Social Networks and Venture Capital Investments around the World

Abstract

Constructing social networks of large global venture capital (VC) firms, we find that social connections between VC firms increase their syndication likelihood, and the effect is more pronounced when the VC firm pair exhibits a larger experience gap. Importantly, VC firms that are central in social networks tend to lead investment syndicates and achieve superior performance. We document better access to deal flow and value-added services as two channels through which central VC firms improve their investment success. Overall, our results demonstrate the positive values of social networks in VC investments which is beyond what is posed by investment networks.

Keywords: Venture capital, social network, network centrality, syndication, performance

JEL Classification: G24; G41

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"You can't succeed in business without making personal connections."

Richard Branson, Founder of the Virgin Group

1. Introduction

In recent years, social finance has emerged as a new and rapidly growing paradigm that studies the financial impact of social interactions. Among different types of social interactions, personal connections in the form of social networks affect financial outcomes through generating and disseminating information. In studies on public firms, there is evidence that information in social networks flows into asset prices and corporate policy decisions. For example, Cohen, Frazzini, and Malloy (2008, 2010) find that portfolio managers and sell-side analysts who are socially connected to corporate board members outperform their nonconnected peers. Fracassi (2017) documents the similarity in the capital investment policies of socially connected firms. A recent study by Houston, Lee, and Suntheim (2018) on the global banking system shows that soft information generated in social networks facilitates banking syndication, but the positive performance correlation among connected banks leads to greater systemic risk. In this study, we examine the role of social networks in venture capital (VC), a major financing source for young, privately held, and informationally opaque firms.[1]

[1] Hochberg, Ljungqvist, and Lu (2007) study the role of VC firms' investment networks on investment performance and suggest VC firms' personal network ties as a central question for future research.

We utilize two sets of measures of social connections. The first set focuses on the social connections between two VC firms, which we refer to as pairwise social connections. The second set contains measures of the relative importance of a VC firm's position in a social network, which is referred to as social network centrality. We explore two related research questions: (i) how social connections drive VC investment decisions and (ii) how social network position affects VC investment performance.

The literature emphasizes the importance of information in VC investments. For example, a VC firm needs to collect information about a deal before making an investment decision. It also needs to verify its own evaluation of a potential portfolio company by surveying whether other VC firms are willing to co-invest (Lerner, 1994). In addition, it is crucial for a lead VC firm to collect information about potential syndicate members' heterogeneous skills, expertise, and networks so that it can select those that could offer value-added services (Brander, Amit, and Antweiler, 2002; Tian, 2012), as well as mitigate syndicate frictions.[2] Since social networks generate valuable soft information and allow for cheaper information gathering (Cohen et al., 2008; Butler and Gurun, 2012; Cai and Sevilir, 2012; Fracassi and Tate, 2012; El-Khatib et al., 2015; Houston et al., 2018), they facilitate the transmission and communication of information among connected VC firms and alleviate frictions in their syndicates. This, in turn, has two implications. First, two VC firms that are socially connected are more likely to partner in a VC syndicate.

[2] A study by Nanda and Rhodes-Kropf (2019) discusses coordination frictions that arise in VC syndicates and how these affect syndicate composition. These frictions include the information asymmetry between insiders (existing VC investors) and outsiders (potential VC investors), systematic differences in VC strategy, incentives, and investment horizons, and moral hazard and hold-up problems.

Second, because of superior access to information and ability to communicate with other VC firms, a central VC firm tends to play an active role in a syndicate, that is, to lead the syndicate.

To empirically test the first implication, we start with all global VC firms with at least $100 million of capital under management listed in the VentureXpert database.[3] We then identify their social ties using data on the educational and professional backgrounds of their directors and executives (hereafter referred to as executives) obtained from the BoardEx database.[4] We measure the pairwise social connection between two VC firms, *Social ties*, as the number of social ties, either educational or professional, scaled by their average number of executives. Based on the pool of VC firms with actual investments each year, we construct all possible pairwise co-investment decisions, which results in a sample of 458,250 pairs. We find that VC firms with a higher *Social ties* value are more likely to be syndicate partners. A one-standard-deviation increase in *Social ties* is associated with a 2.40% increase in the likelihood of VC syndicate partnership, *ceteris paribus*.

