Whom You Know Matters:

Venture Capital Networks and Investment Performance [*] [†]

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April 20, 2005

[*] Thanks for helpful comments and suggestions go to Steve Drucker, Jan Eberly, Eric Green, Yaniv Grinstein, Josh Lerner, Laura Lindsey, Max Maksimovic, Roni Michaely, Maureen O'Hara, Mitch Petersen, Ludo Phalippou, Jesper Sorensen, Morten Sorensen, Per Strömberg, and seminar participants at the University of Texas at Austin, University of Utah, Northwestern University, Cornell University, Stockholm School of Economics, Binghamton University, Bar Ilan University, Tel Aviv University, and the Spring 2005 NBER Entrepreneurship meeting.

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Abstract

Many financial markets are characterized by strong relationships and networks, rather than arm's-length, spot-market transactions. We examine the performance consequences of this organizational choice in the context of relationships established when VCs syndicate portfolio company investments, using a comprehensive sample of U.S. based VCs over the period 1980 to 2003. VC funds whose parent firms enjoy more influential network positions have significantly better performance, as measured by the proportion of portfolio company 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. Once we control for network effects in our models of fund and portfolio company performance, the importance of how much investment experience a VC has is reduced, and in some specifications, eliminated. Finally, we provide initial evidence on the evolution of VC networks.

Key words: Venture Capital, Networks, Syndication, Investment Performance

JEL classification: G24, L14.

Networks are widespread in many financial markets. Bulge-bracket investment banks, for instance, have strong relationships with institutional investors which they make use of when pricing and distributing corporate securities (Benveniste and Spindt (1989), 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 they have long-standing relationships with (Corwin and Schultz (2005)).

In the same spirit, networks feature prominently in the venture capital 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 (2003), Hsu (2004)). The capital VCs invest in promising new ventures comes from a small set of institutional and other investors with whom they tend to have long-established relationships. In all these instances, many VCs show a preference for networks rather than arm's-length, spot-market transactions.

While the prevalence of networking in many financial markets has been documented in the literature, the performance consequences of this organizational choice remain 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 their clout, investment opportunity sets, access to information, etc. In this study, we ask whether these differences help explain the cross-section of VC investment performance.

We focus on the co-investment networks that VC syndication gives rise to, and leave the other two main networks VCs use (involving service providers and institutional investors in their funds) to future research. 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 are vital to a VC's performance. The two main drivers of a VC's performance are the ability to source high-quality deal flow (i.e., the ability to select promising companies), and the ability to nurture its investments (i.e., the ability to add value to portfolio companies). Syndication likely affects both of these performance drivers.

There are at least three reasons to expect syndication networks to improve the quality of deal flow. First, VCs invite others to co-invest in their promising deals in 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 may 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, thus 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.[1] Syndication networks facilitate the sharing of information, contacts, and resources among VCs (Bygrave (1988)), for instance by expanding the range of strategic alliance partners and launch customers 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 head hunters 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 describing networks at a "macro" level and for measuring the relative importance, or "centrality," of each actor in the network. Our centrality measures capture five different aspects of a VC firm's influence: The number of VCs it has relationships with, 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 co-invest in other VCs' deals, thereby expanding its investment opportunity set; its ability to generate such co-investment 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

[1] The literature has documented a number of ways in which VCs add value to their portfolio companies, such as addressing weaknesses in the original business plan or the entrepreneurial team (Kaplan and Strömberg (2004)), professionalizing the company (Hellmann and Puri (2002)), reducing the time to product market (Hellmann and Puri (2000)), facilitating strategic alliances among portfolio companies (Lindsey (2003)), and ensuring strong governance structures at the time of the IPO (Hochberg (2004)).

[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.

ability to act as an intermediary who can bring together VCs with complementary skills or investment opportunities who lack a direct relationship between them.

In addition to measures of how well networked each VC is, we require data on the performance of VC investments. We examine both the performance of the VC fund and of the fund's portfolio companies. At the fund level, we examine "exit rates" in the absence of publicly available data on VC fund returns. We define a fund's exit rate 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 or not the portfolio company achieved a successful exit, but also intermediate performance, namely whether the portfolio company survived 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 facing 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 ability 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 two percentage points from the 34.2% sample average. Using limited data on fund IRRs disclosed following recent Freedom of Information Act lawsuits, we estimate that this is roughly equivalent to a two 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 large economically. 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.

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 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, eliminated. It is also not the case that the better-networked VCs are simply the ones with better past performance records: While we do find evidence of persistence in performance 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 10-12 years. Thus, we are relating 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.

We also explore an alternative explanation for the positive relation between exit rates and network centrality, namely that better networked VCs may simply be better at hoodwinking the public markets into buying their more marginal companies, but find little support for this explanation.

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. Our results are not only robust to these modifications, but their economic significance increases substantially. In the California network, exit rates improve by approximately five percentage points relative to the unconditional mean of 35.7% among California VCs.

Our contribution is fivefold. This is the first paper to examine the performance consequences of the VC industry's predominant choice of organizational form: Networks. Previous work has focused on describing the structure of syndication networks (Bygrave (1987, 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 returns to being well-networked 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. Third, our findings have ramifications for institutional investors choosing VC funds 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 and discusses their implementation in the VC context. A simple example illustrating network analysis is presented in the Appendix. Section II describes our data. In Section III, we analyze the effect of VC networking on fund performance. Section IV examines the relation between networking and portfolio company survival. Section V presents additional robustness checks, including an examination of the effects of industry-specific and spatially separated networks. Section VI investigates how a VC becomes influential in the VC network. Section VII concludes.

I. Network Analysis Methodology

The aim of network analysis is to describe the structure of networks, by focusing first and foremost on the relationships that exist among a set of economic actors and less on the individual actors' characteristics (such as age, wealth, etc.). For instance, a network might be described as "dense" (if many actors are tied to one another via reciprocated relationships) or "sparse" (if actors tend to be more autarkic). It might have one dense area surrounded by a periphery of sparsely connected actors, or it might have several clusters of dense areas that occasionally interact with each other. The network might be populated by uniformly influential actors, or there may be variation in actors' influence. And so on.

Influence is usually measured by how "central" an actor's network position is. An actor is considered central if he is extensively involved in relationships with other actors. Consider the most centralized of networks, the "star," in which one actor is connected to all other actors, none of whom is connected to anyone else. Clearly, the actor at the center of the star is the most influential. Contrast this with a ring-shaped network, in which all actors are equally central. In the VC market, greater centrality may translate into better access to information, deal flow, deeper pools of capital, expertise, contacts, and so on.

Network analysis uses a branch of mathematics called 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 co-invest 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.

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 co-investing 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, the 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 actor'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: 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.

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[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 method of coding ties 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. While the results reported in the following sections utilize the binary matrix, we note that 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 who were members of the same syndicate if neither led the syndicate in question.

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 who 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, i.e., the number of unique VCs a VC has co-invested with. Let p_{ij} be an indicator equaling one if at least one syndication relationship exists between VCs i and j, and zero otherwise. VC i's *degree* then equals $\Sigma_i\, p_{ij}$.

In undirected data, where we do not distinguish between the originator and receiver of a tie, 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 two directed measures of degree centrality.

Indegree is a measure of the frequency with which a VC firm is invited to co-invest in other VCs' deals, thereby expanding its investment opportunity set and gaining access to information and resources it otherwise may not have had access to. Formally, let q_{ji} be an indicator equaling one if at least one syndication relationship exists in which VC j was the lead investor and VC i was a syndicate member, and zero otherwise. VC i's *indegree* then equals $\Sigma_i\, q_{ji}$.

Outdegree is a measure of a VC's ability to generate future co-investment opportunities by inviting others into its syndicates today (i.e., reciprocity). Outdegree counts the number of other VCs a VC firm invites into its own syndicates. Formally, as before, let q_{ij} be an indicator equaling one if at least one syndication relationship exists in which VC i was the lead investor and VC j was a syndicate member, and zero otherwise. VC i's *outdegree* then equals $\Sigma_j\, q_{ij}$.

