-level rates of return data, we focus on company survival. The dependent variable in Table V is an indicator variable that equals one if the company survived from round *N* to receive another funding round or exited via an IPO or M&A transaction, and zero if it was written off after round *N*. Clearly, as survival to round *N*+1 is conditional on having survived to round *N*, the sample size decreases from round to round. Figure 2 illustrates.[25] For the sake of brevity, we focus on survival from the first three rounds (i.e., *N*=1..3), so we estimate three separate models labeled in the table as "survived round 1," "…2," and "…3." Our results do not change if we consider later rounds as well.[26]

TABLE V APPROXIMATELY HERE

We relate company survival to the same variables used to model fund performance in Table III: The characteristics of the lead investor (such as fund size and whether it is a first-time fund); the VC inflow proxy for competition for deal flow, measured as of the year in which the funding round took place; the B/M proxy for investment opportunities in the portfolio company's Venture Economics industry as of the funding year; the lead investor's investment experience, measured from the investor's founding date to the date of the funding round; and our set of network measures.[27] We measure the VC parent firm's network centrality over the five-year window preceding the investment round. (For example, for a second-round

investment made in 1995, the centrality measures are calculated from data for the years 1991 to 1995.) To mitigate collinearity problems, we add the five network measures one at a time, resulting in 15 models. All models are estimated using probit maximum likelihood estimation (MLE). Beyond round 1, we also include a dummy coded one if a more influential VC takes over as lead investor (based on a comparison of its network centrality to that of the previous lead). This is the case in approximately 17% of all rounds.

A. The Determinants of Portfolio Company Survival

The pseudo-R^2s in Table V decrease across the three funding rounds considered, suggesting that as companies become more established, company-specific variables (which we cannot control for) become relatively more important drivers of company survival. Our models explain approximately 9% to 10% of the variation in survival rates for round 1, 5% for round 2 survival, and 3% to 4% for round 3 survival.

We find a significant increasing and at times concave relation between the lead investor's fund size and a portfolio company's survival from any of the first three rounds. This echoes the finding in the previous section that larger funds have higher exit rates. First-time funds that lead an investment are associated with significantly worse survival probabilities from round 3. First-round investments led by corporate VCs (accounting for 5.7% of the sample rounds) are significantly less likely to survive. The more money the VC industry raises from investors at the time of the funding round, the less likely a portfolio company is to survive; this is true across all three rounds. Interpreting fund inflows as a proxy for competition for deal flow, this suggests that funds make more marginal investment choices at times when investment capital is plentiful, leading to poorer survival records. A more favorable investment environment, as proxied by a lower average industry B/M ratio, significantly improves a company's chances of survival, again across all three rounds. The beneficial effect of low competition and favorable investment opportunities is economically strongest in the first two rounds. More experienced VCs are associated with a significantly *lower* survival probability in rounds 2 and 3, perhaps because such investors are better at liquidating hopeless investments.

Controlling for these factors, we find, in each of the 15 probit models, that better-networked investors are associated with significantly higher company survival probabilities. To illustrate the economic magnitude, consider a one-standard deviation increase in the lead VC's *eigenvector* centrality measure. This increases the survival probability in the first round from the unconditional expectation of 66.8% to

72.4%, in the second round from 77.7% to 82.8%, and in the third round from 79.2% to 86.6%. As in the fund-level models, the network measures capturing the number and quality of relationships (*degree* and *eigenvector*) and access to other VCs' deal flow (*indegree*) have stronger economic effects on performance than do measures of future reciprocity (*outdegree*) and brokerage (*betweenness*).

Conceptually, one channel through which networking benefits a portfolio company is the VC's ability to draw on network resources to provide value-added services. This interpretation needs to be distinguished from the following alternative hypothesis. Suppose an investor enjoys privileged access to high-quality deal flow for reasons (possibly historical) unrelated to its network position. High quality deals are more likely to survive. At the same time, its high quality deal flow makes the investor a desirable syndication partner, resulting in high centrality scores. Thus, we might find a mechanical but economically spurious link between portfolio company survival and network centrality.

We find that a portfolio company's survival from round 2 increases by a significant 4.2 to 4.8 percentage points from the 77.7% sample average after a more influential outside VC has taken over as lead investor in round 2. Since the new lead did not originate the deal, this finding is more nearly consistent with the interpretation that our network centrality measures capture an investor's ability to add value to the portfolio company, rather than a mechanical relation between survival and centrality. From round 3 onwards, switching to a more influential lead has no further effect on subsequent survival on the margin, consistent with our earlier finding that company-specific factors assume greater importance in later rounds.

B. Syndication vs. Networking

Using a sample of Canadian companies, Brander, Amit, and Antweiler (2002) find that syndicated VC deals have higher returns, raising the possibility that syndication itself may improve a company's survival chances. If better-networked VCs are more likely to syndicate a given deal, we may be confusing the beneficial effects of syndication with the beneficial effect of being backed by a well-networked VC. To rule out this concern, we reestimate our models adding dummy variables for (a) whether the current round is syndicated or (b) whether any of the company's previous investment rounds were syndicated. To conserve space, the results are not reported in tables. The positive effect of our network measures on portfolio company survival remains robust to controlling for whether or not the deal was syndicated.

We also re-estimate the models focusing only on rounds that were not syndicated. Here, we continue to

find that portfolio companies benefit from receiving funding from well-networked VCs even if the investment itself is not syndicated. Thus, the influence a VC derives from having many syndication partners is useful even when the VC does not formally syndicate a given investment, which validates our choice of using syndication networks to proxy for the broader networks VCs in which operate.

C. Pooled Portfolio Company Survival Models

Instead of modeling round-by-round survival, we now take the panel nature of the data explicitly into account. We track each sample company from its first funding round across all rounds to the earlier of its exit or November 2003. The dependent variable equals one in round N if the company survived to round N+1 or exited via an IPO or M&A transaction, and zero otherwise. All models are estimated using panel probit estimators with random company effects. The panel is unbalanced as companies go through varying numbers of rounds. We estimate five models, including the five network measures one at a time. As before, network centrality is measured from the VC syndication network over the five-year window preceding the investment round. Note that the identity of the lead investor is allowed to change across rounds.

The results are reported in Table VI. Irrespective of which aspect of the lead investor's network connections we control for, we find a significant increasing and concave relation between the lead investor's fund size and a portfolio company's survival. Investments lead-managed by corporate VCs are significantly less likely to survive. Greater VC fund inflows and a less favorable investment environment significantly reduce a company's chances of survival, as before. The effect of the lead investor's investment experience again *reduces* a company's survival chances in each of the five specifications.

TABLE VI APPROXIMATELY HERE

Controlling for these factors, we find that a portfolio company's survival probability increases significantly, the better-networked its lead investor. This is true for all five centrality measures. Except for *betweenness*, the economic effect in each case is large. A one-standard deviation increase in the other four centrality measures is associated with a 6.4 to 8.0 percentage point increase from the unconditional survival probability of 66.8%, holding all other covariates at their sample means. The emergence of a new, more influential lead investor boosts the survival probability by between 1.5 and 2.1 percentage points.

D. Portfolio Company Exit

Finally, we equate good performance with a successful exit (ignoring survival to another funding

round) and ask whether the VC firm's network centrality helps accelerate a portfolio company's exit. For this purpose, we compute the number of quarters between a company's first funding round and the earlier of a) its exit, b) the end of the VC fund's ten-year life, or c) November 2003. Companies that have not exited by the fund's tenth anniversary are assumed to have been liquidated. Companies backed by funds that are in existence beyond November 2003 are treated as "right-censored" (to allow for the possibility that they may yet exit successfully after the end of our sample period). Allowing for right-censoring, the average time-to-exit in our sample is 24 quarters.

We relate the log time-to-exit to our network measures controlling for fund and firm characteristics, competition for deal flow and investment opportunities at the time of the company's first funding round, and conditions in the stock market in general and the IPO and M&A markets in particular. Market conditions are allowed to vary over time, to allow VC firms to react to improvements in (say) IPO conditions by taking a portfolio company public. We proxy for conditions in the stock market using the quarterly return on the NASDAQ Composite Index. To measure exit market conditions, we use the quarterly log number of IPOs and the quarterly log number of M&A deals in the portfolio company's Venture Economics industry. All three variables are lagged by a quarter, to allow for the necessary delay in preparing a company for exit.

Our time-to-exit models are estimated in the form of accelerated-time-to-failure models.[28] These are hazard (or duration) models written with log time as the dependent variable. Parametric hazard models require that we specify a distribution for log time. While our results are robust to alternative choices, we assume that log time is normally distributed. This has the advantage that the hazard rate (the instantaneous probability of exiting in the next instant given that a company has not exited so far) first increases and then decreases over time. Other distributions imply either a constant hazard rate (e.g., exponential) or hazards that increase (or decrease) monotonically over time (e.g., Weibull or Gompertz). In the context of VC investments, monotonic hazard functions are implausible, as it is neither the case that companies are never more likely to exit than at the time of their first round (a monotonically decreasing hazard function) nor that companies become ever more likely to exit the longer they have languished in the VC's portfolio (a monotonically increasing hazard function).[29]

Table VII reports the results. While fund size has no effect on time-to-exit, we find that first-time funds

exit their portfolio companies significantly faster, in around 20.5 rather than 24 quarters, all else equal. This is consistent with Gompers' (1996) finding that younger funds "grandstand" by taking portfolio companies public as early as possible. Companies that received their first funding at a time of larger VC fund inflows (interpreted as increased competition for deal flow) or when industry B/M ratios were low (interpreted as relatively poor investment opportunities) take significantly longer to exit. More experienced VC firms exit their portfolio companies significantly faster. These results mirror those in the previous tables. In addition, we find that higher returns on the NASDAQ Composite Index and an increase in the number of IPOs (but not M&A deals) are associated with a significant increase in the probability that a portfolio company will exit in the next quarter. This is consistent with Lerner's (1994b) findings.

TABLE VII APPROXIMATELY HERE

Controlling for these effects, we find that each of the five centrality measures has a negative and significant effect on time-to-exit. *Eigenvector* has the largest effect economically. A one-standard deviation increase in the lead VC's *eigenvector* centrality is associated with a two-quarter decrease from the unconditional time-to-exit of 24 quarters. The corresponding effects for the three degree network measures are around one quarter. Thus, companies benefit from being backed by VCs who have many ties (*degree*), especially when these ties involve other well-connected VCs (*eigenvector*).

V. How Does Networking Affect Performance?

Kaplan and Schoar (2005) attribute performance persistence of the kind we document in Table IV to three possible explanations: 1) Better VCs may have access to high quality deal flow; 2) skilled VCs may be scarce; and 3) better VCs are expected to add more value and thus may obtain better deal terms when negotiating with entrepreneurs (Hsu (2004)). While our results suggest skill and experience play a role, we also find that it is the better-networked VC firms that perform the best. We now ask whether networking improves performance simply through access to better deal flow, or whether it also contributes to the VC's ability to add value to its portfolio companies. The results of two indirect tests suggest that while access to deal flow is important, network centrality appears to affect a VC's ability to provide value-added services.

Our first test assumes high *indegree* is, in part, an indication of access to a better selection of deals. If so, it may be instructive to use differences in *indegree* to control for a firm's access to deal flow and then examine whether the remaining networking measures affect performance. To this end, we classify firms as

having above or below median *indegree* and interact this classification with each of the other four network measures in our fund-level performance regressions. This allows us to separately study the effect of (say) *eigenvector* when the VC enjoys "good" or "poor" access to deal flow. Table VIII presents the results. The beneficial effects of *outdegree* and *betweenness* do not differ significantly between firms with high or low *indegree*. The effects of *degree* and *eigenvector*, on the other hand, are significantly stronger among firms with low *indegree* centrality. In other words, networking boosts performance much more precisely when the VC does not enjoy better access to deals. The economic magnitude of these effects is very large. While a one-standard deviation increase in *eigenvector* centrality among high-*indegree* VCs is associated with a 3.2 percentage point increase in fund exit rates, low-*indegree* VCs enjoy an additional 3.3 percentage point increase in their fund exit rates (a total effect of 6.5 percentage points). The corresponding numbers for *degree* are 3.1 and 2.7 percentage points, respectively (giving a total effect of 5.8 percentage points for low-*indegree* VCs).