According to Cestone, Lerner, and White (2006), Casamatta and Haritchabalet (2007), and Nanda and Rhodes-Kropf (2019), syndicate partners with vastly different

[3] Our data on VC firms' capital under management were last updated in April 2021. The total amount and number of investments by top $100 million VC firms account for 85.0% and 75.1%, respectively, of the global VC market for the period 2000–2020.

[4] We present a sample of Correlation Venture LLC's executives covered by BoardEx in the Internet appendix IA.1. The executives play different roles in the management of the VC firm, including managing directors, CFO, partners, principals, senior associate, controllers, senior finance manager, and office manager.

experience are less likely to have aligned incentives, leading to greater syndicate frictions. As social connections mitigate syndicate frictions, we expect their impact on the syndication likelihood to be more pronounced when VC pairs exhibit larger experience gaps. To test this conjecture, we measure the experience gap between two VC firms as the difference in (i) the number of investment transactions that each VC firm has conducted (*Investment gap*), (ii) the number of each VC firm's portfolio companies that exit successfully through an initial public offering (IPO) or a merger and acquisition (M&A) (*Success gap*), and (iii) the number of each VC firm's portfolio companies that exit through an IPO (*IPO gap*). Our tests provide consistent results, lending further support to the role of social connections in alleviating syndicate frictions.

We next test the second implication, that central VC firms, having greater access to soft information from social networks, are more likely to lead a VC syndicate. Employing four metrics of network centrality, including degree centrality, eigenvector centrality, betweenness centrality, and closeness centrality (e.g., Hochberg et al., 2007; El-Khatib et al., 2015; Houston et al., 2018), we document supporting evidence.

After determining the impact of social networks on investment decisions, we examine the relation between social network centrality and VC investment performance. We argue that a central VC firm leads a VC syndicate through superior access to information and effective communication with other VC firms. Thus, investment deals where a central VC firm plays a leading role tend to have better performance. We conduct our empirical analyses at both the portfolio company and VC fund levels to test this conjecture. Following Hochberg et al. (2007) and Ewens, Gorbenko, and Korteweg (2022), we measure the interim success of portfolio companies across financing rounds as their ability to secure the subsequent financing round or to exit through an IPO or M&A. We also measure the ultimate success of portfolio companies based on their eventual exit through an IPO or M&A as of the end of the data period. Meanwhile, at the VC fund level, we employ an indirect measure of fund performance, which is a ratio of the number of portfolio companies that exit via an IPO or M&A to the total number of portfolio companies that a VC fund invests in since its vintage year. We find results consistent with our hypothesis.

To shed further light on how social networks benefit VC firms, we examine two underlying mechanisms leading to improved VC performance including (i) a better access to high-quality deal flow and (ii) an ability to add value to portfolio companies. Since a central VC firm can obtain correlated signals from its connected VC firms in the social networks and gets invited to join a VC syndicate, it has advantages in sourcing high-quality deals. If this better access to deal flow provided by social networks improves VC performance, we expect a more pronounced effect of social network centrality on VC performance when the VC firm itself has limited access to high-quality deal flow. To test this conjecture, we measure a VC firm's deal flow as the number of syndicated investments in which the VC firm participates but does not lead. We find empirical evidence supporting this first channel. To establish the second channel, it is necessary to isolate the ability to add value of well-connected VC firms from the impact of their better access to deal flow. We overcome this challenge by constructing a sample of second-round deals where the lead VC firms are not among the first-round VC investors. We document supporting evidence that the social network centrality of these lead VC firms positively influences the portfolio company's likelihood of survival to the next financing round.