Clearly, all three degree centrality measures are a function of network size, which in our dataset varies over time due to entry and exit by VCs. To ensure comparability over time, we normalize each degree centrality measure by dividing by the maximum possible degree in an n-actor network (i.e., n–1).[7]

[7] While we normalize the centrality measures used in the empirical analysis, we note that all our results are robust to using non-normalized network centrality measures instead.

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 centrality of an actor is defined as the sum of his ties to other actors, weighted by their respective centralities.

Formally, let p_{ij} be an indicator equaling one if at least one syndication relationship exists between VC i and VC j, and zero otherwise. VC i's eigenvector centrality is then defined as $ev_i = \Sigma_j\, p_{ij}\, ev_j$ (which is equivalent to the components of the principal eigenvector of the adjacency matrix).[8] In our setting, eigenvector centrality measures the extent to which a VC is connected to other well-connected VCs. This is normalized by the highest eigenvector centrality measure possible in a network of n actors.

C. Betweenness Centrality

Betweenness attributes influence to actors on whom many others must rely to make connections within the network. For example, in a star, the actor at the center stands between every pair of actors, who must involve him to reach one another. 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 who lack a direct relationship between them. Formally, let b_{jk} be the proportion of all paths linking actors j and k which pass through actor i. The *betweenness* of actor i is defined as the sum of all b_{jk} where i, j, and k are distinct. It is normalized by dividing by the maximum *betweenness* in an n-actor network.

II. Sample and Data

Data for our analysis are obtained from Thomson Financial's Venture Economics database. Venture Economics began compiling data on venture capital investments in 1977, and has since backfilled the data to the early 1960s. Gompers and Lerner (1999) investigate the completeness of the Venture Economics database and conclude that it covers more than 90% of all venture investments.

Most VC funds are structured as closed-end, often ten-year, limited partnerships. They are not stock

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[8] Formally, 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 non-trivial 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.

market 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 and Richardson (2003)). Successful portfolio companies are exited via IPOs or sales to other companies, which generate capital inflows (and hopefully capital gains) that are distributed to the fund's investors. The exit phase typically occupies the second half of the fund's life. At the end of the fund's life, any remaining portfolio holdings are sold or liquidated and the proceeds distributed to the investors.

Owing to this investment cycle, relatively recent funds have not yet operated for long enough to measure their lifetime performance. But simply excluding relatively recent 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 the 1980 ERISA "Safe Harbor" regulation.[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 investments by angels and buyout funds.[10] We distinguish between *funds* and *firms*. While VC funds have a limited (usually ten-year) life, the VC management firms that manage the funds have no predetermined lifespan. A first-time fund that is successful 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 will measure VC experience and networks at the parent firm-level rather than the fund-level.[11] This assumes that experience and contacts acquired in the running of

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[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 allowed pension funds to invest in higher-risk asset classes; the 1980 Small Business Investment Act which redefined VC fund managers as business development companies rather than investment advisers, so lowering their regulatory burdens; and the 1980 ERISA "Safe Harbor" regulation which sanctioned limited partnerships which are now the dominant organizational form in the industry.

[10] We do, however, include corporate venture programs as long as Venture Economics reports data for their size.

[11] Occasionally, Venture Economics assigns more than one name to the same VC firm (e.g. "Alex Brown and Sons," "Alex Brown & Sons"). We manually consolidate VC firm names where applicable.

one fund carry over to the firm's next fund.

In the estimation datasets, there are 3,469 VC funds managed by 1,974 VC firms which 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 two different ways. For the two directed centrality measures, *indegree* and *outdegree*, we need to distinguish between VCs who lead syndicates and those who are co-investors. 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.[12]

For the remaining undirected centrality measures, we are primarily interested in the ties among VCs instanced by co-investment in the same portfolio company. Here, we are less concerned with whether the co-investment 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 who invested in the company's first round may interact with a VC who 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.

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.

A. Fund Characteristics

Table I describes our sample funds. The average VC fund in our sample had \$64 million of capital available for investment, with a range from \$0.1 million to \$5 billion. (Fund size information is unavailable for 364 of the 3,469 sample funds.) Once successful, VC management firms tend to raise new funds. The fund sequence number denotes 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 a third of the funds. A quarter of funds are identified as first-time funds. Around a third (36.5%) focus on seed or early-stage investment opportunities.

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

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 does not identify which industry a fund specializes in, but it classifies the funds' portfolio companies into six broad 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 "Non-high-technology," 9.2% in "Medical, health, life sciences," 15.5% in "Communications and media," 6% in "Biotechnology," and 4.3% in "Semiconductors, other electronics."

B. Measuring Fund Performance

Ideally, we would measure fund performance directly, using for instance the internal rate of return a fund achieved over its ten-year life. However, fund returns in the form required for this study are not systematically available to researchers as VC funds generally do not disclose their performance to anyone other than their own investors. Venture Economics collects fund performance data from VC investors, but only makes them publicly available in aggregate form (e.g., "the median IRR for funds raised in 1993 was..."). 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 performance data to their network characteristics and other cross-sectional variables, these anonymized data would not help us examine the effect of VC networking on investment performance.

Instead, we measure fund performance indirectly. Ljungqvist and Richardson (2003) report that 75.3% of investments are written off completely in the average VC fund in their sample. This implies that VC funds earn their capital gains from a small subset of their portfolio companies, namely those that they exit via an IPO or a sale to another company (M&A).[13] 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.E, we show that this is a reasonable proxy for fund returns.

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

Table I provides descriptive statistics on our performance measure. In the sample of 3,469 funds raised between 1980 and 1999, the exit rate averages 34.2%. IPOs outnumber M&A transactions three-to-two (with exit rates of 20.7% and 13.6%, respectively). These exit rates are comparable to those reported in Gompers and Lerner (2000) for the 1987-1991 period. 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%.

Figure 2 illustrates the evolution of exit rates over time, plotting the average exit rate of all sample funds by vintage year. Exit rates peaked among funds raised in 1988, and there is mild evidence of an 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 – have markedly lower exit rates. This could be because they have yet to complete their ten-year investment lives. Alternatively, 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 may result in these funds never matching the performance of earlier VC vintages. Whatever the reason, to capture the pronounced time pattern evident in Figure 2, 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 (2003) in taking the

[14] But see Cochrane (2005) for an analysis of company-level rates of return using data from an alternative database (VentureOne), and see Ljungqvist and Richardson (2003) for similar analysis using a proprietary dataset of 4,000 private equity-backed companies.

occurrence of an IPO or M&A transaction as a final signal of the investment's success.[15]

We restrict the dataset 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 3 shows what happened to these 16,315 companies. Around a third of the companies do not survive beyond the first funding round and are thus written off. 1,020 companies (6.3%) proceed to an IPO or M&A transaction after the first round. 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 having survived 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%) have successfully exited by November 2003. The median company receives two funding rounds.

It is important to realize that Venture Economics provides next to 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 dataset, 32.7% are classified by Venture Economics as "Computer related," 30.9% as "Non-high-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) provide convincing evidence of persistence in returns across a sequence of funds managed by the same VC firm. Such persistence highlights the importance of investment skill and experience. While skill is difficult to measure, we derive four proxies of investment experience for each VC firm and for each year the VC firm is active in the sample. These control variables measure 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

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[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 dataset does, however, include companies that received a *non-institutional* funding round prior to 1980 (typically involving angel investors or friends and family).

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.

E. Network Measures

Over our sample period, the VC industry saw 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 co-investors; is invited to become a syndicate member by around 1% of all VCs; and has co-investment relationships with a little over 4% of the other VCs (ignoring its and their roles in the syndicate). Coupled with the fact that more than half of all investments are syndicated, these low degree centrality scores suggest that VCs each repeatedly co-invest with a small set of other VCs, that is, that relationships are relatively exclusive and stable.