TABLE VII APPROXIMATELY HERE

Our second test assumes that one way VCs add value to their portfolio companies is by introducing them to corporate investors that may become launch customers, suppliers, or strategic alliance partners – in other words, value-added investors. To identify which VC firms enjoy strong relationships with corporate VCs, we construct separate measures of centrality, subscripted "C", using a block-diagonalization of the adjacency matrices.[30] We then consider the effect on a portfolio company's survival of how well connected a VC firm is among corporate investors, focusing on a subset of deals chosen to reduce as much as possible the effect of better access to deal flow. Specifically, we impose two filters. First, we consider only second-round deals lead-managed by a VC firm that was not among the first-round investors. Since the new second-round lead VC did not originate the deal, any effect of its network centrality presumably picks up value-added rather than simply better screening. Second, we exclude deals that involve corporate investors in the first or second round. In the absence of corporate investors it is less likely the deal was referred by a corporate investor. Thus, strong relationships with corporate investors should not pick up better access to deal flow in general or to this deal in particular. Of the 8,650 second-round investments in our data set, 2,811 involve a lead that did not originate the deal in the first round and where there were no corporate investors present in the first or second rounds.

In Table IX, we estimate a portfolio company's chance of surviving to a third round of financing or to exit as a function of its lead VC's corporate-specific and network-wide centralities and our usual control variables. To reduce collinearity problems, we orthogonalize each pair of centrality measures. The positive coefficients estimated for $degree_C$, $outdegree_C$, and $eigenvector_C$ indicate that a company's survival chances increase the better-networked its new lead investor is in the corporate investor community. In other words, companies benefit from being backed by VCs that frequently coinvest with corporations, that often invite corporates into their syndicates, and that have many ties with well-connected corporate investors. Interestingly, the same is not true for $indegree_C$: Being backed by a VC that is frequently invited into syndicates lead-managed by corporate VCs confers no special advantage. This makes economic sense if we interpret $indegree_C$ as a measure of access to (corporate) deal flow. The positive coefficients estimated for *outdegree*, *indegree*, and *eigenvector* indicate that network-wide relationships make a distinct contribution to a portfolio company's survival after controlling for corporate-specific relationships.

TABLE IX APPROXIMATELY HERE

The most natural interpretation for our finding that a portfolio company's survival chances depend on how well networked its new second-round lead is among corporate investors is that networking does reflect access to value-added services, in this case the possibility of corporate investors becoming customers, suppliers, strategic alliance partners, etc. Note that no corporate VCs actually invest in these deals, lending weight to the interpretation that the portfolio company benefits from the new lead's relationships with corporate investors, rather than their presence directly.

VI. Further Robustness Tests

A. Robustness to Alternative Explanations

It is possible that better-networked VCs are simply better at taking more marginal companies public, thus generating the *appearance* of better performance as measured by the VC's exit rate or a portfolio company's survival probability, but which would not be reflected in returns, if observed. To test this alternative hypothesis, we focus on two quality indicators, specifically, whether the portfolio company had positive net earnings when it went public, and whether it survived the first three years of trading on the public markets.

We gather data on earnings for the last 12-month (LTM) period before the IPO from Compustat and

supplement these data with LTM earnings from Thomson Financial's SDC IPO database as well as hard copies of IPO prospectuses as necessary. We then sort all 16,315 portfolio companies that received their first institutional round of funding from a sample VC fund between 1980 and 1999 into quartiles based on the network centrality of their lead first-round VC. Contrary to the alternative hypothesis, the best-networked VCs take public those companies that are *less* likely to have negative earnings at the time of the IPO. For instance, 51% of companies in the highest quartile by *degree* have negative pre-IPO earnings vs. nearly two-thirds of companies in the lowest quartile.

To investigate post-IPO survival, we code a company as delisting involuntarily if CRSP has assigned it a delisting code in the 400s or 500s and the delisting date occurs on or before the third anniversary of the IPO.[31] Of the 2,527 sample companies that go public by November 2003, 7% are delisted involuntarily.[32] We again sort the sample into quartiles by the lead VC's network centrality and find a positive relation between firm quality and the lead VC's network centrality, contrary to what we would expect under the alternative hypothesis. For instance, 4.9% of companies backed by the VCs with the highest *outdegree* are delisted involuntarily within three years of going public vs. 10.5% of companies backed by the worst-networked VCs.

When we estimate probit models of the likelihood that a firm delists involuntarily within three years of going public (as a function of fund characteristics, proxies for competition for deal flow and investment opportunities, fund experience, and our measures of how well networked each fund's parent firm is), we also find no support for the alternative hypothesis. The only variables that predict delisting are the proxy for competition for deal flow and the lead VC's investment experience: Companies funded at times when more money was raised by the VC industry have a significantly higher delisting probability,[33] while companies backed by more experienced VCs have a significantly lower delisting probability.

In conclusion, better-networked VCs do not appear to be associated with lower-quality IPO exits.

B. Location- and Industry-specific Networks

Our network measures implicitly assume that each VC in the U.S. potentially has ties to every other VC in the U.S. To the extent that in reality, VC networks are more geographically concentrated, or involve only VCs specializing in a certain industry, we may underestimate a VC's network centrality. For instance, a given biotech VC firm may be central in a network of biotech VCs, but may lack connections to

nonbiotech VCs in the overall network of U.S.-based VCs. Similarly, a VC firm headquartered in Silicon Valley may be well connected in California but not in a network that includes East Coast VC firms.

Our findings are robust to using centrality measures derived from (a) industry-specific networks defined using the six broad Venture Economics industries, and (b) a network of Californian VC firms. (We refrain from constructing networks for other geographic areas due to the comparatively small number of VC firms in areas outside California.) In each case, we continue to construct the networks on the basis of trailing five-year windows. To conserve space, we do not report the results in tables.

Using industry-specific networks slightly strengthens our fund-level results, in the sense of both higher adjusted-R^2s and larger economic effects. For instance, a one-standard deviation increase in a firm's *indegree* increases its fund's exit rate by 2.7 percentage points in the industry-specific model, compared to 2.4 percentage points using the overall network. In the company-level models, the results are qualitatively unchanged compared to Tables V through VII, and the industry network measures do not obviously dominate the overall network measures.

Restricting the network to Californian VCs reduces the sample of funds to 872 funds (for which all necessary variables are available) and the sample of portfolio companies to 4,691. The network measures continue to improve fund performance significantly, and the economic magnitude of the effects is considerably larger than before, with on the order of 3.7 to 5.3 percentage point improvements in fund exit rates (from the unconditional mean of 35.7%), compared to around 2.5 percentage points in the overall sample. In the company-level models, our network measures continue to be positively and significantly related to company survival and exit probabilities, and the economic magnitude of the effects is similar to before.

VII. How do VC Firms Become Networked?

Our results so far suggest that VC firms that occupy more central, or influential, positions in the VC network enjoy better investment performance, both at the fund and the portfolio company levels. But how do VC firms become networked in the first place? It seems likely that an emerging track record of successful investing would make a VC firm a more desirable syndication partner in the future, which in turn would improve its network position over time. Such a track record might be built around successful

portfolio exits, particularly eye-catching IPOs, or – according to conversations we have had with venture capitalists – the ability to persuade unrelated VCs to lead a follow-on funding round for a portfolio company.

To explore the evolution of a first-time VC firm's network position empirically, we model its network centrality in year t (using each of the five centrality measures as the dependent variable) as a function of the log number of portfolio companies that it exited via an IPO or an M&A transaction in year t-1, the log number of portfolio companies that received follow-on funding in year t-1 in a round led by an outside VC (defined as a VC firm that was not already an investor in the portfolio company), and its accumulated investment experience in year t-1.[34] To control for how "eye-catching" its IPOs were, we also include the average first-day return of its prior-year IPOs. Finally, we control for the fact that a VC firm's network position may naturally slip as the network grows in size by including the log number of new funds raised during the year.

We expect persistence in a VC firm's network position, in part because economically, while relationships take time to establish, they likely endure over time, and in part due to the way we construct the network measures. Therefore, we estimate dynamic panel data models under the assumption that the errors follow an AR(1) process. To control for unobserved heterogeneity in firm characteristics, we include firm fixed effects, and we allow for unbalanced panels to capture the fact that some VC firms are in the sample longer than others. The resulting estimator is due to Baltagi and Wu (1999). We report the results in columns (1) through (5) of Table X.

TABLE X APPROXIMATELY HERE

The models have high pseudo-R^2s, ranging from 17.6% for the *betweenness* model to 28.7% for the *indegree* model. Autocorrelation is around 83%, consistent with persistence in network position. The firm fixed effects are significant throughout, suggesting that there is VC firm-specific heterogeneity omitted from the specification. Likely candidates are investment skill and personal network contacts that VCs may have acquired through prior employment at an established VC firm.

Across all five models, first-time funds improve their network positions as they become more experienced through time. In part, this may capture their increased ability to certify the quality of start-ups in the eyes of other VCs (Hsu (2004)). Growth in the size of the network generally has no effect on centrality, though a VC firm's *eigenvector* centrality actually improves as more new funds enter the industry. Controlling for these factors, we find that a VC firm's network position is unrelated to the number of portfolio companies it has exited through an IPO or M&A transaction, with one exception: In the case of *outdegree*, we find a statistically weak relation to the lagged number of IPOs and a stronger relation to the lagged number of M&A deals. One plausible interpretation for this finding is that a VC firm has to prove its ability to find and produce winners before many other VCs will accept invitations into its syndicates. Refinancings lead-managed by an outside VC, on the other hand, have the conjectured positive and significant effect on a VC firm's future network position in all five models.

The evidence relating how eye-catching the VC firm's prior-year IPOs are to its network centrality varies in magnitude and significance across the five models. For *indegree*, *degree*, and *eigenvector*, higher first-day returns are associated with subsequent improvement in the VC firm's network position. This reinforces Gompers' (1996) argument that young VC firms grandstand by taking their portfolio companies public early in order to increase their ability to raise follow-on funds. When we use other plausible proxies for eye-catching IPOs (such as the average first-day market capitalization of the VC firm's IPOs, to capture "home runs"), we find no relation to network position (results not shown). The same is true when we attempt to make an allowance for the quality (rather than quantity) of a VC firm's exits using the quality measures explored in Section VI.A (such as the fraction of IPOs with negative earnings at the time of the IPO or that were delisted within three years, lagged appropriately) and the average three-year post-IPO buy-and-hold abnormal return of the firm's IPOs.

Finally, we investigate the dynamic relation between *outdegree* and *indegree*. In Section III, we argue that *outdegree* may have a relatively smaller economic effect on fund performance than the other network measures because it captures a VC firm's investment in *future* reciprocity, which takes some time to pay

off. The dynamic models in Table X enable us to test this conjecture formally, by using lagged *outdegree* to explain the evolution of a VC firm's *indegree*. The model shown in column (6) uses a one-year lag of *outdegree*, though we note that our results are robust to using three- or five-year lags instead. The positive and significant coefficient estimated for lagged *outdegree* is consistent with the notion that inviting many VCs into one's syndicates in the past results in many coinvestment opportunities in the future. Thus, high *indegree* today does appear to reflect, in part, payback on past investment in reciprocity.

VIII. Conclusions

Many financial markets are characterized by strong relationships and networks, rather than arm's-length, spot market transactions. We examine the performance consequences of this organizational choice in the context of relationships established when VCs syndicate portfolio company investments in a comprehensive sample of U.S. based VCs over the period 1980 to 2003. To the best of our knowledge, this is the first study to examine the relation between fund and portfolio company performance and measures of networking among VCs.

Controlling for known determinants of VC investment performance, we find that VC funds whose parent firms enjoy more influential network positions realize significantly better performance, as measured by the proportion of portfolio investments that are successfully exited through an initial public offering or a sale to another company. Similarly, the portfolio companies of better-networked VC firms are significantly more likely to survive to subsequent rounds of financing and to eventual exit. The magnitude of these effects is economically large, and is robust to a wide range of specifications.

Economically, VC firms benefit the most from having a wide range of relationships, especially if these involve other well-networked VC firms, and from having access to other VCs' deal flow. One way to gain access to deal flow is for a VC firm to invite other VCs into its syndicates today, which over time appears to lead to reciprocal coinvestment opportunities. The network measure with the least economic significance is *betweenness*, which captures a VC firm's ability to act as a broker between other VCs. This suggests that indirect relationships (those requiring intermediation) play a lesser role in the venture capital market. Interestingly, once we control for network effects, the importance of how much investment experience a VC has is reduced, and in some specifications, eliminated.