One could be concerned that our results might be subject to reverse causality and could result from VC investment networks rather than social networks. We conduct a battery of tests to rule out these concerns. First, while the executives of two VC firms could decide to join the same organization (forming professional ties) after knowing each other through a previous joint-investment, it is unlikely that their co-investment experience could drive their choice of college which happened many years ago (i.e., educational ties). We decompose social ties into professional ties and educational ties and estimate their impacts on the likelihood of syndication. Second, we reconstruct our social networks and measure social connections using educational and professional ties formed at least five years before VC investment dates. Third, we explicitly control for VC investment networks by (i) taking into account whether two VC firms were syndicate partners in the previous year; (ii) constructing Hochberg et al. (2007)'s VC investment networks and controlling for investment network centrality in related models; and (iii) examining the effect of social connections on first-time syndication decisions. Overall, the regression results confirm the positive value of social networks on VC investment decisions and performance after controlling for the mutual existence of investment networks.

In addition, we investigate whether the impact of social networks varies in the subsamples of cross-border investments and U.S. VC investments. Finally, we conduct multiple robustness tests, including a pseudo-analysis and a difference-in-differences (DiD) analysis using the deaths of connected executives as exogenous shocks. Our results remain robust.

Our contribution is threefold. First, we contribute to the literature on the value creation of networks (e.g., Cohen, Frazzini and Malloy, 2008, 2010; Larcker et al., 2013; Cao et al., 2015; El-Khatib et al., 2015; Faleye et al., 2015; Bajo et al., 2016; Fracassi, 2017; Houston et al., 2018; Rossi et al., 2018). In the VC context, while Hochberg et al. (2007) focus on investment networks between U.S. VC firms, our study constructs global social networks and documents a significant impact of these networks on VC firms' investment decisions and performance. Second, our study adds social network centrality to the list of determinants of VC success.[5] Our paper is related to that of Gompers, Mukharlyamov, and Xuan (2016). However, while Gompers et al. (2016) examine pairwise friendships between individual venture capitalists, we focus on the aggregate social connections between VC firms. More importantly, to the best of our knowledge, our research is the first study to construct global VC social networks and investigate a new dimension of social networks in the VC context, that is, social network centrality, which measures the

[5] Some common VC success determinants include VC firm reputation (e.g., Hsu, 2006; Gompers, Kovner, Lerner, and Scharfstein, 2008; Krishnan et al., 2011; Amor and Kooli, 2020; Nanda, Samila and Sorenson, 2020), VC activism (Hellman and Puri, 2002; Casamatta, 2003), investment staging (Kaplan and Strömberg, 2003; Tian, 2011), venture contract design (Casamatta, 2003; Cornelli and Yosha, 2003; Schmidt, 2003; Hellmann, 2006; Cumming, 2008), and VC syndication (Tian, 2012; Bayar, Chemmanur, and Tian, 2020).

relative importance of each VC firm's position in the social networks. Third, by investigating the role of social networks in investment decisions, we add to the literature on the determinants of VC syndication (Lerner, 1994; Tian, 2012; Bayar et al., 2019; Liu and Tian, 2021) and VC firm strategies to mitigate syndicate frictions (Nanda and Rhodes-Kropf, 2019; Zheng et al., 2021; Kang et al., 2022).

The remainder of our paper is organized as follows. In Section 2, we describe our data and social connection measures. In Sections 3 and 4, we provide our main results on the role of VC firms' social connections on their investment decisions and performance. We further explore the impact of VC social networks given the existence of investment networks in Section 5. Section 6 offers additional analyses, and Section 7 concludes the paper.

2. Data collection and social connection measures

2.1. Data collection

In this study, we employ VC investment data from VentureXpert and data on educational background and employment history of directors and executives from BoardEx. Because the BoardEx data coverage starts in 1999, to examine how VC investments are affected by lagged social connections between VC firms, we collect round-by-round VC investments from 2000 to 2020. We first identify VC firms from the VentureXpert database with capital under management of at least $100 million. Because the BoardEx data contains four separate data files for North America, Europe, the United Kingdom, and the rest of the world, we divide our global VC data into four corresponding subsets to match them with the BoardEx data files. We then employ fuzzy matching to match VC firms' full legal names with the company names in the BoardEx data.[6] Finally, we manually check other details of VC firms in the BoardEx dataset to confirm that our matched data is correct. The final sample consists of 458 VC firms from VentureXpert that have executive information available in BoardEx. The starting year and ending year of each executive's position allow us to identify all executives of VC firms in each calendar year. We then calculate the social ties between VC firms based on the educational and professional background of their executives.