To illustrate the variation in the *degree* measures, we 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 1995-1999 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), only to be overtaken by Intel Capital, the venture capital arm of Intel Corp, in 1999.

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[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.

F. The Macro Structure of VC Networks

Table II provides a macro-level description of each of our five-year networks, from 1976-1980 to 1999-2003. We list the number of VC firms that lead-manage an investment round in each five-year window, the total number of VCs that participate in investment rounds, and the number of investment rounds concluded during the window. For instance, during the five years to 1980, 374 VC firms participated in 1,541 investment rounds, 243 of whom acted one or more times as lead investor.

Overall, VC syndication networks are not particularly dense. As a proportion of all the relationships between every pair of VCs that could be present, the density of undirected ties peaked at 4.5% in 1987-1991 and has been declining to below 2% since. Directed ties (i.e., those between lead VC and syndicate members) are even less dense. In part, this simply reflects the large number of VCs and the tendency of some VCs never to syndicate their investments,[19] but it likely also reflects the aforementioned exclusivity and repeated nature of syndication relationships evident in the low individual *degree* centrality scores.

Low density can suggest high centralization. A simple way to measure the overall centralization of a network (as opposed to the centrality of individual actors) is to express the network-wide variation in the actors' *degree*, *betweenness*, and *eigenvector* centralities as a percentage of the variation we would observe in the most centralized network, a perfect star, of equivalent size. The resulting centralization numbers can be interpreted as measures of the degree of inequality in the network. As Table II shows, *outdegree*, *degree*, and *eigenvector* centrality are each relatively unequally distributed, suggesting that the influence of individual VCs varies substantially. In other words, positional advantage is quite unequally distributed in our networks.

G. 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 up valuations. 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

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

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. This ranges from a low of \$2.3 billion (1980) to a high of \$84.6 billion (1999).

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 inter-industry 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 therefore SIC codes are available. We then identify which Venture Economics industry each available four-digit SIC code is linked to most often.[20] We 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. Thus, we have to decide over what time period to measure their investment opportunities. 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 the average fund to face 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.

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[20] Similar results are obtained 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).

III. Fund-level Analysis

A. Benchmark Determinants of Fund Performance

We begin by replicating Kaplan and Schoar's (2005) fund performance model, to validate our use of exit rates instead of fund returns as the measure of performance. Kaplan and Schoar relate VC fund performance to two fund characteristics (as well as a set of vintage year dummies): Log fund size and log fund sequence number, each of which is included in levels and squares. Our results are reported in Table III. When we include both fund size and fund sequence number in the model, only the year dummies are significant (see column (1)).[22] Consistent with Kaplan and Schoar, we find only weak evidence that higher sequence number 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 dataset 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%.

Because fund sequence number appears to have little effect on fund performance in our dataset, and because it is frequently unavailable in the Venture Economics database, we replace it with a dummy equaling 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 so have relatively fewer successful exits. The resulting model is shown in column (4). In addition to the positive and concave effect of fund size, we find that first-time funds perform significantly worse, mirroring Kaplan and Schoar's (2005) results: All else equal, first-time funds have exit rates that are 3.6 percentage points below average (that is, 30.9% rather than 34.5%). In this specification, seed and early-stage funds do not perform differently from other funds.

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

[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.C for company-level models that control explicitly for exit market conditions.

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 funds faced when deploying their committed capital. Whether we use industry P/E ratios or industry 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 7.7 percentage point increase in subsequent exit rates. The models that follow will include industry B/M ratios, though we note that all results are robust to using industry P/E ratios instead.

B. The Effect of Firm Experience on Fund Performance

From now on, we take the model shown in column (7) of Table III as our baseline fund performance model. Before we turn to the effect of network position on fund performance, we control for the investment experience of the fund's parent firm using the four proxies described in Table I. Due to the high degree of correlation among the four proxies, we include them in the baseline model one at a time. In each case, the explanatory power of the models, shown in Table IV, improves substantially.

However we measure it, funds with more experienced parents perform significantly better. One-standard-deviation increases in the log number of days since the parent's first-ever investment, the log number of rounds the parent has participated in, the log aggregate amount it has invested, and the log number of portfolio companies it has funded, each measured up to the year the VC fund was raised, increase exit rates by 3.7, 3.5, 4.4, and 3.3 percentage points, respectively. Note that the first-fund dummy loses significance in these models, indicating that it is a poor proxy for experience.

Since the log aggregate investment amount proxy has the largest economic effect, we will use it in all subsequent models to proxy for the parent firm's experience. Our results are generally robust to using any of the other three proxies instead.

C. 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 V, indicate that it is does. We estimate five separate regression models, adding our five centrality measures to the specification shown in column (3) of Table IV. We add them one at a time given the relatively high degree of correlation among them.[23] Each specification in Table V suggests that better networked VC firms are associated with significantly better fund performance, and the adjusted R^2 increases to around 19%.[24]

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 a more than two percentage point increase 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 true 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, which is 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 co-investment opportunities for one's future funds (i.e., high future *indegree*). We will explore this dynamic relation between *indegree* and *outdegree* further in Section VI.

D. Reverse Causality and Performance Persistence

We do not believe that our results are driven simply by reverse causality, i.e., 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

[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. *Indegree*, *degree*, and *eigenvectors* continue to be positively and significantly related to fund performance.

truly affects performance.

A potentially more serious concern is persistence in performance from fund to fund. To rule out that the network measures are simply proxying for omitted persistence in performance, we re-estimate 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.[25]

The results are shown in Table VI. 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 4.9 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 magnitude remains similar: All else equal, a one-standard-deviation increase in network centrality is associated with a 2.3, 1.9, and 2.1 percentage point increase in fund performance, for *indegree*, *degree*, and *eigenvectors*, respectively. As in the previous analysis, *outdegree* and *betweenness* have a lesser effect on performance.

E. 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 re-estimate 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*

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[25] We obtain similar (and somewhat stronger) results if we include all funds, setting the prior performance variable equal to zero for first-time funds and including a dummy variable identifying first-time funds.

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 two percentage point increase in exit rates (from the mean of around 35%) is roughly equivalent to a two 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 measure company performance indirectly. In terms of Figure 3, we model the likelihood that a company survives – in the sense of proceeding to another funding round or exiting via an IPO or M&A transaction – rather than being written off.[26] Our analysis focuses on the first three funding rounds, for the sake of brevity. While the choice of three rounds is arbitrary, our results do not change if we consider later rounds as well.

The models shown in Table VII relate company survival over the first three rounds to the variables used to model fund performance in Table V: 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; a proxy for 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. We measure the VC parent firm's network centrality over the five-year window

[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.

preceding the investment round. (For example, for a second round investment made in 1995, the centrality measures are calculated from data for the years 1991-1995.) 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.

The dependent variable in Table VII is an indicator variable, equaling one if the company survived from round N to receive another funding round or exited successfully, and zero if it was written off after round N. Since we focus on survival from the first three rounds (i.e., N=1..3), we estimate three separate models labeled in the table as "survived round 1," "…2," and "…3." Clearly, as survival to round N+1 is conditional on having survived to round N, the sample size decreases from round to round. (Note also that due to missing fund size data, there are fewer observations available for estimation than are shown in Figure 3.) To mitigate collinearity problems, we add the five network measures one at a time, resulting in 15 models. All models are estimated using probit MLE.

A. The Determinants of Portfolio Company Survival

The pseudo R^2s in Table VII 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 9-10% of the variation in survival rates from round 1, 4-5% for round 2 survival, and 3-4% 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 round are associated with significantly worse survival probabilities from round 3. The more money the VC industry raised from investors at the time of the funding round, the less likely a portfolio company is to survive, and 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 strongest economically in the first two rounds. Surprisingly, more experienced VCs are associated with a significantly *lower* survival probability.[27]

Controlling for these factors, we find, in each of the fifteen 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 83.4%, and in the third round from 79.2% to 86.4%. 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*).