If more highly networked VCs enjoy better investment performance, our findings have clear ramifications for institutional investors choosing which VC fund to invest in. Additionally, our analysis provides a deeper understanding of the possible drivers of the cross-sectional performance of VC funds. Our findings also shed light on the industrial organization of the VC market. Given the large returns to being well-networked that we document, enhancing one's network position should be an important strategic consideration for an incumbent VC, while presenting a potential barrier to entry for new VCs.

Finally, our finding that better-networked VCs enjoy superior performance raises the question of how VCs become networked in the first place. Our evidence suggests that an emerging track record of successful investing (as proxied by the ability to persuade outside VCs to lead-manage a follow-on funding round for a portfolio company) improves a VC firm's network position over time. However, many central questions remain for future research. For instance, VCs likely benefit from personal network ties which we do not take into account. More broadly, what determines a VC's choice whether or not to network, what are the costs associated with becoming well-networked, and how does one form relationships with influential VCs in the network?

Appendix: Network Analysis Example

Consider a network of four VCs labeled A, B, C, and D. Suppose their syndication history is as follows:

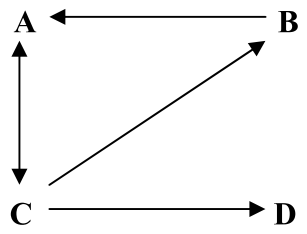
Syndicate 1: C (lead), D

Syndicate 2: C (lead), A, B

Syndicate 3: A (lead), C

Syndicate 4: B (lead), A

Graphically, these relationships can be represented as follows:



,

And the corresponding adjacency matrix is

	Syndicate member			
Lead VC	**A**	**B**	**C**	**D**
A	-	1	1	0
B	1	-	1	0
C	1	1	-	1
D	0	0	1	-

.

This matrix is symmetric, reflecting the "undirected" ties among the VCs. Each cell is coded one or zero to denote the presence or absence of a syndication relationship, respectively. The following "directed" adjacency matrix accounts for the difference between leading a syndicate and being a non-lead member:

	Syndicate member			
Lead VC	**A**	**B**	**C**	**D**
A	-	0	1	0
B	1	-	0	0
C	1	1	-	1
D	0	0	0	-

.

The rows show that A has led (at least) one syndicate in which C was a member, B has led at least one syndicate in which A was a member, C has led one syndicate each in which A, B, and D were members, and D has led no syndicates. The columns show that A has been a (non-lead) member of syndicates led by B and C, B has been a (non-lead) member of syndicate(s) led by C, C has been a (non-lead) member of syndicate(s) led by A, and D has been a (non-lead) member of syndicate(s) led by C.

Intuitively, C appears the best connected: C leads the most syndicates, participates in more syndicates than any VC except A (with which C ties), and is the only VC to have syndicated with D. Thus, C is said to have greater "centrality," in the sense of having a highly favored position in the network. C's only apparent shortcoming is the fact that it is not often (invited to be) present in syndicates led by the other VCs.

We calculate the following five centrality measures from the two adjacency matrices:

VC	Normalized *degree*	Normalized *indegree*	Normalized *outdegree*	Normalized *eigenvector*	Normalized *betweenness*
A	66.7%	66.7	33.3	73.9	0.0
B	66.7	33.3	33.3	73.9	0.0
C	100.0	33.3	100.0	86.5	66.7
D	33.3	33.3	0.0	39.9	0.0

.

Degree counts the number of undirected ties an actor has, which we calculate by summing the actor's row (or column) vector in the undirected adjacency matrix. In our setting, this is the number of (unique) VCs with which a VC has syndicated deals. Thus, A's degree is 2, B's is 2, C's is 3, and D's is 1. *Degree* increases with network size, which in turn varies over time. To ensure comparability over time, we normalize *degree* by dividing by the maximum possible *degree* in an *n*-actor network. With n=4, a given VC can be tied to at most three other unique VCs. This gives normalized *degrees* of 66.7%, 66.7%, 100%, and 33.3% for A, B, C, and D, respectively. By this measure, C is the most central and D the least central VC in the network.

Degree does not distinguish between initiating and receiving ties, or in our context, between leading or simply participating in a syndicate. *Indegree* counts the number of directed ties an actor received, which we calculate by summing its column vector in the directed adjacency matrix. In our setting, this is the number of unique VCs in whose syndicates the VC in question participated as a non-lead member. A's *indegree* of 2 (or 66.7% when normalized) is the highest in the network. O*utdegree* measures the number of ties an

actor initiates, which we calculate by summing the actor's row vector. In our setting, this is the number of unique VCs that have participated as (non-lead) members in syndicates led by the VC in question. C's *outdegree* is 3 (or 100% when normalized), reflecting the fact that C has involved every other VC in its syndicates at least once.

A popular measure of closeness in large networks is *eigenvector* centrality (Bonacich (1972, 1987)), which attempts to find the most central actors by taking into account the centrality of the actors each actor is tied to. It is computed by taking the (scaled) elements of the eigenvector corresponding to the largest eigenvalue of the adjacency matrix. This yields eigenvector centrality measures of 0.523, 0.523, 0.612, and 0.282 for A, B, C, and D, respectively. These can be normalized by dividing by the maximum possible eigenvector element value for a four-actor network, yielding normalized eigenvector centrality measures of 73.9%, 73.9%, 86.5%, and 39.9% for A, B, C, and D, respectively.

Finally, *betweenness* measures the proportion of shortest-distance paths between other actors in the network that the actor in question lies upon. Imagine a star-shaped network, with one actor connected to all other actors, none of whom is connected to anyone else. Clearly, the actor at the center of the star stands "between" all other actors. In our undirected matrix, C occupies such a position with respect to D: A can reach B and C directly, but must go through C to reach D; B can reach A and C directly, but must also go through C to reach D; and D can reach C directly, but must go through C to reach either of A or B. Thus, A, B, and D have zero *betweenness* while C stands between D and A and between D and B and so has a *betweenness* measure of 2. The maximum *betweenness* in a four-actor network is three,[35] so the normalized *betweenness* measures are 0% for A, B, and D, and 66.7% for C.

It is clear from the table that C is the most central VC in the network by all measures save *indegree*. This reflects the fact that C is connected to every VC in the network, whereas the other VCs are not, and the fact that C is present in almost every syndicate that was formed, and led most of the syndicates. C's relatively low *indegree* suggests it is not invited to join many deals (though it may also reflect C's tendency to lead deals). C's high *degree* and *eigenvector* centrality measures reflect its central position, or importance, in the network. Similarly, C's high *betweenness* reflects its potential role as a "broker" in the network, in that C is the sole connector between D and the other VCs.

This example illustrates the importance of considering more than one measure of a VC's centrality,

as each captures certain unique elements of the VC’s ties to other VCs. That said, it also provides an indication of the fact that despite these differences, these five centrality measures are still likely to be highly correlated with each other.

REFERENCES

Baltagi, Badi H., and Ping X. Wu, 1999, Unequally spaced panel data regressions with AR(1) disturbances, *Econometric Theory* 15, 814-823.

Bonacich, Philip, 1972, Factoring and weighting approaches to status scores and clique identification, *Journal of Mathematical Sociology* 2, 113-120.

Bonacich, Philip, 1987, Power and centrality: A family of measures, *American Journal of Sociology* 92, 1170-1182.

Brander, James, Raphael Amit, and Werner Antweiler, 2002, Venture capital syndication: Improved venture selection versus the value-added hypothesis, *Journal of Economics and Management Strategy* 11, 423-452.

Bygrave, William D., 1988, The structure of the investment networks of venture capital firms, *Journal of Business Venturing* 3, 137-158.

Cochrane, John, 2005, The risk and return of venture capital, *Journal of Financial Economics* 75, 3-52.

Cornelli, Francesca, and David Goldreich, 2001, Bookbuilding and strategic allocation, *Journal of Finance* 56, 2337-2369.

Gompers, Paul A., 1995, Optimal investment, monitoring, and the staging of venture capital, *Journal of Finance* 50, 1461-1490.

Gompers, Paul A., 1996, Grandstanding in the venture capital industry, *Journal of Financial Economics* 42, 133-156.

Gompers, Paul A., and Josh Lerner, 1998, What drives fundraising? *Brookings Papers on Economic Activity: Microeconomics*, 149-192.

Gompers, Paul A., and Josh Lerner, 2000, Money chasing deals? The impact of fund inflows on private equity valuations, *Journal of Financial Economics* 55, 281-325.

Gorman, Michael, and William A. Sahlman, 1989, What do venture capitalists do? *Journal of Business Venturing* 4, 231-248.

Hellmann, Thomas J., and Manju Puri, 2002, Venture capital and the professionalization of start-up firms: Empirical evidence, *Journal of Finance* 57, 169-197.

Hochberg, Yael V., 2005, Venture capital and corporate governance in the newly public firm, Working paper, Northwestern University.

Hsu, David, 2004, What do entrepreneurs pay for venture capital affiliation? *Journal of Finance* 59, 1805-1844

Jones, Charles M., and Matthew Rhodes-Kropf, 2003, The price of diversifiable risk in venture capital and private equity, Working paper, Columbia University.

Kaplan, Steven N., and Antoinette Schoar, 2005, Private equity returns: Persistence and capital flows,

Journal of Finance 60, 1791-1823.

Kaplan, Steven N., and Per Strömberg, 2004, Characteristics, contracts and actions: Evidence from venture capital analyses, *Journal of Finance* 59, 2177-2210.

Kaplan, Steven N., Frederic Martel, and Per Strömberg, 2003, How do legal differences and learning affect financial contracts? Working paper, University of Chicago.

Lerner, Josh, 1994a, The syndication of venture capital investments, *Financial Management* 23, 16-27.

Lerner, Josh, 1994b, Venture capitalists and the decision to go public, *Journal of Financial Economics* 35, 293-316.

Lindsey, Laura A., 2005, Blurring boundaries: The role of venture capital in strategic alliances, Working paper, Arizona State University.

Ljungqvist, Alexander, Felicia Marston, and William J. Wilhelm, 2005, Scaling the hierarchy: How and why investment banks compete for syndicate co-management appointments, Unpublished working paper, New York University.

Ljungqvist, Alexander, Matthew Richardson, and Daniel Wolfenzon, 2005, The investment behavior of private equity fund managers, Working paper, New York University.

Podolny, Joel M., 2001, Networks as pipes and prisms of the market, *American Journal of Sociology* 107, 33-60.

Robinson, David T., and Toby E. Stuart, 2004, Network effects in the governance of biotech strategic alliances, Working paper, Columbia University.

Sah, Raj K., and Joseph E. Stiglitz, 1986, The architecture of economic systems: Hierarchies and poliarchies, *American Economic Review* 76, 716-727.

Sahlman, William A., 1990, The structure and governance of venture capital organizations, *Journal of Financial Economics* 27, 473-421.

Stuart, Toby E., Ha Hoang, and Ralph C. Hybels, 1999, Inter-organizational endorsements and the performance of entrepreneurial ventures, *Administrative Science Quarterly* 44, 315-349.

Stuart, Toby E., and Olav Sorensen, 2001, Syndication networks and the spatial distribution of venture capital investments, *American Journal of Sociology* 106, 1546-1588.

Sorensen, Morten, 2005, How smart is smart money? An empirical two-sided matching model of venture capital, Working paper, University of Chicago.

Tobin, James, 1969, A general equilibrium approach to monetary theory, *Journal of Money, Credit, and Banking* 1, 15-19.

Wasserman, Stanley, and Katherine Faust, 1997, *Social Network Analysis: Methods and Applications*. (Cambridge University Press, New York, NY).

Wilson, Robert, 1968, The theory of syndicates, *Econometrica* 36, 199-132.

Endnotes

[1] The ways in which VCs add value include addressing weaknesses in the business model or the entrepreneurial team (Kaplan and Strömberg (2004)), professionalizing the company (Hellmann and Puri (2002)), facilitating strategic alliances (Lindsey (2005)), and ensuring strong governance structures at the time of the IPO (Hochberg (2005)).

[2] Examples of prior applications of network analysis in a financial context include Robinson and Stuart (2004), who study the governance of strategic alliances, and Stuart, Hoang, and Hybels (1999), who focus on the effect of strategic alliance networks on the performance of biotech ventures.

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

[4] For tractability, the graph excludes biotech-focused VC firms that have no syndication relationships during this period.

[5] As the example in the Appendix illustrates, this coding produces a binary adjacency matrix. It is possible to construct a valued adjacency matrix accounting not only for the existence of a tie between two VCs but also for the number of times there is a tie between them. All our results are robust to using network centrality measures calculated from valued matrices.