2.2. *Social connection measures*

2.2.1. *Pairwise social connection*

According to Ishii and Xuan (2014) and Bruynseels and Cardinaels (2014), two individuals are socially connected through their educational networks if they attended the same academic institution in the past or do so currently; and two individuals are linked through a professional tie if they share the same past or present membership in a private or public corporate board or the same membership in other institutions. We follow and measure *Social ties* as the number of social ties, either educational or professional, between two VC firms, scaled by the average number of their executives. To avoid duplications caused by pairs of executives connected through both educational and professional networks, we only count such instances once when measuring *Social ties*. We

[6] Julio Raffo, 2015. "MATCHIT: Stata module to match two datasets based on similar text patterns," Statistical Software Components S457992, Boston College Department of Economics, revised May 20, 2020.

also retain the unscaled measure of social connection, *Social ties* (*unscaled*), which is the natural logarithm of one plus the number of social ties between two VC firms. In addition, we measure *Connected,* a binary variable that equals one if there is at least one social tie between the executives of two VC firms, and zero otherwise.

[Insert Figure 1 here]

Figure 1 presents a snapshot of the socially connected world of VC firms. A large number of central nodes are from the U.S. VC market, indicating the dominance of U.S. VC firms in the global VC market. This is consistent with the fact that, among 458 top $100 million VC firms, 278 are located in the United States, representing a large proportion of 60.7%, and they are also densely connected to each other. We also observe VC firms in the central position from other countries, such as the United Kingdom and France, and their social connections with U.S. VC firms.

Figure 2 presents the time trend of the average of the scaled measures of *Social ties*, *Professional ties*, and *Educational ties* and the fraction of connected pairs between 1999 and 2019.[7] Overall, we observe a relatively stable value for *Educational ties* and an increase in the value of *Professional ties* over time, which is the major driver of an upward trend in the average of *Social ties* during the 1999–2019 period. The average value of *Professional ties* in 1999 is 0.008, while it reaches 0.018 in 2019, having increased by more than 100%. The *Educational ties* average remains around 0.008 during the whole sample period. VC

[7] In Section 3.1, we discuss in detail how to generate the input data to construct Fig. 2.

firms are increasingly pairwise connected, with the ratio of two VC firms being connected being 15.3% in 2019.

[Insert Figure 2 here]

2.2.2. Social network centrality

In addition to the pairwise social connection measures, we calculate four measures of social network centrality. Each centrality measure captures the position of a VC firm in the global social network from a different perspective. We rely on the social ties between pairs of VC firms, that is, VC_i and VC_j, and define a pair as connected if the two VC firms share at least one educational or professional tie. For each year t, we build a $v \times v$ unweighted adjacency matrix whose (i, j) element is defined as the connectedness between VC_i and VC_j, where v is the number of VC firms (nodes) in year t. Our social networks are, therefore, time varying, undirected, and unweighted. The approach of using an unweighted network to measure centrality at the VC firm level follows a broad literature of network studies, such as those of Hochberg et al. (2007), El-Khatib et al. (2015), and Houston et al. (2018). To make our centrality measures comparable across time, we scale them to one, with a value of zero being the lowest measure of centrality and one being the highest.[8]

[8] Our main empirical results hold when we use raw measures of social network centrality or percentile-based measures as described in El-Khatib et al. (2015).

2.2.2.1. Degree centrality

The first centrality measure is degree centrality, *Degree*, which counts the number of nodes in the network to which a VC firm is connected, and the measure is normalized by a factor of v - 1 to take into account network size:

$$Degree_i = \frac{\sum_{j \neq i} x_{ij}}{v - 1},$$

where x_{ij} is equal to one if VC_i has a social tie with VC_j. A higher degree centrality indicates that a VC firm is directly connected with more VC firms in the social network.