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 re-estimate our models adding dummy variables for (a) whether the current round was syndicated or (b) whether any of the company's previous investment rounds was 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 was 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 operate in.

B. Pooled Portfolio Company Survival Models

So far, we have modeled 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

[27] This is based on using invested dollars to proxy for investment experience. Results are robust to using any of the other three experience proxies.

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. The panel is unbalanced since portfolio companies receive varying numbers of funding 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 VIII. 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. 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, measured as the lead investor's log aggregate amount invested, again *reduces* a company's survival chances in each of the five specifications.

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 6.6 to 8.2 percentage point increase from the unconditional survival probability of 66.8%, holding all other covariates at their sample means.

C. 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.[28] 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, and 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.

[28] Econometrically, this is similar in spirit to Hellmann and Puri (2000) who investigate whether VC backing reduces the time it takes a start-up company to bring its product to market.

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.[29] 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 instance 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: 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).[30]

The results are reported in Table IX. 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 when a lot of

[29] 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. 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; and 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.

[30] A way of avoiding a specific distribution is to estimate semi-parametric Cox models. This does not affect our results.

money flowed into the VC industry (interpreted as increased competition for deal flow) or when industry book-to-market 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.

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. Further Robustness Tests

A. Robustness to Alternative Explanations

We now investigate an alternative hypothesis for the positive relation between exits and network centrality found in Sections III and IV. Better networked VCs may be able to take 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 presumably not be reflected in actual investment returns (which we do not observe). To test this alternative hypothesis, we focus on two quality indicators: 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[31] and supplement these data with LTM earnings from Thomson Financial's SDC IPO database as well as hard copies of IPO prospectuses where 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

[31] Compustat backfills data when companies go public.

based on the network centrality of their lead first-round VC. Contrary to the alternative hypothesis, the best networked VCs take companies public 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. This suggests that being well-networked either helps the VC select more promising companies to begin with, or allows the VC to add more value to the start-up resulting in a higher-quality company by the time of the IPO. Either of these interpretations is consistent with the motivation for our study.

Next, we estimate the probability that a company has negative earnings at the time of the IPO, 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 find no significant relation between four of the five network centrality measures and the probability of having negative earnings at the time of the IPO (not reported).[32]

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.[33] Of the 2,527 sample companies that go public by November 2003, 7% are delisted involuntarily.[34] 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 predicting delisting are the proxy for

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[32] The exception is *indegree* which has a positive and significant coefficient. We interpret this as providing at best weak support for the alternative hypothesis.

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

[34] 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 in 2001-2003.

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,[35] 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 (as measured by earnings at the time of the IPO and subsequent survival).

B. Location- and Industry-specific Networks

The network measures we have used thus far implicitly assume that each VC in the U.S. potentially has ties to every other VC in the U.S. To the extent that VC networks in truth 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 non-biotech 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.

To assess the robustness of our findings we have re-estimated all our models 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 funds' exit rates by 2.5 percentage points in the industry-specific models, compared to 2.2 percentage points using the overall network. In the company-level models, our results are qualitatively unchanged compared to Tables VII through IX, 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

[35] 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.

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: On the order of 4-5 percentage point improvements in fund exit rates (from the unconditional mean of 35.7%), compared to around two 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 the models shown in Tables VII through IX.

VI. 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 level. But how do VC firms become networked in the first place? It seems likely that an emerging track record of successful investing makes a VC firm a more desirable syndication partner in the future, which in turn will 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 (using the log aggregate dollar amount it has invested since inception).[36] To control for how "eye-catching" its IPOs were, we also include the average degree of underpricing 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.

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

We expect persistence in a VC firm's network position, in part because economically, relationships take time to establish but once they are, 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, such as skill or personal contacts, we include firm fixed effects, and we allow for unbalanced panels to capture the fact that some VC firms are in the sample for longer than others. The resulting estimator is due to Baltagi and Wu (1999). The results are reported in columns (1) through (5) of Table X.

The models have high pseudo-R^2s, ranging from 17.6% for the *betweenness* model to 28.7% for the *indegree* model. Auto-correlation 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 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. 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 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 on how eye-catching the VC firm's prior-year IPOs were varies in magnitude and significance across the five models. For *indegree*, *degree*, and *eigenvector*, higher underpricing is associated with subsequent improvement in the VC firm's network position. 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 allowance for the quality (rather than quantity) of a VC firm's exits using the quality measures explored in Section V.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 argued 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 co-investment opportunities in the future. Thus, high *indegree* today does appear to reflect, in part, payback on past investment in reciprocity.

VII. 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. We use 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 have 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 co-investment 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.

Our analysis provides a first look at the economic importance of networks as a choice of organizational form in the venture capital industry. We leave for future research the question how networking affects performance in other financial markets, such as syndicated lending, bond or equity underwriting, and investment bank-institutional investor relationships.

If more highly networked VCs enjoy better investment performance, our findings have ramifications for institutional investors choosing which VC fund to invest in. Additionally, our analysis provides a deeper understanding of the possible drivers of 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 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.

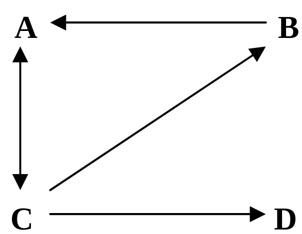
Finally, our finding that better networked VCs enjoy superior performance raises the question of how VCs become networked in the first place. Our evidence suggests that an emerging track record of successful investing (as proxied by the ability to persuade unrelated VCs to lead-manage a follow-on funding 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 have not so far taken account of. 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

To illustrate the application of network analysis tools to VC syndication networks, 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 can be represented as follows:



The corresponding adjacency matrix is

Syndicate members

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

Note that the matrix is symmetric. It reflects the "undirected" ties between the VCs (i.e., ignoring the direction of the ties). 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 members

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

Here, row vectors record syndicate leadership while column vectors record syndicate membership, and the matrix is no longer symmetric. The row vectors 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 column vectors 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 more syndicates than the other VCs, participates in more syndicates than any VC except A (with whom 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 giving access to information, deal flow, deeper pools of capital, contacts, expertise, and so on. C's only apparent shortcoming (in this network) is the fact that it is not often (invited to be) present in syndicates led by the other VCs.

The five centrality measures used in our study are calculated from the two adjacency matrices, and are summarized for the four VCs in the following table:

VC	Normalized *degree*	Normalized *indegree*	Normalized *outdegree*	Normalized *eigenvector*	Normalized *betweenness*
A	66.67%	66.67	33.33	73.92	0.00
B	66.67	33.33	33.33	73.92	0.00
C	100.00	33.33	100.00	86.50	66.67
D	33.33	33.33	0.00	39.86	0.00

Degree counts the number of undirected ties an actor has, 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. Clearly, *degree* is a function of network size, which in our dataset varies over time. To ensure comparability over time, we normalize *degree* by dividing by the maximum possible *degree* in an n-actor network. With n=4, a given VC can be tied to at most three other unique VCs. This gives normalized *degrees* of 66.67%, 66.67%, 100% and

33.33% 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 a syndicate or simply participating in it. *Indegree* counts the number of directed ties an actor received, by summing the actor's column vector in the directed adjacency matrix. In our setting, this is the number of unique VCs that have led syndicates in which the VC was invited to participate as a non-lead member. A's *indegree* of 2 (or 66.67% when normalized) is the highest in the network. O*utdegree* measures the number of ties an actor initiates, 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)). It 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 73.92%, 73.92%, 86.5% and 39.86% 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,[37] so the normalized *betweenness* measures are 0% for A, B and D, and 66.67% 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.

[37] 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.

References

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

Benveniste, Lawrence M., and Paul A. Spindt, 1989, How investment bankers determine the offer price and allocation of new issues, *Journal of Financial Economics* 24, 343-361.