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

[7] All results are robust to using nonnormalized network centrality measures instead.

[8] Given an adjacency matrix A, the eigenvector centrality of actor i is given by $ev_i=a\sum A_{ij}ev_j$ where a is a parameter required to give the equations a nontrivial solution (and is therefore the reciprocal of an eigenvalue). As the centrality of each actor is determined by the centrality of the actors he is connected to, the centralities will be the elements of the principal eigenvector.

[9] The institutionalization of the VC industry is commonly dated to three events: The 1978 Employee

Retirement Income Security Act (ERISA), whose "Prudent Man" rule allows pension funds to invest in higher-risk asset classes; the 1980 Small Business Investment Act, which redefines VC fund managers as business development companies rather than investment advisers, thus lowering their regulatory burdens; and the 1980 ERISA "Safe Harbor" regulation, which sanctions the limited partnerships that are now the dominant organizational form in the industry.

[10] Ties are broken by defining the lead investor as the VC with the largest cumulative investment in the company to date.

[11] All our results are robust, both in terms of economic and statistical significance, to employing either definition of syndicate for both the directed and undirected centrality measures.

[12] Unsuccessful investments are typically shut down or sold to management for a nominal sum.

[13] Our results are robust to computing exit rates using instead the fraction of dollars invested in companies that are successfully exited. Dollar exit rates are a little higher, averaging 35.8%.

[14] See Cochrane (2005) for an analysis of company-level rates of return using data from an alternative database (VentureOne), and see Ljungqvist, Richardson, and Wolfenzon (2005) for similar analysis using a proprietary data set of 4,000 private equity-backed companies.

[15] Unlike Gompers and Lerner (1998) and Brander, Amit, and Antweiler (2002), we account for successful exits via M&A transactions as well as IPOs.

[16] We thus exclude companies (and all their funding rounds) that received their first *institutional* funding round before 1980, even if they subsequently received follow-on funding after 1980. Our data set does includes companies that received a *noninstitutional* funding round prior to 1980 (typically involving angel investors or friends and family).

[17] Since Venture Economics' data are somewhat unreliable before 1980, we ignore investments dated earlier than 1975. This coding convention does not affect our results.

[18] All our results are robust to using three-, seven-, or ten-year windows instead, with shorter windows generally being associated with stronger effects.

[19] Our results are robust to excluding VC firms that never syndicate.

[20] Similar results obtain when using three-digit SIC codes.

[21] We define a public company's P/E ratio as the ratio of stock price (COMPUSTAT data item #199) to earnings-per-share excluding extraordinary items (#58). We define the B/M ratio as the ratio of book equity to market equity, where book equity is defined as total assets (#6) minus liabilities (#181) minus preferred stock (#10, #56, or #130, in order of availability) plus deferred tax and investment tax credit (#35), and market equity is defined as stock price (#199) multiplied by shares outstanding (#25). To control for outliers, we follow standard convention and winsorize the P/E and B/M ratios at the 5th and 95th percentiles for the universe of firms in COMPUSTAT in that year. (The results are robust to other winsorization cutoffs.) To calculate a value-weighted average, we consider as weights both the firm's market value (market value of equity plus liabilities minus deferred tax and investment tax credit plus preferred stock) and the dollar amount of investment in each four-digit SIC code each year (as calculated from the Venture Economics database).

[22] It is difficult to control directly for exit market conditions over the life of a fund, as market conditions may vary widely over the 7+ years in which portfolio companies are likely to reach exit stage. The year fixed effects may help control for heterogeneity in exit rates related to the fund's vintage year timing (and hence subsequent exit market conditions). See Section IV.D for company-level models that control explicitly for exit market conditions.

[23] One obvious concern is that our network centrality measures merely proxy for (or are cleaner measures of) VC parent firm experience. However, the pairwise correlations between the experience measure and the five measures of network centralities are relatively low, ranging from 36.8% to 43.9%.

[24] If we restrict the sample to funds raised prior to 1995, to ensure each sample fund has completed its ten-year life, *betweenness* and *outdegree* cease to be significant at conventional levels and *indegree*, *degree*, and *eigenvector* continue to be positively and significantly related to fund performance.

[25] Note that due to missing fund size data, fewer observations are available for estimation than are shown in Figure 2.

[26] All results in this section are robust to restricting the sample to funds raised prior to 1995, to ensure each sample fund has completed its ten-year life.

[27] Though not shown, we also include industry effects to control for unobserved heterogeneity in company-level survival rates. Recall that Venture Economics provides no data on company characteristics such as sales or earnings.

[28] We obtain qualitatively similar results if we estimate simple probits of whether or not a portfolio company exits successfully. However, probits have two shortcomings in our setting. First, they cannot account for the right-censoring caused by the fact that some funds remain active beyond the November 2003 end of our sample period. Second, they cannot easily accommodate controls for exit market conditions, since it is unclear at what point in time such conditions should be measured in the case of companies that do not exit.

[29] A way of avoiding a specific distribution is to estimate semiparametric Cox models. This does not affect our results.

[30] Except for *betweenness* which is undefined in subblocks of the adjacency matrix this is straightforward. For instance, a noncorporate VC's $degree_C$ is simply a count of the number of unique corporate investors it had relationships with over the relevant time period, normalized as before.

[31] Following standard practice, mergers and exchange offers are not classified as involuntary delisting events.

[32] Note that as we do not have a full three-year window for very recent IPOs, it is conceivable that this understates the delisting rate somewhat. On the other hand, there were extremely few VC-backed IPOs between 2001 and 2003.

[33] This is consistent with the "money chasing deals" phenomenon of Gompers and Lerner (2000) resulting in more marginal companies being funded by the VC industry.

[34] Our results are robust to using longer lags, though we lose observations.

[35] To illustrate this, consider the network taking the form of a "Y," where actors A, C, and D sit on the three end points of the "Y" and actor B sits at the center. This is the network configuration that provides the highest number of shortest-distance paths upon which a single actor sits, in this case actor B, who sits upon the shortest-distance paths from A to C, from A to D, and from C to D.

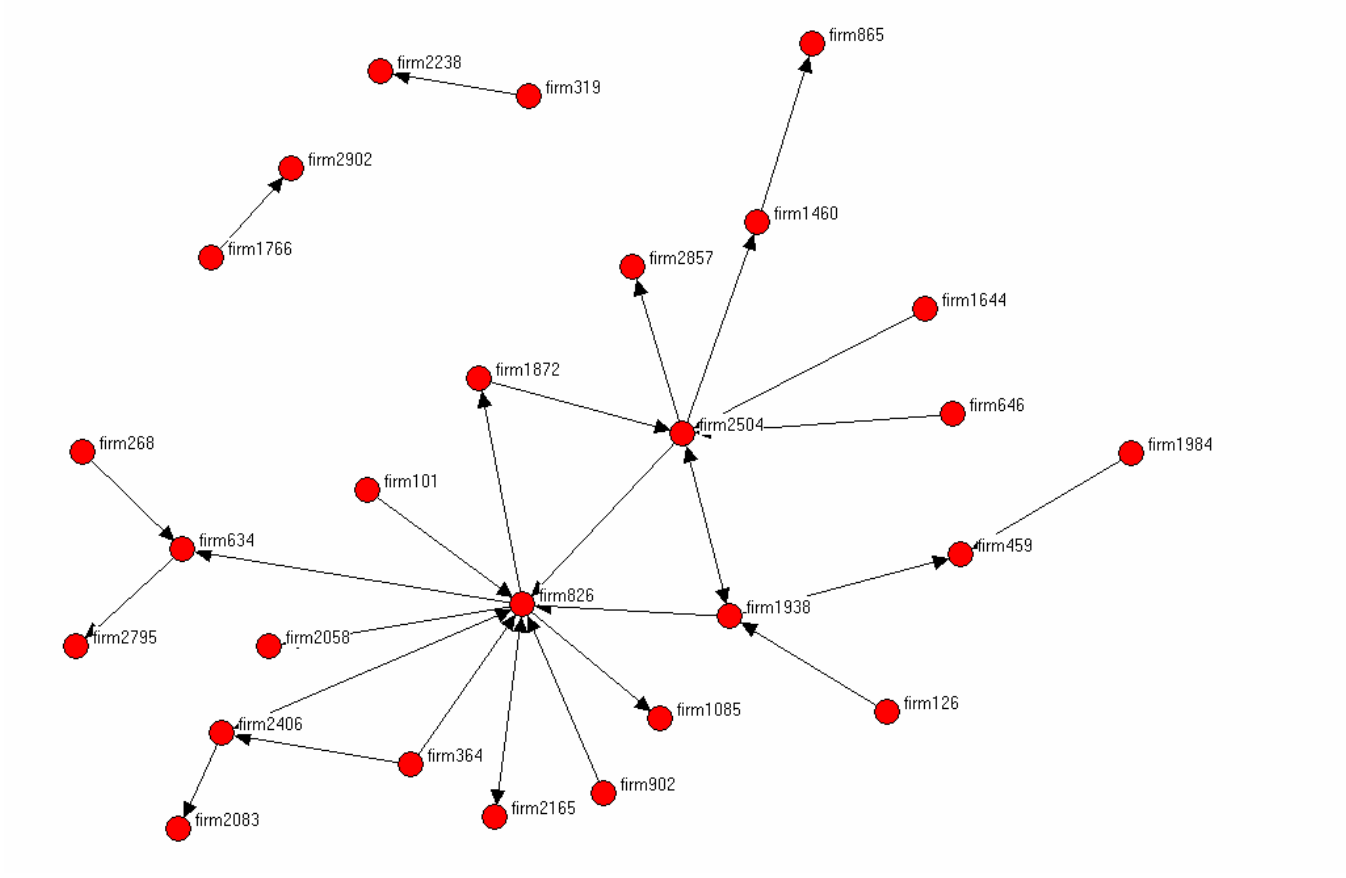


Figure 1. Network of biotech VC firms, 1990-1994. The figure shows the network that arises from syndication of portfolio company investments by biotech-focused VC firms over the five-year window 1990 to 1994. For tractability purposes, VC firms with no syndication relationships over the time period are excluded from the graph. 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 some point in the time window led a syndicate in which the other was a non-lead member.