2.2.2.2. Eigenvector centrality

Eigenvector centrality is a more refined measure of degree centrality, which considers the network position of nodes with which an actor shares a connection. In the context of a VC network, an eigenvector is larger when the VC firm is connected to more well-connected VC firms. Following Bonacich (1972), eigenvector centrality, *Eigenvector*, is calculated by assuming that firm VC_i's centrality measure (e_i) is proportional to the sum of the centrality of VC_i's neighbors, $\lambda e_i = \sum_{j \neq i} x_{ij} \, e_j$, where λ is a proportional factor. In matrix terms, the eigenvector centrality of VC_i is the ith element of the vector x:

$$\lambda x = Ax$$

where A is the adjacency matrix of the network with (the largest) eigenvalue λ.

2.2.2.3. Betweenness centrality

Our third measure of network centrality is betweenness centrality, *Betweenness*, which is the sum of the fraction of all pairs' shortest paths that pass through node i:

$$Betweenness_i = \sum_{j,k \in V} \frac{\sigma(j,k|i)}{\sigma(j,k)} \times \frac{2}{(v-1)(v-2)}$$

where V is the set of nodes of the global VC network, v is the number of nodes, $\sigma(j,k)$ is the number of shortest (j,k) paths, and $\sigma(j,k|i)$ is the number of those paths that pass through node i other than nodes j and k.[9]

Different from *Degree* and *Eigenvector,* which are measured based on the direct contacts of VC firms in networks, *Betweenness* represents the role of a VC firm as a broker of information and signals how important the VC firm is in connecting other VC firms.

2.2.2.4. Closeness centrality

Our last measure of network centrality, *Closeness*, is the reciprocal of the average shortest path distance to VC_i over all n - 1 reachable nodes:

$$Closeness_i = \frac{n-1}{\sum_{j \neq i} d(j,i)} \times \frac{n-1}{v-1}$$

where $d(j, i)$ is the shortest path distance between nodes j and i and n is the number of nodes that can reach node i, including i itself, and v is the size of the network constructed annually. The variable *Closeness* captures how quickly a VC firm can obtain information from other VC firms in the network.

[9] If j equals k, then $\sigma(j,k)$ equals one. If $i \in (j,k)$, then $\sigma(j,k|i)$ equals zero.

3. Social ties and global VC syndication

3.1. Are connected VC firms more likely to join the same VC syndicate?

The literature has documented the role of information in forming VC syndicates. A lead VC firm needs to obtain second opinions from other VC firms to verify its evaluation of a potential portfolio company (Lerner, 1994). It also collects information about potential syndicate members, that is, their willingness, skill, expertise, and networks, before inviting them to join the syndicate (Brander, Amit, and Antweiler, 2002). Syndication coordination frictions arise due to the information asymmetry between existing VC firms (insiders) and potential VC firms (outsiders) and the misalignment of VC firms' strategies, incentives, investment horizons, and moral hazard and hold-up problems (Nanda and Rhodes-Kropf, 2019). Social networks, by generating valuable soft information (Houston et al., 2018) and allowing for cheaper information gathering (Cohen et al., 2008), can enhance information sharing among connected VC firms (Cohen et al., 2008; Fracassi and Tate, 2012). Therefore, social connections help reduce syndicate frictions and increase the likelihood of syndication between VC firms.

To test whether global VC firms that have social ties are more likely to form a syndicate in a portfolio company, we start with the sample of round-by-round investments from VentureXpert. For each year t, we generate all possible investment pairs between VC firms that have information on executives available from BoardEx. Specifically, if there are v VC firms in year t, there will be a total of $v(v-1)/2$ possible pairwise connections.[10] We then search all investment rounds in year t to identify whether two VC firms actually co-invest (i.e., form a syndicate) in a portfolio company. We construct a dummy variable, $Syndication_{i,j,t}$, that equals one if VC_i forms a syndicate with VC_j in a portfolio company in year t, and zero otherwise. We then compile investment pairs across years and drop those with missing data for empirical analyses. This data procedure results in 458,250 observations.