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., 1987, Syndicated investments by venture capital firms: A networking perspective, *Journal of Business Venturing* 2, 139-154.

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.

Corwin, Shane, and Paul Schultz, 2005, The role of IPO underwriting syndicates: Pricing, information production, and underwriter competition, *Journal of Finance* 60, 443-486.

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*, 149-92.

Gompers, Paul A., and Josh Lerner, 1999, *The Venture Capital Cycle* (MIT Press).

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, and Manju Puri, 2000, The interaction between product market and financing strategy: The role of venture capital, *Review of Financial Studies* 13, 959-984.

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., 2004, Venture capital and corporate governance in the newly public firm, Unpublished working paper, Cornell 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, Unpublished working paper, Columbia University.

Kaplan, Steven N., and Antoinette Schoar, 2005, Private equity returns: Persistence and capital flows, *Journal of Finance*, forthcoming.

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? Unpublished 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., 2003, The venture capital keiretsu effect: An empirical analysis of strategic alliances among portfolio firms, Unpublished working paper, Stanford University.

Ljungqvist, Alexander, and Matthew Richardson, 2003, The investment behavior of private equity fund managers, Unpublished 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, Unpublished 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, 2003, How smart is smart money? An empirical two-sided matching model of venture capital, Unpublished working paper, Stanford University.

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.

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 1990-1994. 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 one point in the time window led a syndicate in which the other was a non-lead member.

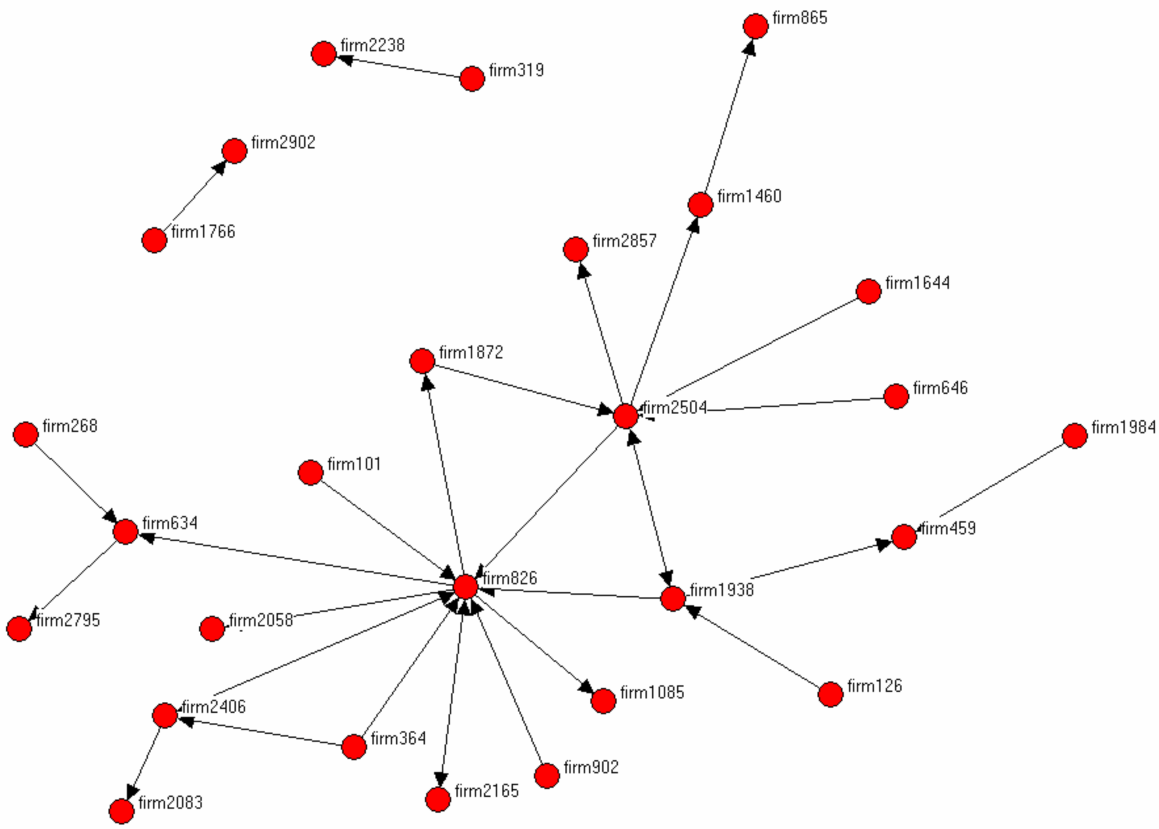


Figure 2. Mean Exit Rates by Fund Vintage Year

The fund-level sample consists of 3,469 venture capital funds headquartered in the U.S. that were started between 1980 and 1999. The figure shows the average exit rate by the year a fund was raised (its vintage year). Exit rates are 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.

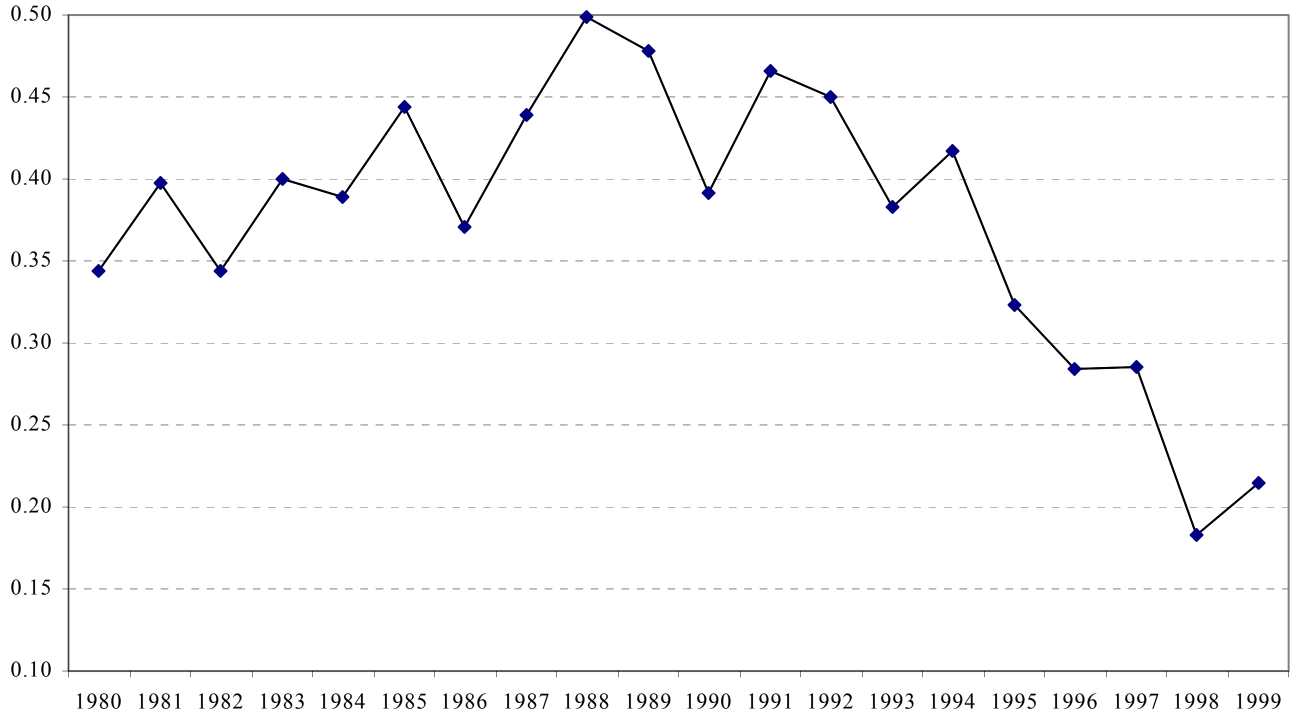


Figure 3.