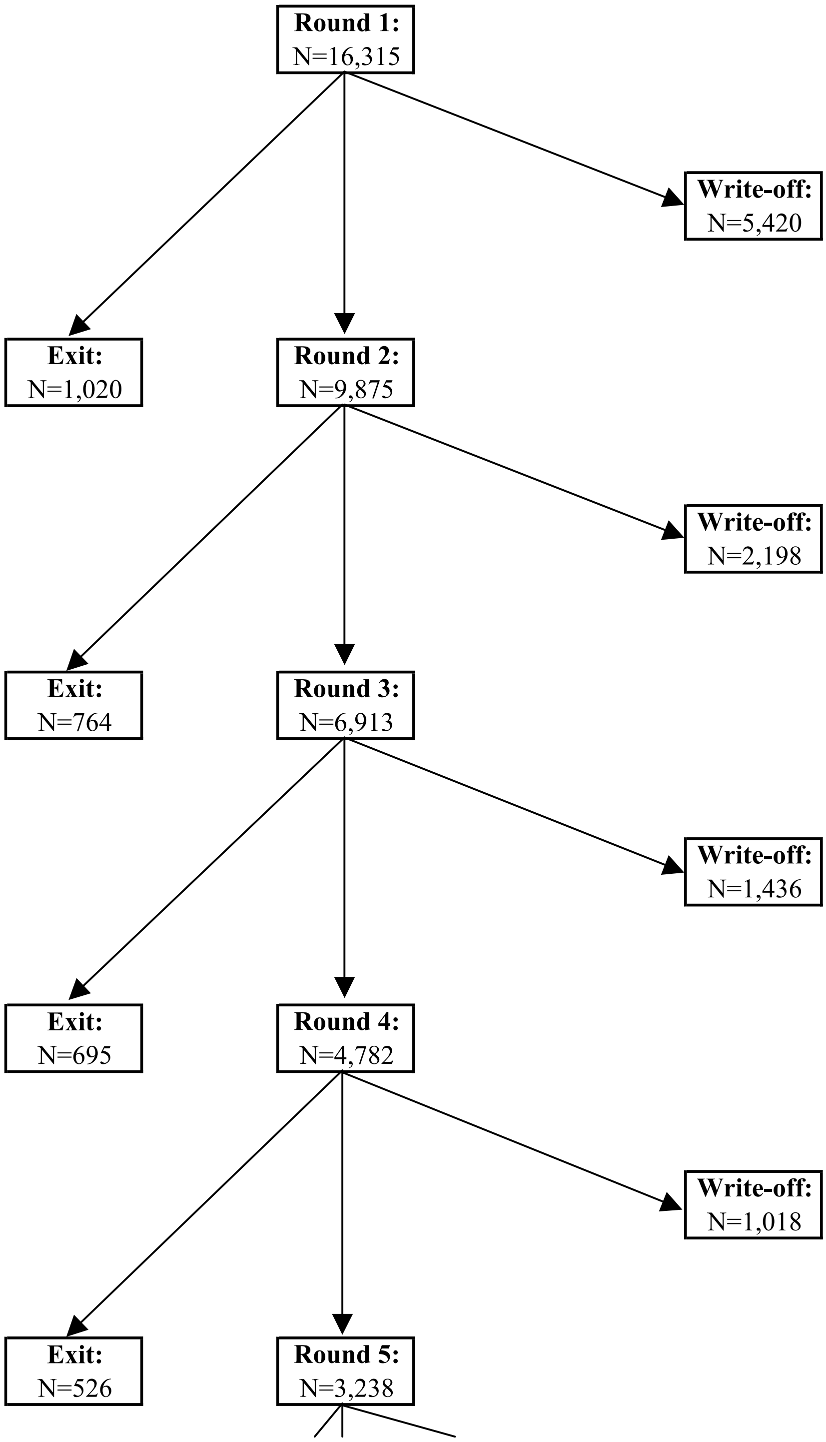


Figure 2. The company-level sample consists of 16,315 portfolio companies that received their first institutional round of funding (according to Venture Economics) from a sample VC fund between 1980 and 1999. We track each company through November 2003, recording whether it received further funding or exited via an IPO or M&A transaction. The figure shows the number of companies over the first five rounds, as well as the number of exits and write-offs. The median company receives two funding rounds.

Table I
Descriptive Statistics

The sample consists of 3,469 venture capital funds headquartered in the U.S. that were started between 1980 and 1999 (the "vintage years"). Fund size is the amount of committed capital reported in the Venture Economics database. Sequence number denotes whether a fund is the first, second and so forth fund raised by a particular VC management firm. The classification into seed or early-stage funds follows Venture Economics' fund focus variable. Corporate VCs are identified manually starting with Venture Economics' firm type variable. Absent data on fund returns, we measure a fund's performance by its exit rate, defined as the fraction of its portfolio companies that have been successfully exited via an initial public offering (IPO) or a sale to another company (M&A), as of November 2003. We also report dollar exit rates, defined as the fraction of the portfolio by invested dollars that has been successfully exited. The four controls for the investment experience of a sample fund's parent (management) firm are based on the parent's investment activities measured between the parent's creation and the fund's vintage year. By definition, the experience measures are zero for first-time funds. The network measures are derived from adjacency matrices constructed using all VC syndicates over the five years prior to a sample fund's vintage year. We view networks as existing among VC management firms, not among VC funds, so that a newly-raised fund can benefit from its parent's pre-existing network connections. A management firm's *outdegree* is the number of unique VCs that have participated as non-lead investors in syndicates lead-managed by the firm. (The lead investor is identified as the fund that invests the largest amount in the portfolio company.) A firm's *indegree* is the number of unique VCs that have led syndicates the firm was a non-lead member of. A firm's *degree* is the number of unique VCs it has syndicated with (regardless of syndicate role). *Eigenvector* measures how close to all other VCs a given VC is. *Betweenness* is the number of shortest-distance paths between other VCs in the network upon which the VC sits. Each network measure is normalized by the theoretical maximum (e.g., the *degree* of a VC who has syndicated with every other VC in the network.) The VC inflows variable is the aggregate amount of capital raised by other VC funds in the sample fund's vintage year. P/E and B/M are the price/earnings and book/market ratios of *public* companies in the sample fund's industry of interest. We take a fund's industry of interest to be the Venture Economics industry that accounts for the largest share of its portfolio, based on dollars invested. Venture Economics classifies portfolio companies into the following six industries: biotechnology, communications and media, computer related, medical/health/life science, semiconductors/other electronics, and nonhigh-technology. We map public-market P/E and B/M ratios to these industries based on four-digit SIC codes. The ratios are value-weighted averages measured over a sample fund's first three years of existence, to control for investment opportunities during the fund's most active investment phase.

Table I
Descriptive Statistics (continued)

	No.	Mean	Std. dev.	Min	Median	Max
Fund characteristics						
fund size ($m)	3,105	64.0	169.2	0.1	20.0	5,000
sequence number	2,242	3.4	3.7	1	2	32
first fund (fraction, %)	3,469	25.1				
seed or early-stage fund (fraction, %)	3,469	36.5				
corporate VC (fraction, %)	3,469	15.9				
Fund performance						
exit rate (% of portfolio companies exited)	3,469	34.2	29.2	0	33.3	100
IPO rate (% of portfolio companies sold via IPO)	3,469	20.7	25.1	0	13.6	100
M&A rate (% of portfolio companies sold via M&A)	3,469	13.6	18.7	0	8.5	100
dollar exit rate (% of invested $ exited)	3,411	35.8	32.3	0	30.6	100
dollar IPO rate (% of invested $ exited via IPO)	3,411	22.2	28.2	0	10.6	100
dollar M&A rate (% of invested $ exited via M&A)	3,411	13.6	20.9	0	5.3	100
Fund parent's experience (as of vintage year)						
days since parent's first investment	3,469	1,701	2,218	0	486	9,130
no. of rounds parent has participated in so far	3,469	76.6	199.4	0	5	2,292
aggregate amount parent has invested so far ($m)	3,469	71.7	249.6	0	4.9	6,564
no. of portfolio companies parent has invested in so far	3,469	30.8	65.3	0	4	601
Network measures (as of vintage year)						
outdegree	3,469	1.203	2.463	0	0.099	22.91
indegree	3,469	1.003	1.671	0	0.210	13.54
Degree	3,469	4.237	6.355	0	1.245	41.29
betweenness	3,469	0.285	0.750	0	0.004	7.16
Eigenvector	3,469	3.742	5.188	0	1.188	30.96
Competition						
VC inflows in fund's vintage year ($bn)	3,469	23.842	29.349	2.295	6.474	84.632
Investment opportunities						
average P/E ratio in fund's first 3 years	3,469	16.4	3.7	8.5	16.1	27.1
average B/M ratio in fund's first 3 years	3,469	0.514	0.237	0.177	0.526	1.226

Table II.
Benchmark Determinants of Fund Performance

The sample consists of 3,469 U.S. VC funds started between 1980 and 1999. The dependent variable is a fund's exit rate, defined as the fraction of a fund's portfolio companies that have been successfully exited via an initial public offering or a sale to another company, as of November 2003. All results in this and the following tables are robust to computing exit rates using the fraction of invested dollars that are successfully exited instead. Fund size is the amount of committed capital reported in the Venture Economics database. Sequence number denotes whether a fund is the parent firm's first, second and so forth fund. Sequence numbers are missing for 1,186 funds. The classification into seed or early-stage funds follows Venture Economics' fund focus variable. The VC inflows variable is the aggregate amount of capital raised by other VC funds in the year the sample fund was raised (its vintage year). P/E and B/M are the price/earnings and book/market ratios of *public* companies in the sample fund's industry of interest. We take a fund's industry of interest to be the Venture Economics industry that accounts for the largest share of the fund's portfolio, based on dollars invested. Venture Economics uses six industries: biotechnology, communications and media, computer related, medical/health/life science, semiconductors/other electronics, and nonhigh-technology. We map public-market P/E and B/M ratios to these industries based on four-digit SIC codes. The ratios are value-weighted averages measured over a sample fund's first three years of existence, to control for investment opportunities during the fund's most active investment phase. We measure the investment experience of a sample fund's parent firm as the aggregate dollars invested between the parent's creation and the fund's creation. All models are estimated using ordinary least-squares. Year dummies controlling for vintage year effects are included but not reported. They are jointly significant but their exclusion does not affect our results. Intercepts are not shown. White heteroskedasticity-consistent standard errors are shown in italics. (Results are robust to clustering the standard errors on firm id instead.) We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Table II (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fund characteristics								
ln fund size	0.024		0.038***	0.047***	0.047***	0.045***	0.040***	0.031***
	0.016		*0.011*	*0.011*	*0.011*	*0.011*	*0.011*	*0.011*
ln fund size squared	-0.001		-0.003*	-0.004***	-0.004***	-0.004**	-0.003**	-0.003**
	0.002		*0.002*	*0.002*	*0.002*	*0.002*	*0.0016*	*0.0016*
ln sequence number	0.017	0.026*						
	0.016	*0.016*						
ln sequence number squared	0.004	0.003						
	0.007	*0.007*						
=1 if first fund				-0.037***	-0.037***	-0.038***	-0.039***	0.005
				0.010	*0.010*	*0.010*	*0.010*	*0.011*
=1 if seed or early-stage fund				-0.005	-0.005	-0.008	-0.020**	-0.022**
				0.010	*0.010*	*0.010*	*0.010*	*0.010*
=1 if corporate VC				0.033*	0.033*	0.031	0.021	0.022
				0.019	*0.019*	*0.019*	*0.019*	*0.019*
Competition								
ln VC inflows in fund's vintage year					-0.063***	-0.066***	-0.109***	-0.114***
					0.008	*0.008*	*0.009*	*0.009*
Investment opportunities								
average P/E ratio in fund's first 3 years						0.008***		
						0.002		
average B/M ratio in fund's first 3 years							-0.322***	-0.314***
							0.030	*0.030*
Fund parent's experience								
ln parent's aggregate investment amount								0.011***
								0.002
Diagnostics								
Adjusted-R^2	21.7 %	20.7 %	13.6 %	14.0 %	14.0 %	14.8 %	17.2 %	18.7 %
Test: all coefficients = 0 (F)	36.2***	35.3***	39.5***	35.0***	35.0***	34.7***	40.1***	42.6***
No. of observations	2,242	2,283	3,105	3,105	3,105	3,105	3,105	3,105

Table III
The Effect of Firm Networks on Fund Performance

The sample consists of 3,469 venture capital funds headquartered in the U.S. that were started between 1980 and 1999. The dependent variable is a fund's exit rate, defined as the fraction of a fund's portfolio companies that have been successfully exited via an initial public offering (IPO) or a sale to another company (M&A), as of November 2003. Fund size is the amount of committed capital reported in the Venture Economics database. Sequence number denotes whether a fund is the parent firm's first, second and so forth fund. Sequence numbers are missing for 1,186 funds. The classification into seed or early-stage funds follows Venture Economics' fund focus variable. The VC inflows variable is the aggregate amount of capital raised by other VC funds in the year the sample fund was raised (its vintage year). B/M is the book/market ratio of *public* companies in the sample fund's industry of interest. We take a fund's industry of interest to be the Venture Economics industry that accounts for the largest share of the fund's portfolio, based on dollars invested. Venture Economics uses six industries: biotechnology, communications and media, computer related, medical/health/life science, semiconductors/other electronics, and nonhigh-technology. We map public-market B/M ratios to these industries based on four-digit SIC codes. The ratios are value-weighted averages measured over a sample fund's first three years of existence, to control for investment opportunities during the fund's most active investment phase. We measure the investment experience of a sample fund's parent firm as the aggregate dollars invested between the parent's creation and the fund's creation. In addition, we control for the effect of the *parent's* network centrality on a sample fund's performance. The network measures are derived from adjacency matrices constructed using all VC syndicates over the five years prior to a sample fund's vintage year. We view networks as existing among VC management firms, not among VC funds, so that a newly-raised fund can benefit from its parent's pre-existing network connections. A management firm's *outdegree* is the number of unique VCs that have participated as non-lead investors in syndicates lead-managed by the firm. (The lead investor is identified as the fund that invests the largest amount in the portfolio company.) A firm's *indegree* is the number of unique VCs that have led syndicates the firm was a non-lead member of. A firm's *degree* is the number of unique VCs it has syndicated with (regardless of syndicate role). *Eigenvector* measures how close to all other VCs a given VC is. *Betweenness* is the number of shortest-distance paths between other VCs in the network upon which the VC sits. Each network measure is normalized by the theoretical maximum (e.g., the *degree* of a VC who has syndicated with every other VC in the network). All models are estimated using ordinary least squares. Year dummies controlling for vintage year effects are included but not reported. They are jointly significant but their exclusion does not affect our results. Intercepts are not shown. White heteroskedasticity-consistent standard errors are shown in italics. (Results are robust to clustering the standard errors on firm id instead, except that *betweenness* ceases to be significant at conventional levels.) We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Table III (continued)

	(1)	(2)	(3)	(4)	(5)
Fund characteristics					
ln fund size	0.030***	0.029***	0.028**	0.031***	0.029***
	0.011	*0.011*	*0.011*	*0.011*	*0.011*
ln fund size squared	-0.003**	-0.003**	-0.003**	-0.003**	-0.003**
	0. 0016	*0. 0016*	*0.0016*	*0. 0016*	*0. 0016*
=1 if first fund	0.007	0.009	0.009	0.005	0.010
	0.011	*0.011*	*0.011*	*0.011*	*0.011*
=1 if seed or early-stage fund	-0.023**	-0.025**	-0.023**	-0.022**	-0.023**
	0.010	*0.010*	*0.010*	*0.010*	*0.010*
=1 if corporate VC	0.026	0.028	0.029	0.024	0.028
	0.019	*0.019*	*0.019*	*0.019*	*0.019*
Competition					
ln VC inflows in fund's vintage year	-0.109***	-0.107***	-0.106***	-0.110***	-0.103***
	0.009	*0.009*	*0.009*	*0.009*	*0.009*
Investment opportunities					
average B/M ratio in fund's first 3 years	-0.309***	-0.306***	-0.305***	-0.311***	-0.301***
	0.030	*0.030*	*0.030*	*0.030*	*0.030*
Fund parent's experience					
ln aggregate $ amount parent has invested so far	0.009***	0.008***	0.008***	0.010***	0.008***
	0.002	*0.002*	*0.002*	*0.002*	*0.002*
Network measures					
Outdegree	0.006***				
	0.002				
Indegree		0.014***			
		0.003			
Degree			0.004***		
			0.001		
betweenness				0.014**	
				0.006	
Eigenvector					0.005***
					0.001
Diagnostics					
Adjusted-R^2	18.9 %	19.1 %	19.1 %	18.8 %	19.1 %
Test: all coefficients = 0 (*F*)	41.7***	42.5***	42.4***	41.2***	42.4***
No. of observations	3,105	3,105	3,105	3,105	3,105

Table IV
Performance Persistence

The sample consists of 1,293 second- or higher sequence number venture capital funds headquartered in the U.S. that were started between 1980 and 1999. The dependent variable is a fund's exit rate, defined as the fraction of a fund's portfolio companies that have been successfully exited via an initial public offering (IPO) or a sale to another company (M&A), as of November 2003. Fund size is the amount of committed capital reported in the Venture Economics database. Sequence number denotes whether a fund is the parent firm's first, second and so forth fund. Sequence numbers are missing for 1,186 funds. The classification into seed or early-stage funds follows Venture Economics' fund focus variable. The VC inflows variable is the aggregate amount of capital raised by other VC funds in the year the sample fund was raised (its vintage year). B/M is the book/market ratio of *public* companies in the sample fund's industry of interest. We take a fund's industry of interest to be the Venture Economics industry that accounts for the largest share of the fund's portfolio, based on dollars invested. Venture Economics uses six industries: biotechnology, communications and media, computer related, medical/health/life science, semiconductors/other electronics, and nonhigh-technology. We map public-market B/M ratios to these industries based on four-digit SIC codes. The ratios are value-weighted averages measured over a sample fund's first three years of existence, to control for investment opportunities during the fund's most active investment phase. We measure the investment experience of a sample fund's parent firm as the aggregate dollars invested between the parent's creation and the fund's creation. Lagged exit rate is the exit rate of the VC parent firm's most recent past fund. We include lagged exit rate to control for persistence in VC performance. The network measures are derived from adjacency matrices constructed using all VC syndicates over the five years prior to a sample fund's vintage year. We view networks as existing among VC management firms, not among VC funds, so that a newly-raised fund can benefit from its parent's pre-existing network connections. A management firm's *outdegree* is the number of unique VCs that have participated as non-lead investors in syndicates lead-managed by the firm. (The lead investor is identified as the fund that invests the largest amount in the portfolio company.) A firm's *indegree* is the number of unique VCs that have led syndicates the firm was a non-lead member of. A firm's *degree* is the number of unique VCs it has syndicated with (regardless of syndicate role). *Eigenvector* measures how close to all other VCs a given VC is. *Betweenness* is the number of shortest-distance paths between other VCs in the network upon which the VC sits. Each network measure is normalized by the theoretical maximum (e.g., the *degree* of a VC who has syndicated with every other VC in the network). All models are estimated using ordinary least-squares. Year dummies controlling for vintage year effects are included but not reported. They are jointly significant but their exclusion does not affect our results. Intercepts are not shown. White heteroskedasticity-consistent standard errors are shown in italics. (Results are robust to clustering the standard errors on firm id instead.) We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Table IV (continued)

	(1)	(2)	(3)	(4)	(5)
Fund characteristics					
ln fund size	0.019	0.018	0.018	0.019	0.020
	0.018	*0.018*	*0.018*	*0.018*	*0.018*
ln fund size squared	-0.002	-0.001	-0.001	-0.002	-0.002
	0.002	*0.002*	*0.002*	*0.002*	*0.002*
=1 if seed or early-stage fund	-0.015	-0.016	-0.014	-0.014	-0.015
	0.013	*0.013*	*0.013*	*0.013*	*0.013*
=1 corporate VC	-0.037	-0.035	-0.037	-0.039	-0.038
	0.037	*0.037*	*0.037*	*0.037*	*0.036*
Competition					
ln VC inflows in fund's vintage year	-0.103***	-0.099***	-0.099***	-0.102***	-0.094***
	0.016	*0.017*	*0.017*	*0.016*	*0.017*
Investment opportunities					
average B/M ratio in fund's first 3 years	-0.256***	-0.249***	-0.249***	-0.256***	-0.244***
	0.045	*0.045*	*0.046*	*0.046*	*0.046*
Fund parent's experience					
ln aggregate $ amount parent has invested so far	0.007	0.004	0.005	0.008*	0.004
	0.005	*0.005*	*0.005*	*0.004*	*0.005*
Fund parent's lagged performance					
lagged exit rate	0.265***	0.258***	0.260***	0.266***	0.257***
	0.032	*0.032*	*0.032*	*0.031*	*0.032*
Network measures					
Outdegree	0.003				
	0.003				
Indegree		0.012***			
		0.004			
Degree			0.003**		
			0.001		
betweenness				0.013	
				0.009	
Eigenvector					0.004**
					0.002
Diagnostics					
Adjusted-R^2	30.4 %	30.8 %	30.6 %	30.4 %	30.6 %
Test: all coefficients = 0 (F)	29.4***	29.8***	29.5***	29.0***	29.6***
No. of observations	1,293	1,293	1,293	1,293	1,293

Table V
Panel A. Effect of Firm Networks on Portfolio Company Survival

The sample consists of up to 13,761 portfolio companies that received their first institutional round of funding from a sample VC fund between 1980 and 1999 (and for which relevant cross-sectional information is available). We track each company from its first funding round across all rounds to the date of its exit or November 2003, whichever is sooner. The dependent variable is an indicator equal to one if the company survived from round *N* to round *N*+1 or if it exited via an IPO or M&A transaction. Note that survival to round *N*+1 is conditional on having survived to round *N*, so the sample size decreases from round to round. Fund size is the amount of committed capital reported in the Venture Economics database. Sequence number denotes whether a fund is the parent firm's first, second and so forth fund. Sequence numbers are missing for 1,186 funds. The classification into seed or early-stage funds follows Venture Economics' fund focus variable. The VC inflows variable is the aggregate amount of capital raised by other VC funds in the year the sample fund was raised (its vintage year). B/M is the book/market ratio of *public* companies in the sample fund's industry of interest. We take a fund's industry of interest to be the Venture Economics industry that accounts for the largest share of the fund's portfolio, based on dollars invested. Venture Economics uses six industries: biotechnology, communications and media, computer related, medical/health/life science, semiconductors/other electronics, and nonhigh-technology. We map public-market B/M ratios to these industries based on four-digit SIC codes. The ratios are value-weighted averages measured over a sample fund's first three years of existence, to control for investment opportunities during the fund's most active investment phase. We measure the investment experience of a sample fund's parent firm as the aggregate dollars invested between the parent's creation and the fund's creation. The network measures are derived from adjacency matrices constructed using all VC syndicates over the five years prior to a sample fund's vintage year. We view networks as existing among VC management firms, not among VC funds, so that a newly-raised fund can benefit from its parent's pre-existing network connections. A management firm's *outdegree* is the number of unique VCs that have participated as non-lead investors in syndicates lead-managed by the firm. (The lead investor is identified as the fund that invests the largest amount in the portfolio company.) A firm's *indegree* is the number of unique VCs that have led syndicates the firm was a non-lead member of. A firm's *degree* is the number of unique VCs it has syndicated with (regardless of syndicate role). *Eigenvector* measures how close to all other VCs a given VC is. *Betweenness* is the number of shortest-distance paths between other VCs in the network upon which the VC sits. Each network measure is normalized by the theoretical maximum (e.g., the *degree* of a VC who has syndicated with every other VC in the network). In addition, we include a dummy coded one if in round $N>1$ a more influential VC takes over as lead investor (based on a comparison of its network centrality to that of the previous lead). The measures of the parent's network centrality are estimated over the five-year window ending in the year the funding round is concluded. All models are estimated using probit maximum likelihood estimation. Industry effects using the Venture Economics industry groups are included but not reported. Intercepts are not shown. Heteroskedasticity-consistent standard errors are shown in italics. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Table V (continued)

	Survived round			Survived round		
	1	2	3	1	2	3
Fund characteristics						
ln fund size	0.215***	0.156***	0.094	0.202***	0.142***	0.072
	0.030	*0.044*	*0.059*	*0.030*	*0.045*	*0.059*
ln fund size squared	-0.009**	-0.012**	-0.007	-0.006	-0.009*	-0.003
	0.004	*0.005*	*0.007*	*0.004*	*0.005*	*0.007*
=1 if first fund	-0.006	-0.039	-0.162***	-0.005	-0.037	-0.158***
	0.025	*0.036*	*0.044*	*0.026*	*0.036*	*0.044*
=1 if corporate VC	-0.169***	-0.031	-0.053	-0.162***	-0.031	-0.049
	0.055	*0.075*	*0.084*	*0.055*	*0.075*	*0.083*
Competition						
ln VC inflows in funding year	-0.125***	-0.164***	-0.080***	-0.123***	-0.169***	-0.088***
	0.021	*0.023*	*0.027*	*0.021*	*0.023*	*0.027*
Investment opportunities						
mean B/M ratio in funding year	-0.448***	-1.083***	-1.037***	-0.436***	-1.064***	-0.922***
	0.114	*0.153*	*0.197*	*0.114*	*0.153*	*0.196*
Fund parent's experience						
ln aggregate $ amount invested	-0.010	-0.041**	-0.147***	-0.011	-0.032*	-0.126***
	0.010	*0.017*	*0.024*	*0.010*	*0.017*	*0.023*
Network measures						
Outdegree	0.035***	0.040***	0.075***			
	0.005	*0.007*	*0.009*			
Indegree				0.056***	0.054***	0.103***
				0.008	*0.011*	*0.014*
=1 if new lead is more influential than previous lead		0.156***	0.015		0.177***	-0.033
		0.039	*0.046*		*0.040*	*0.047*
Diagnostics						
Pseudo-R^2	9.5%	4.9 %	4.0 %	9.5 %	4.9 %	3.6 %
Test: all coeff. = 0 (χ^2)	1518.0***	405.2***	204.9***	1521.3***	404.1***	195.4***
No. of observations	13,761	8,650	6,164	13,761	8,650	6,164

Table V (continued)