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.

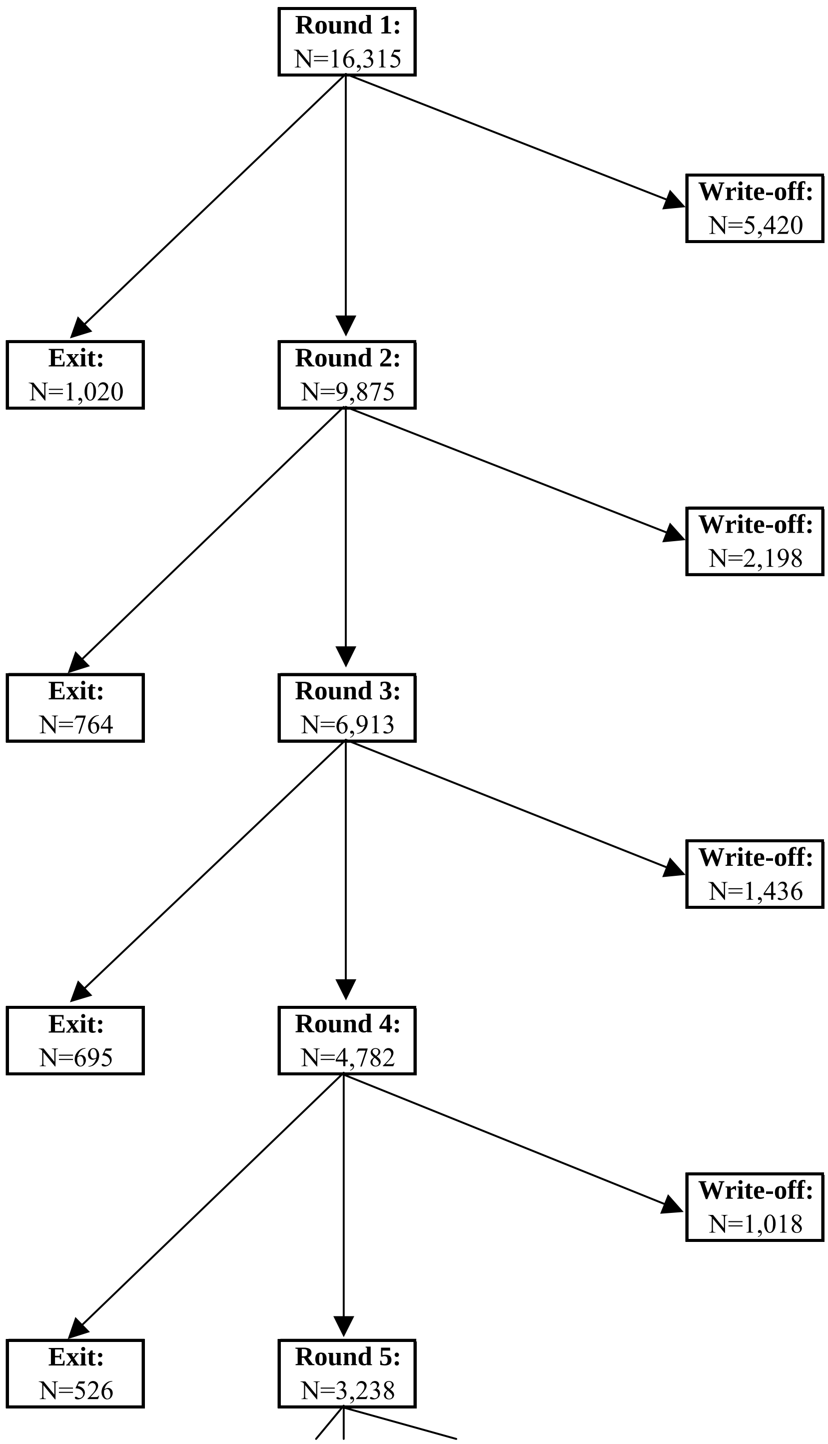


Table I. Descriptive Statistics

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. 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 non-high-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				
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. Network Density and Centralization Over Time

The network characteristics of the VC industry are measured in rolling five-year windows. In each window, we count the number of VC firms that lead-manage a portfolio company, the total number of VCs that participate in investment rounds, and the number of investment rounds. For instance, in 1976-1980, 374 VC firms participated in 1,541 investment rounds, 243 of whom acted one or more times as lead investor. For each window, we construct two matrices. The cells in the "directed" matrix record whether VC firm *i* participated in one or more investment rounds lead-managed by VC firm *j*. The cells in the "undirected" matrix record whether VC firms *i* and *j* co-invested in one or more portfolio companies (regardless of who was the lead VC). The density of the resulting ties are reported as a proportion of all ties that could be present (which increases in network size). Network centralization measures the inequality in the VCs' network positions. It is computed as the observed variation in the five centrality measures defined in Table I relative to the variation in the most unequal network (a perfect star) of equivalent size.

				Density of ties (% of theoretical max.)				Network centralization (% of theoretical max.)				
	Number of ...			undirected ties		directed ties						
Estimation window	lead VC firms	VC firms	investment rounds	mean	s.d.	mean	s.d.	outdegree	indegree	degree centrality	between-ness	eigen-vectors
1976-1980	243	374	1,541	3.7	19.0	0.8	9.0	10.5	6.2	25.1	6.4	28.0
1977-1981	308	496	2,267	3.7	18.8	0.7	8.6	10.8	7.6	29.8	6.9	25.9
1978-1982	398	638	3,256	3.5	18.4	0.7	8.3	10.8	7.6	30.8	6.4	23.2
1979-1983	499	807	4,436	3.6	18.7	0.7	8.2	14.1	9.8	34.4	6.4	20.3
1980-1984	589	952	5,750	3.5	18.4	0.7	8.1	15.8	10.3	36.1	6.6	19.2
1981-1985	654	1,061	6,876	3.5	18.3	0.7	8.0	16.4	10.8	37.7	6.8	18.5
1982-1986	714	1,115	7,805	4.1	19.9	0.7	8.3	16.1	11.8	37.8	6.4	17.5
1983-1987	703	1,092	8,702	4.0	19.6	0.8	8.8	17.5	12.9	37.5	5.7	16.5
1984-1988	690	1,057	9,117	4.1	19.9	0.8	9.1	17.5	12.7	35.8	4.8	16.5
1985-1989	653	1,007	9,387	4.2	20.0	0.9	9.4	16.4	12.2	36.2	5.1	16.9
1986-1990	622	927	9,517	4.5	20.6	1.0	9.8	16.0	11.8	33.3	4.1	16.7
1987-1991	558	847	9,206	4.5	20.7	1.0	9.9	18.9	9.7	33.1	4.7	17.8
1988-1992	527	788	8,965	4.4	20.4	1.0	10.0	21.6	10.7	33.7	5.5	18.8
1989-1993	495	730	8,561	4.2	20.0	1.0	9.9	21.9	11.1	34.1	6.4	20.7
1990-1994	468	696	8,147	3.9	19.3	1.0	9.7	21.0	10.6	33.4	6.7	22.4
1991-1995	551	815	8,342	2.8	16.5	0.7	8.3	17.8	9.8	30.6	7.2	23.7
1992-1996	700	965	9,656	2.2	14.7	0.6	7.4	14.4	8.9	26.3	6.1	23.2
1993-1997	869	1,134	11,324	1.8	13.4	0.5	6.8	13.1	8.2	23.9	6.0	23.1
1994-1998	1,098	1,375	14,087	1.5	12.2	0.4	6.2	11.7	7.0	20.4	4.3	21.8
1995-1999	1,405	1,812	18,093	1.4	11.6	0.3	5.7	10.9	6.6	19.0	3.7	19.1
1996-2000	1,842	2,325	24,381	1.2	11.1	0.3	5.4	10.5	6.7	21.7	4.5	18.5
1997-2001	1,966	2,483	26,551	1.2	11.0	0.3	5.4	10.4	7.2	22.9	4.9	18.9
1998-2002	2,009	2,580	26,727	1.2	10.8	0.3	5.3	10.3	7.1	23.8	5.9	19.2
1999-2003	1,927	2,518	25,228	1.2	11.0	0.3	5.3	10.3	7.0	24.1	6.0	19.7