	Survived round			Survived round			Survived round		
	1	2	3	1	2	3	1	2	3
Fund characteristics									
ln fund size	0.203***	0.149***	0.073	0.217***	0.172***	0.135**	0.201***	0.134***	0.081
	0.030	*0.044*	*0.059*	*0.031*	*0.044*	*0.057*	*0.030*	*0.044*	*0.059*
ln fund size squared	-0.007*	-0.011**	-0.003	-0.009**	-0.014***	-0.012*	-0.007*	-0.008	-0.004
	0.004	*0.005*	*0.007*	*0.004*	*0.005*	*0.007*	*0.004*	*0.005*	*0.007*
=1 if first fund	-0.010	-0.040	-0.162***	-0.016	-0.050	-0.183***	-0.008	-0.035	-0.156***
	0.026	*0.036*	*0.044*	*0.025*	*0.036*	*0.044*	*0.026*	*0.036*	*0.044*
=1 corporate VC	-0.178***	-0.052	-0.081	-0.179***	-0.045	-0.083	-0.174***	-0.053	-0.092
	0.055	*0.076*	*0.084*	*0.055*	*0.075*	*0.084*	*0.055*	*0.075*	*0.084*
Competition									
ln VC inflows in funding year	-0.120***	-0.170***	-0.072***	-0.154***	-0.190***	-0.121***	-0.134***	-0.162***	-0.086***
	0.021	*0.023*	*0.027*	*0.020*	*0.022*	*0.026*	*0.021*	*0.022*	*0.026*
Investment opportunities									
mean B/M ratio in funding year	-0.447***	-1.105***	-1.090***	-0.448***	-1.027***	-0.797***	-0.563***	-1.118***	-0.893***
	0.114	*0.154*	*0.196*	*0.115*	*0.154*	*0.199*	*0.115*	*0.153*	*0.198*
Fund parent's experience									
ln aggregate $ amount invested	-0.009	-0.029	-0.139***	0.013	-0.012	-0.091***	-0.027***	-0.065***	-0.161***
	0.010	*0.018*	*0.024*	*0.009*	*0.016*	*0.021*	*0.010*	*0.018*	*0.024*
Network measures									
degree	0.013***	0.014***	0.033***						
	0.002	*0.003*	*0.004*						
betweenness				0.051***	0.081***	0.149***			
				0.015	*0.021*	*0.027*			
Eigenvector							0.027***	0.032***	0.050***
							0.003	*0.004*	*0.005*
=1 if new lead is more influential than previous lead		0.178***	-0.031		0.172***	0.055		0.159***	-0.040
		0.039	*0.046*		*0.039*	*0.046*		*0.040*	*0.047*
Diagnostics									
Pseudo-R^2	9.4 %	4.8 %	3.7 %	9.3 %	4.7 %	3.1 %	9.7 %	5.3 %	4.0 %
Test: all coeff. = 0 (χ^2)	1520.1***	401.7***	206.4***	1506.6***	393.1***	174.1***	1562.4***	445.1***	239.2***
No. of observations	13,761	8,650	6,164	13,761	8,650	6,164	13,761	8,650	6,164

Table VI
Pooled Portfolio Company Survival Models

The sample pools 42,074 funding rounds for 13,761 portfolio companies that were concluded from 1980 onwards. We track each company from its first funding round across all rounds to the date of its exit or November 2003, whichever is sooner. In this panel structure, the dependent variable is an indicator equaling one in round N if the company survived to the next round $N+1$. Unless it subsequently exited via an IPO or M&A transaction, the dependent variable is zero in the company's last recorded round. All models are estimated using panel probit estimators with random company effects. Fund size is the amount of committed capital reported in the Venture Economics database. Sequence number denotes whether a fund is the parent firm's first, second and so forth fund. Sequence numbers are missing for 1,186 funds. The classification into seed or early-stage funds follows Venture Economics' fund focus variable. The VC inflows variable is the aggregate amount of capital raised by other VC funds in the year the sample fund was raised (its vintage year). B/M is the book/market ratio of *public* companies in the sample fund's industry of interest. We take a fund's industry of interest to be the Venture Economics industry that accounts for the largest share of the fund's portfolio, based on dollars invested. Venture Economics uses six industries: biotechnology, communications and media, computer related, medical/health/life science, semiconductors/other electronics, and nonhigh-technology. We map public-market B/M ratios to these industries based on four-digit SIC codes. The ratios are value-weighted averages measured over a sample fund's first three years of existence, to control for investment opportunities during the fund's most active investment phase. We measure the investment experience of a sample fund's parent firm as the aggregate dollars invested between the parent's creation and the fund's creation. The network measures are derived from adjacency matrices constructed using all VC syndicates over the five years prior to a sample fund's vintage year. We view networks as existing among VC management firms, not among VC funds, so that a newly-raised fund can benefit from its parent's pre-existing network connections. A management firm's *outdegree* is the number of unique VCs that have participated as non-lead investors in syndicates lead-managed by the firm. (The lead investor is identified as the fund that invests the largest amount in the portfolio company.) A firm's *indegree* is the number of unique VCs that have led syndicates the firm was a non-lead member of. A firm's *degree* is the number of unique VCs it has syndicated with (regardless of syndicate role). *Eigenvector* measures how close to all other VCs a given VC is. *Betweenness* is the number of shortest-distance paths between other VCs in the network upon which the VC sits. Each network measure is normalized by the theoretical maximum (e.g., the *degree* of a VC who has syndicated with every other VC in the network). In addition, we include a dummy coded one if in round $N>1$ a more influential VC takes over as lead investor (based on a comparison of its network centrality to that of the previous lead). The measures of the parent's investment experience and network centrality are estimated as of the year in which the funding round is concluded. Industry effects using the Venture Economics industry groups are included but not reported. Intercepts are not shown. Standard errors are shown in italics. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Table VI (continued)

	(1)	(2)	(3)	(4)	(5)
Fund characteristics					
ln fund size	0.272***	0.248***	0.245***	0.293***	0.253***
	0.021	*0.021*	*0.021*	*0.021*	*0.021*
ln fund size squared	-0.025***	-0.021***	-0.020***	-0.027***	-0.022***
	0.003	*0.003*	*0.003*	*0.003*	*0.003*
=1 if first fund	-0.023	-0.022	-0.027	-0.041**	-0.022
	0.018	*0.018*	*0.018*	*0.018*	*0.018*
=1 if corporate VC	-0.068*	-0.060*	-0.089**	-0.092***	-0.089**
	0.035	*0.035*	*0.035*	*0.035*	*0.036*
Competition					
ln VC inflows in funding year	-0.022**	-0.022**	-0.006	-0.052***	-0.024**
	0.010	*0.010*	*0.010*	*0.010*	*0.010*
Investment opportunities					
mean B/M ratio in funding year	-0.526***	-0.490***	-0.594***	-0.425***	-0.570***
	0.070	*0.070*	*0.071*	*0.070*	*0.071*
Fund parent's experience					
ln aggregate $ amount parent has invested so far	-0.066***	-0.061***	-0.076***	-0.029***	-0.092***
	0.007	*0.007*	*0.007*	*0.007*	*0.008*
Network measures					
outdegree	0.056***				
	0.003				
indegree		0.084***			
		0.005			
degree			0.028***		
			0.001		
betweenness				0.101***	
				0.009	
eigenvector					0.044***
					0.002
=1 if new lead is more influential than previous lead	0.067***	0.052**	0.048**	0.105***	0.047**
	0.022	*0.022*	*0.022*	*0.022*	*0.022*
Diagnostics					
Pseudo-R^2	5.7 %	5.6 %	5.7 %	5.2 %	6.0 %
Test: all coeff. = 0 (χ^2)	1930.3***	1915.7***	1942.0***	1760.1***	1986.8***
No. of observations	42,074	42,074	42,074	42,074	42,074
No. of companies	13,761	13,761	13,761	13,761	13,761

Table VII
Effect of Network Position on Portfolio Company Exit Duration

The sample consists of 13,761 portfolio companies that received their first institutional round of funding (according to Venture Economics) from a sample VC fund between 1980 and 1999 (and for which relevant cross-sectional information is available). We estimate accelerated time-to-exit models (i.e., hazard models written with log time as the dependent variable) where log time is assumed to be normally distributed. (We obtain similar results using other distributions, such as the exponential, Gompertz, and Weibull. Our results are also robust to estimating semiparametric Cox models.) Positive (negative) coefficients indicate that the covariate increases (decreases) the time a company takes to exit via an IPO or an M&A transaction. Companies that have not exited by the fund's tenth anniversary are assumed to have been liquidated. Companies backed by funds that are in existence beyond November 2003 are treated as right-censored (to allow for the possibility that they may yet exit successfully after the end of our sample period), and the likelihood function is modified accordingly. The models allow for time-varying covariates. We treat market conditions as time-varying, that is, market conditions change every quarter between the first investment round and the final exit (or the fund's tenth anniversary, or November 2003). All other independent variables are treated as time-invariant. Fund size is the amount of committed capital reported in the Venture Economics database. Sequence number denotes whether a fund is the parent firm's first, second and so forth fund. Sequence numbers are missing for 1,186 funds. The classification into seed or early-stage funds follows Venture Economics' fund focus variable. The VC inflows variable is the aggregate amount of capital raised by other VC funds in the year the sample fund was raised (its vintage year). B/M is the book/market ratio of *public* companies in the sample fund's industry of interest. We take a fund's industry of interest to be the Venture Economics industry that accounts for the largest share of the fund's portfolio, based on dollars invested. Venture Economics uses six industries: biotechnology, communications and media, computer related, medical/health/life science, semiconductors/other electronics, and nonhigh-technology. We map public-market B/M ratios to these industries based on four-digit SIC codes. The ratios are value-weighted averages measured over a sample fund's first three years of existence, to control for investment opportunities during the fund's most active investment phase. We measure the investment experience of a sample fund's parent firm as the aggregate dollars invested between the parent's creation and the fund's creation. The network measures are derived from adjacency matrices constructed using all VC syndicates over the five years prior to a sample fund's vintage year. We view networks as existing among VC management firms, not among VC funds, so that a newly-raised fund can benefit from its parent's pre-existing network connections. A management firm's *outdegree* is the number of unique VCs that have participated as non-lead investors in syndicates lead-managed by the firm. (The lead investor is identified as the fund that invests the largest amount in the portfolio company.) A firm's *indegree* is the number of unique VCs that have led syndicates the firm was a non-lead member of. A firm's *degree* is the number of unique VCs it has syndicated with (regardless of syndicate role). *Eigenvector* measures how close to all other VCs a given VC is. *Betweenness* is the number of shortest-distance paths between other VCs in the network upon which the VC sits. Each network measure is normalized by the theoretical maximum (e.g., the *degree* of a VC who has syndicated with every other VC in the network). The measures of the parent's investment experience and network centrality are estimated as of the year in which the portfolio company received its first funding round. Intercepts are not shown. Heteroskedasticity-consistent standard errors are shown in italics. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Table VII (continued)

	(1)	(2)	(3)	(4)	(5)
Fund characteristics					
ln fund size	0.026	0.030	0.030	0.021	0.039
	0.038	*0.038*	*0.038*	*0.038*	*0.038*
ln fund size squared	0.000	-0.001	-0.001	0.001	-0.002
	0.005	*0.005*	*0.005*	*0.005*	*0.005*
=1 if first fund	-0.158***	-0.159***	-0.157***	-0.153***	-0.161***
	0.030	*0.030*	*0.030*	*0.030*	*0.030*
=1 if corporate VC	-0.100	-0.101	-0.096	-0.097	-0.098
	0.064	*0.064*	*0.064*	*0.064*	*0.064*
Competition					
ln VC inflows in funding year	0.190***	0.189***	0.188***	0.199***	0.184***
	0.026	*0.026*	*0.026*	*0.025*	*0.025*
Investment opportunities					
mean B/M ratio in funding year	1.399***	1.391***	1.400***	1.405***	1.385***
	0.078	*0.078*	*0.078*	*0.078*	*0.078*
Fund parent's experience					
ln aggregate $ amount parent has invested so far	-0.098***	-0.097***	-0.098***	-0.102***	-0.081***
	0.013	*0.013*	*0.014*	*0.012*	*0.013*
Market conditions (time-varying)					
lagged NASDAQ Composite Index return	-0.718***	-0.718***	-0.718***	-0.718***	-0.718***
	0.085	*0.085*	*0.085*	*0.085*	*0.085*
lagged *ln* no. of VC-backed IPOs in same VE industry	-0.271***	-0.271***	-0.271***	-0.271***	-0.271***
	0.014	*0.014*	*0.014*	*0.014*	*0.014*
lagged *ln* no. of VC-backed M&A deals in same VE industry	0.018	0.020	0.018	0.018	0.013
	0.016	*0.016*	*0.016*	*0.016*	*0.016*
Network measures					
outdegree	-0.012**				
	0.005				
Indegree		-0.018**			
		0.007			
Degree			-0.005**		
			0.002		
betweenness				-0.035***	
				0.013	
Eigenvector					-0.014***
					0.003
Diagnostics					
Pseudo-R^2	8.3 %	8.3 %	8.3 %	8.3 %	8.4 %
Test: all coeff. = 0 (χ^2)	993.0***	1002.3***	992.0***	995.8***	1042.0***
No. of observations	13,761	13,761	13,761	13,761	13,761

Table VIII
The Effect of Firm Networks on Fund Performance Conditional on Indegree

The sample consists of 3,469 venture capital funds headquartered in the U.S. that were started between 1980 and 1999. Fund size is the amount of committed capital reported in the Venture Economics database. Sequence number denotes whether a fund is the parent firm's first, second and so forth fund. Sequence numbers are missing for 1,186 funds. The classification into seed or early-stage funds follows Venture Economics' fund focus variable. The VC inflows variable is the aggregate amount of capital raised by other VC funds in the year the sample fund was raised (its vintage year). B/M is the book/market ratios of *public* companies in the sample fund's industry of interest. We take a fund's industry of interest to be the Venture Economics industry that accounts for the largest share of the fund's portfolio, based on dollars invested. Venture Economics uses six industries: biotechnology, communications and media, computer related, medical/health/life science, semiconductors/other electronics, and nonhigh-technology. We map public-market B/M ratios to these industries based on four-digit SIC codes. The ratios are value-weighted averages measured over a sample fund's first three years of existence, to control for investment opportunities during the fund's most active investment phase. We measure the investment experience of a sample fund's parent firm as the aggregate dollars invested between the parent's creation and the fund's creation. In addition, we control for the effect of the *parent's* network centrality on a sample fund's performance. The network measures are derived from adjacency matrices constructed using all VC syndicates over the five years prior to a sample fund's vintage year. We view networks as existing among VC management firms, not among VC funds, so that a newly-raised fund can benefit from its parent's pre-existing network connections. A management firm's *outdegree* is the number of unique VCs that have participated as non-lead investors in syndicates lead-managed by the firm. (The lead investor is identified as the fund that invests the largest amount in the portfolio company.) A firm's *indegree* is the number of unique VCs that have led syndicates the firm was a non-lead member of. A firm's *degree* is the number of unique VCs it has syndicated with (regardless of syndicate role). *Eigenvector* measures how close to all other VCs a given VC is. *Betweenness* is the number of shortest-distance paths between other VCs in the network upon which the VC sits. Each network measure is normalized by the theoretical maximum (e.g., the *degree* of a VC who has syndicated with every other VC in the network). We interact each network centrality measure with a dummy equaling one if the VC fund's parent firm had below-median *indegree* over the sample period. All models are estimated using ordinary least-squares. Year dummies and intercepts are not shown. White heteroskedasticity-consistent standard errors are shown in italics. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Table VIII (continued)

	(1)	(2)	(3)	(4)
Fund characteristics				
ln fund size	0.030***	0.034***	0.030***	0.036***
	0.011	*0.011*	*0.011*	*0.011*
ln fund size squared	-0.003**	-0.004**	-0.003**	-0.004***
	0.002	*0.002*	*0.002*	*0.002*
=1 if first fund	0.007	0.005	0.005	0.004
	0.011	*0.011*	*0.011*	*0.011*
=1 if seed or early-stage fund	-0.023**	-0.018*	-0.022**	-0.018*
	0.010	*0.010*	*0.010*	*0.010*
=1 if corporate VC	0.026	0.025	0.024	0.023
	0.019	*0.019*	*0.019*	*0.019*
Competition				
ln VC inflows in fund's vintage year	-0.109***	-0.105***	-0.110***	-0.102***
	0.009	*0.009*	*0.009*	*0.009*
Investment opportunities				
Average B/M ratio in fund's first 3 years	-0.309***	-0.296***	-0.311***	-0.284***
	0.030	*0.030*	*0.030*	*0.030*
Fund parent's experience				
ln aggregate $ amount parent has invested so far	0.010***	0.007***	0.010***	0.006***
	0.002	*0.002*	*0.002*	*0.002*
Network measures				
outdegree	0.006***			
	0.002			
… X dummy=1 if VC firm has below-median *indegree*	-0.018			
	0.023			
Degree		0.005***		
		0.001		
… X dummy=1 if VC firm has below-median *indegree*		0.051***		
		0.011		
betweenness			0.014**	
			0.006	
… X dummy=1 if VC firm has below-median *indegree*			0.048	
			0.141	
eigenvector				0.006***
				0.001
… X dummy=1 if VC firm has below-median *indegree*				0.058***
				0.010
Diagnostics				
Adjusted-R^2	18.9 %	19.8 %	18.8 %	20.3 %
Test: all coefficients = 0 (*F*)	40.4***	41.9***	39.7***	42.2***
No. of observations	3,105	3,105	3,105	3,105

Table IX
The Effect of VC Firm Relationships with Corporate Investors

The sample consists of 2,811 second-round investments satisfying the following two conditions: 1) The lead investor in round 2 was not among the first-round investors; and 2) there were no corporate investors in the first two rounds. The dependent variable is an indicator equal to one if the company survived from round 2 to round 3 or if it exited via an IPO or M&A transaction. Fund size is the amount of committed capital reported in the Venture Economics database. Sequence number denotes whether a fund is the parent firm's first, second and so forth fund. Sequence numbers are missing for 1,186 funds. The classification into seed or early-stage funds follows Venture Economics' fund focus variable. The VC inflows variable is the aggregate amount of capital raised by other VC funds in the year the sample fund was raised (its vintage year). B/M is the book/market ratio of *public* companies in the sample fund's industry of interest. We take a fund's industry of interest to be the Venture Economics industry that accounts for the largest share of the fund's portfolio, based on dollars invested. Venture Economics uses six industries: biotechnology, communications and media, computer related, medical/health/life science, semiconductors/other electronics, and nonhigh-technology. We map public-market B/M ratios to these industries based on four-digit SIC codes. The ratios are value-weighted averages measured over a sample fund's first three years of existence, to control for investment opportunities during the fund's most active investment phase. We measure the investment experience of a sample fund's parent firm as the aggregate dollars invested between the parent's creation and the fund's creation. The network measures are derived from adjacency matrices constructed using all VC syndicates over the five years prior to a sample fund's vintage year. We view networks as existing among VC management firms, not among VC funds, so that a newly-raised fund can benefit from its parent's pre-existing network connections. A management firm's *outdegree* is the number of unique VCs that have participated as non-lead investors in syndicates lead-managed by the firm. (The lead investor is identified as the fund that invests the largest amount in the portfolio company.) A firm's *indegree* is the number of unique VCs that have led syndicates the firm was a non-lead member of. A firm's *degree* is the number of unique VCs it has syndicated with (regardless of syndicate role). *Eigenvector* measures how close to all other VCs a given VC is. *Betweenness* is the number of shortest-distance paths between other VCs in the network upon which the VC sits. Each network measure is normalized by the theoretical maximum (e.g., the *degree* of a VC who has syndicated with every other VC in the network). The measures of the parent's network centrality are estimated over the five-year window ending in the year the funding round is concluded. We include both network-wide network centrality measures, and network measures for a VC's relationships with corporate VCs only (subscripted "C"). Each pair of network measures is orthogonalized to avoid collinearity problems. All models are estimated using probit maximum likelihood estimation. Industry effects using the Venture Economics industry groups are included but not reported. Intercepts are not shown. Heteroskedasticity-consistent standard errors are shown in italics. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively.

Table IX (continued)

	Survived round 2			
	(1)	(2)	(3)	(4)
Fund characteristics				
ln fund size	0.300***	0.278***	0.294***	0.278***
	0.102	*0.089*	*0.094*	*0.095*
ln fund size squared	-0.031**	-0.027**	-0.030**	-0.028**
	0.014	*0.012*	*0.012*	*0.013*
=1 if first fund	0.034	0.043	0.034	0.039
	0.066	*0.058*	*0.060*	*0.055*
Competition				
ln VC inflows in fund's vintage year	-0.218***	-0.213***	-0.233***	-0.202***
	0.045	*0.047*	*0.055*	*0.041*
Investment opportunities				
average B/M ratio in fund's first 3 years	-1.554***	-1.512***	-1.571***	-1.641***
	0.299	*0.292*	*0.290*	*0.275*
Fund parent's experience				
ln aggregate $ amount parent has invested so far	-0.005	-0.006	0.015	-0.048*
	0.024	*0.029*	*0.024*	*0.026*
Network measures				
outdegree_C (corporate-specific)	0.049***			
	0.018			
Outdegree (network-wide)	0.042*			
	0.021			
indegree_C (corporate-specific)		0.053		
		0.035		
indegree (network-wide)		0.087***		
		0.025		
degree_C (corporate-specific)			0.012*	
			0.006	
degree (network-wide)			0.009	
			0.012	
eigenvector_C (corporate-specific)				0.041***
				0.008
eigenvector (network-wide)				0.037***
				0.010
Diagnostics				
Adjusted-R^2	6.1 %	6.2 %	5.9 %	6.6 %
Test: all coefficients = 0 (F)	766.7***	518.0***	688.9***	925.3***
No. of observations	2,811	2,811	2,811	2,811

Table X
The Evolution of Network Positions

The sample consists of a panel of first-time funds by 823 VC firms that we follow for ten years or up to November 2003, whichever is earlier. The average VC firm spends seven years in the sample. The total number of firm-years in the panel is 5,800. We estimate fixed-effects panel regression models under the assumption that the disturbances are first-order autoregressive, to allow for persistence over time in a VC firm's network position. We use the Baltagi and Wu (1999) algorithm to allow for unbalanced panels. The dependent variable is one of the five network centrality measures studied in the paper. We relate a firm's network position to its experience, increases in the size of the network, and the firm's performance. The latter is proxied for using the number of the firm's portfolio companies that were sold via an IPO or M&A transaction in the previous year, or that received follow-on funding from an outside VC firm that was not already an investor in the company. We also attempt to control for how "eye-catching" its IPOs were by including the average degree of underpricing of its prior-year IPOs. Intercepts are not shown. Standard errors are shown in italics. We use ***, **, and * to denote significance at the 1%, 5%, and 10% level (two-sided), respectively. Note that at present there are no critical value tables for the two tests for zero auto-correlation reported in the table.

Dependent variable:	outdegree (1)	indegree (2)	degree (3)	between-ness (4)	eigen-vector (5)	indegree (6)
Firm characteristics						
lagged *ln* aggregate $ amt. parent has invested	0.046***	0.044***	0.194***	0.008***	0.143***	0.023***
	0.009	*0.005*	*0.021*	*0.003*	*0.017*	*0.005*
Network growth						
ln no. of new funds raised	-0.010	-0.006	-0.029	0.003	0.099***	-0.004
	0.012	*0.007*	*0.029*	*0.003*	*0.023*	*0.007*
Firm performance						
lagged *ln* no. of IPOs	0.033*	0.000	0.024	-0.005	-0.005	-0.002
	0.020	*0.012*	*0.048*	*0.006*	*0.038*	*0.011*
lagged *ln* no. of M&A deals	0.067***	-0.002	-0.011	-0.005	-0.005	-0.005
	0.025	*0.014*	*0.059*	*0.007*	*0.047*	*0.014*
lagged *ln* no. of outside-led follow-on rounds	0.046***	0.041***	0.184***	0.009***	0.044**	0.033***
	0.011	*0.006*	*0.027*	*0.003*	*0.021*	*0.006*
lagged *ln* average IPO underpricing	0.061*	0.041**	0.200***	0.000	0.136**	0.037**
	0.031	*0.018*	*0.075*	*0.009*	*0.059*	*0.018*
Past investment in reciprocity						
lagged *outdegree*						0.226***
						0.005
Diagnostics						
R^2	27.4 %	28.7 %	26.7 %	17.6 %	23.5 %	65.5 %
F-test: all coeff. = 0	10.7***	22.0***	25.0***	3.5***	20.9***	87.3***
Auto-correlation (ρ)	0.827	0.863	0.844	0.794	0.832	0.813
Tests for zero auto-correlation:						
Modified Bhargava et al. Durbin-Watson	0.462	0.513	0.535	0.478	0.472	0.560
Baltagi-Wu LBI statistic	0.775	0.825	0.845	0.817	0.827	0.830
Correlation (fixed effects, X variables)	0.422	0.407	0.397	0.346	0.373	0.641
F-test: all fixed effects = 0	4.7***	5.4***	5.5***	3.8***	5.1***	4.4***