Table III. Benchmark Determinants of 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. Exit rates average 34.2% in the overall sample of 3,469 funds, and 34.5% in the estimation sample of 3,105 funds for which all required data are available. 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. Sequence number denotes whether a fund is the first, second and so forth fund raised by a particular VC management firm. Sequence numbers are missing in Venture Economics for a third of the 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 classifies portfolio companies into the following six industries: biotechnology, communications and media, computer related, medical/health/life science, semiconductors/other electronics, and non-high-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. 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fund characteristics							
ln fund size	0.024		0.038***	0.046***	0.046***	0.043***	0.039***
	0.016		*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**
	0.002		*0.002*	*0.002*	*0.002*	*0.002*	*0.0015*
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				-0.036***	-0.036***	-0.037***	-0.038***
				0.010	*0.010*	*0.010*	*0.010*
=1 if seed or early-stage fund				-0.006	-0.006	-0.009	-0.021**
				0.010	*0.010*	*0.010*	*0.010*
Competition							
ln VC inflows in fund's vintage year					-0.063***	-0.065***	-0.110***
					0.008	*0.008*	*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							-0.325***
							0.030
Diagnostics							
Adjusted R^2	21.7 %	20.7 %	13.6 %	13.9 %	13.9 %	14.7 %	17.1 %
Test: all coefficients = 0 (F)	36.2***	35.3***	39.5***	36.4***	36.4***	36.1***	41.5***
No. of observations	2,242	2,283	3,105	3,105	3,105	3,105	3,105

Table IV. The Effect of Firm Experience 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. The first six variables are defined as in Table III. In addition, we include controls for the investment experience of a sample fund's parent (management) firm. These are based on the parent's investment activities measured between the parent's creation and the fund's creation. Investment activities are controlled as the parent's age (days since its first investment), number of rounds participated in, aggregate dollars invested, and number of portfolio companies invested in. By definition, these four measures are zero for first-time funds. The experience measures are highly correlated among each other, so we include them one at a time. 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.

	(1)	(2)	(3)	(4)
Fund characteristics				
ln fund size	0.035***	0.030***	0.030***	0.030***
	0.011	*0.011*	*0.011*	*0.011*
ln fund size squared	-0.003**	-0.003**	-0.003**	-0.003**
	0.002	*0.002*	*0.002*	*0.002*
=1 if first fund	0.003	-0.001	0.007	-0.003
	0.011	*0.012*	*0.011*	*0.012*
=1 if seed or early-stage fund	-0.025***	-0.026***	-0.024**	-0.025**
	0.010	*0.010*	*0.010*	*0.010*
Competition				
ln VC inflows in fund's vintage year	-0.109***	-0.111***	-0.114***	-0.111***
	0.009	*0.009*	*0.009*	*0.009*
Investment opportunities				
average B/M ratio in fund's first 3 years	-0.318***	-0.319***	-0.317***	-0.319***
	0.030	*0.030*	*0.030*	*0.030*
Fund parent's experience				
ln days since parent's first investment	0.015***			
	0.002			
ln no. of rounds parent has participated in so far		0.017***		
		0.003		
ln aggregate $ amount parent has invested so far			0.012***	
			0.002	
ln no. of portfolio companies parent has invested in so far				0.020***
				0.004
Diagnostics				
Adjusted R^2	18.4 %	18.0 %	18.8 %	18.0 %
Test: all coefficients = 0 (F)	44.2***	42.7***	44.3***	42.5***
No. of observations	3,105	3,105	3,105	3,105

Table V. 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. The first six variables are defined as in Table III. The experience measures considered in Table IV are highly correlated among each other. To avoid collinearity problems, we include only one in this table, aggregate dollars invested. This variable has the largest economic effect in Table III. All our results are robust to choosing any of the other experience measures instead. In addition, we control for the effect of the *parent's* network centrality on a sample fund's performance. The five network measures are defined in Table I; they are normalized by their respective 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.

	(1)	(2)	(3)	(4)	(5)
Fund characteristics					
ln fund size	0.029***	0.028**	0.027**	0.029***	0.028**
	0.011	*0.011*	*0.011*	*0.011*	*0.011*
ln fund size squared	-0.003**	-0.003**	-0.003**	-0.003**	-0.003**
	0.002	*0.002*	*0.002*	*0.002*	*0.002*
=1 if first fund	0.008	0.011	0.010	0.007	0.011
	0.011	*0.011*	*0.011*	*0.011*	*0.011*
=1 if seed or early-stage fund	-0.024**	-0.026***	-0.024**	-0.024**	-0.024**
	0.010	*0.010*	*0.010*	*0.010*	*0.010*
Competition					
ln VC inflows in fund's vintage year	-0.110***	-0.108***	-0.107***	-0.111***	-0.105***
	0.009	*0.009*	*0.009*	*0.009*	*0.009*
Investment opportunities					
average B/M ratio in fund's first 3 years	-0.313***	-0.310***	-0.309***	-0.314***	-0.306***
	0.030	*0.030*	*0.030*	*0.030*	*0.030*
Fund parent's experience					
ln aggregate $ amount parent has invested so far	0.010***	0.009***	0.008***	0.011***	0.008***
	0.002	*0.002*	*0.002*	*0.002*	*0.002*
Network measures					
outdegree	0.006***				
	0.002				
indegree		0.013***			
		0.003			
degree			0.003***		
			0.001		
betweenness				0.013**	
				0.006	
eigenvector					0.004***
					0.001
Diagnostics					
Adjusted R^2	18.9 %	19.1 %	19.1 %	18.8 %	19.1 %
Test: all coefficients = 0 (F)	43.4***	44.3***	44.1***	42.8***	44.1***
No. of observations	3,105	3,105	3,105	3,105	3,105

Table VI. 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. All variables are defined as in Table V, except lagged exit rate, which 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 five network measures are defined in Table I; they are normalized by their respective 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.

	(1)	(2)	(3)	(4)	(5)
Fund characteristics					
ln fund size	0.021	0.020	0.020	0.021	0.021
	0.018	*0.018*	*0.018*	*0.018*	*0.018*
ln fund size squared	-0.002	-0.002	-0.002	-0.002	-0.002
	0.002	*0.002*	*0.002*	*0.002*	*0.002*
=1 if seed or early-stage fund	-0.013	-0.015	-0.013	-0.013	-0.013
	0.013	*0.013*	*0.013*	*0.013*	*0.013*
Competition					
ln VC inflows in fund's vintage year	-0.104***	-0.100***	-0.100***	-0.103***	-0.096***
	0.016	*0.017*	*0.017*	*0.016*	*0.017*
Investment opportunities					
average B/M ratio in fund's first 3 years	-0.253***	-0.247***	-0.247***	-0.253***	-0.242***
	0.046	*0.046*	*0.046*	*0.046*	*0.046*
Fund parent's experience					
ln aggregate $ amount parent has invested so far	0.008*	0.005	0.006	0.008**	0.005
	0.004	*0.004*	*0.004*	*0.004*	*0.004*
Fund parent's lagged performance					
lagged exit rate	0.262***	0.256***	0.258***	0.263***	0.255***
	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)	30.6***	31.1***	30.7***	30.2***	30.8***
No. of observations	1,293	1,293	1,293	1,293	1,293

Table VII. 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 equaling 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. All independent variables are defined as in Tables III through VI. 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 MLE. 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.

	Survived round			Survived round			Survived round		
	1	2	3	1	2	3	1	2	3
Fund characteristics									
ln fund size	0.217***	0.159***	0.098*	0.204***	0.141***	0.074	0.206***	0.147***	0.079
	0.030	*0.044*	*0.058*	*0.030*	*0.044*	*0.058*	*0.030*	*0.044*	*0.059*
ln fund size squared	-0.009**	-0.012**	-0.007	-0.007	-0.009*	-0.003	-0.007*	-0.010*	-0.004
	0.004	*0.005*	*0.007*	*0.004*	*0.005*	*0.007*	*0.004*	*0.005*	*0.007*
=1 if first fund	-0.003	-0.039	-0.162***	-0.002	-0.036	-0.158***	-0.007	-0.040	-0.162***
	0.025	*0.036*	*0.044*	*0.026*	*0.036*	*0.044*	*0.025*	*0.036*	*0.044*
Competition									
ln VC inflows in funding year	-0.125***	-0.156***	-0.080***	-0.123***	-0.160***	-0.089***	-0.121***	-0.158***	-0.075***
	0.021	*0.022*	*0.027*	*0.021*	*0.022*	*0.027*	*0.021*	*0.023*	*0.027*
Investment opportunities									
mean B/M ratio in funding year	-0.452***	-1.058***	-1.035***	-0.440***	-1.033***	-0.929***	-0.451***	-1.085***	-1.093***
	0.114	*0.153*	*0.197*	*0.114*	*0.152*	*0.196*	*0.114*	*0.154*	*0.196*
Fund parent's experience									
ln aggregate $ amount invested	-0.009	-0.040**	-0.146***	-0.010	-0.032*	-0.125***	-0.008	-0.030*	-0.136***
	0.010	*0.017*	*0.024*	*0.010*	*0.017*	*0.023*	*0.010*	*0.018*	*0.024*
Network measures									
outdegree	0.035***	0.044***	0.076***						
	0.005	*0.007*	*0.009*						
indegree				0.057***	0.064***	0.101***			
				0.008	*0.011*	*0.014*			
degree							0.014***	0.017***	0.032***
							0.002	*0.003*	*0.004*
Diagnostics									
Pseudo R^2	9.5%	4.7 %	4.0 %	9.5 %	4.7 %	3.6 %	9.4 %	4.6 %	3.7 %
Test: all coeff. = 0 (F)	1509.9***	386.0***	203.3***	1513.7***	380.1***	195.3***	1511.5***	378.2***	205.1***
No. of observations	13,761	8,650	6,164	13,761	8,650	6,164	13,761	8,650	6,164

Table VII. Panel B. Effect of Firm Networks on Portfolio Company Survival

	Survived round			Survived round		
	1	2	3	1	2	3
Fund characteristics						
ln fund size	0.220***	0.177***	0.142***	0.204***	0.134***	0.086
	0.031	*0.044*	*0.056*	*0.030*	*0.044*	*0.059*
ln fund size squared	-0.009**	-0.014***	-0.013*	-0.007*	-0.008	-0.005
	0.004	*0.005*	*0.007*	*0.004*	*0.005*	*0.007*
=1 if first fund	-0.013	-0.051	-0.183***	-0.005	-0.034	-0.157***
	0.025	*0.036*	*0.044*	*0.026*	*0.036*	*0.044*
Competition						
ln VC inflows in funding year	-0.155***	-0.185***	-0.122***	-0.135***	-0.155***	-0.089***
	0.020	*0.022*	*0.026*	*0.021*	*0.022*	*0.026*
Investment opportunities						
mean B/M ratio in funding year	-0.453***	-0.994***	-0.782***	-0.568***	-1.105***	-0.899***
	0.115	*0.153*	*0.198*	*0.115*	*0.153*	*0.198*
Fund parent's experience						
ln aggregate $ amount invested	0.015*	-0.008	-0.087***	-0.026***	-0.066***	-0.158***
	0.009	*0.016*	*0.021*	*0.010*	*0.018*	*0.024*
Network measures						
betweenness	0.052***	0.093***	0.151***			
	0.015	*0.021*	*0.026*			
eigenvector				0.027***	0.036***	0.049***
				0.003	*0.004*	*0.005*
Diagnostics						
Pseudo R^2	9.2 %	4.5 %	3.1 %	9.7 %	5.1 %	4.0 %
Test: all coeff. = 0 (*F*)	1497.9***	371.0***	170.9***	1554.1***	426.8***	236.7***
No. of observations	13,761	8,650	6,164	13,761	8,650	6,164

Table VIII. 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. All independent variables are defined as in Tables III through VII. 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.

	(1)	(2)	(3)	(4)	(5)
Fund characteristics					
ln fund size	0.274***	0.250***	0.247***	0.298***	0.256***
	0.021	*0.021*	*0.021*	*0.021*	*0.021*
ln fund size squared	-0.025***	-0.021***	-0.020***	-0.028***	-0.022***
	0.003	*0.003*	*0.003*	*0.003*	*0.003*
=1 if first fund	-0.021	-0.021	-0.025	-0.040**	-0.020
	0.018	*0.018*	*0.018*	*0.018*	*0.018*
Competition					
ln VC inflows in funding year	-0.019*	-0.019*	-0.004	-0.049***	-0.023**
	0.010	*0.010*	*0.010*	*0.010*	*0.010*
Investment opportunities					
mean B/M ratio in funding year	-0.517***	-0.482***	-0.589***	-0.404***	-0.566***
	0.070	*0.070*	*0.071*	*0.070*	*0.071*
Fund parent's experience					
ln aggregate $ amount parent has invested so far	-0.065***	-0.060***	-0.075***	-0.025***	-0.091***
	0.007	*0.007*	*0.007*	*0.007*	*0.008*
Network measures					
outdegree	0.057***				
	0.003				
indegree		0.086***			
		0.005			
degree			0.028***		
			0.001		
betweenness				0.107***	
				0.009	
eigenvector					0.045***
					0.002
Diagnostics					
Pseudo R^2	5.6 %	5.6 %	5.7 %	5.1 %	5.9 %
Test: all coeff. = 0 (χ^2)	1899.1***	1892.2***	1918.6***	1705.2***	1961.7***
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 IX. 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 semi-parametric 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; they are defined as in Tables III through VIII. 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 IX. Effect of Network Position on Portfolio Company Exit Duration (continued)

	(1)	(2)	(3)	(4)	(5)
Fund characteristics					
ln fund size	0.029	0.033	0.033	0.024	0.042
	0.038	*0.038*	*0.038*	*0.038*	*0.038*
ln fund size squared	0.000	-0.001	-0.001	0.000	-0.002
	0.005	*0.005*	*0.005*	*0.005*	*0.005*
=1 if first fund	-0.157***	-0.157***	-0.156***	-0.152***	-0.160***
	0.030	*0.030*	*0.030*	*0.030*	*0.030*
Competition					
ln VC inflows in funding year	0.189***	0.188***	0.188***	0.198***	0.184***
	0.026	*0.026*	*0.026*	*0.025*	*0.025*
Investment opportunities					
mean B/M ratio in funding year	1.402***	1.395***	1.403***	1.408***	1.388***
	0.078	*0.078*	*0.078*	*0.078*	*0.078*
Fund parent's experience					
ln aggregate $ amount parent has invested so far	-0.096***	-0.096***	-0.097***	-0.100***	-0.080***
	0.013	*0.013*	*0.014*	*0.012*	*0.013*
Market conditions (time-varying)					
lagged NASDAQ Composite Index return	-0.719***	-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	0.019	0.021	0.019	0.019	0.014
	0.016	*0.016*	*0.016*	*0.016*	*0.016*
Network measures					
outdegree	-0.011**				
	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)	991.0***	999.8***	990.1***	994.1***	1039.5***
No. of observations	13,761	13,761	13,761	13,761	13,761

Table X. The Evolution of Network Positions

The sample consists of a panel of first-time funds by 823 VC firms which 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 there are at present 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***