Following Houston et al. (2018), we run a linear probability model regression of $Syndication_{i,j,t}$ on measures of social connections:

$$Syndication_{i,j,t} = \alpha_0 + \beta_t + \theta Social\ connection_{i,j,t-1} + \delta' X_{i,j} + \gamma' Y_{i,j,t-1} + \epsilon_{i,j,t} \quad (1)$$

where α_0 is constant; β_t is a vector of year fixed effects; $X_{i,j}$ and $Y_{i,j,t-1}$ are vectors of time-invariant and time-varying control variables, respectively; and $\epsilon_{i,j,t}$ represents error terms. In all models, we cluster standard errors at the VC firm pair level.

Summary statistics of the variables used for the estimation of Eq. (1) are presented in Table IA.2 of the Internet Appendix. The average ratio of co-investment, *Syndication*, equals 0.024, suggesting that 2.4% of the 458,250 VC pairs actually co-invest in a portfolio company. The binary variable *Connected* has a mean of 0.106, indicating that, on average, 10.6% of VC pairs are socially connected. The mean value of *Social ties* equals 0.021. Both VC firms and paired VC firms show strong historical experience with syndicated

[10] This is because one VC firm can connect with the other v - 1 VC firms, and the connection between VC_i and VC_j is the same as that between VC_j and VC_i .

investments.[11] Among 458,250 VC firm pairs, 46.1% share the same country of location, 6.4% have a similar industry preference, and 28.1% are in the same size (capital under management) tercile. We report the regression results of Eq. (1) in Table 1.[12]

[Insert Table 1 here]

In column (1) of Table 1, following Cai et al. (2012) and Houston et al. (2018), we measure social connection using the lagged scaled measure of social ties, $Social\ ties_{i,j,t-1}$. We control for the syndication history of both VC firms, that is, the cumulative number of syndicated investments that VC_i and VC_j have up to year t - 1. We find that socially connected VC firms are more likely to partner in the same syndicate. The point estimate of *Social ties* is 0.289 and statistically significant at the 1% significance level. This indicates that a one-standard-deviation increase in *Social ties* (0.083) is associated with a 2.4% (= 0.289×0.083) increase in the likelihood of VC syndication partnership. The coefficients for the syndication history of both VC firms are positive and statistically significant, as expected. A VC firm that has a higher number of syndicated investments in the past is more likely to join a syndicate investment in the future.

In column (2) of Table 1, we further control for the common characteristics and preferences of VC firms. Specifically, we include three time-invariant control variables:

[11] Because we systematically keep one pair from two possible VC firm pairs (i.e., VC_i–VC_j and VC_j–VC_i) to form our baseline sample, there are differences between the summary statistics of VC_i and VC_j. This selection does not affect the analysis.
[12] We also conduct rare event logistic regressions introduced by King and Zeng (2001) to correct for rare events bias due to a large proportion of "nonevents" in the sample. Our results are robust.

Same nation, *Same industry preference*, and *Same size*.[13] The variable *Same nation* is a dummy that equals one if VC_i and VC_j are located in the same country, *Same industry preference* is a dummy variable that equals one if VC_i and VC_j share the same industry preference, and *Same size* is a dummy variable that takes the value of one if VC_i and VC_j fall in the same tercile estimated using VC firm capital under management. We obtain consistent results as those in column (1). The variable *Social ties* remains positive and statistically significant. The signs of all the control variables are consistent with the conjecture that VC firms of similar size, in the same country, and with a similar industry preference tend to invest together. In column (3), we replicate the model in column (2) using the unscaled version of *Social ties* as the main independent variable and find consistent results. In column (4), we re-estimate the previous model using *Connected*, a dummy variable equal to one if VC_i is socially connected to VC_j in year t - 1, and zero otherwise. We find a positive and significant coefficient for *Connected*.

In the last column of Table 1, we further include VC firm pair fixed effects, to control for unobserved time-invariant characteristics of pairwise VC firms. Consistent with the previous findings, we obtain a positive and statistically significant coefficient for *Social ties*. Overall, the results from all five models suggest a positive relation between the social connections of VC firms and their likelihood of syndication partnership.

[13] VentureXpert only reports the most recent data for VC firm location, industry preference, and capital under management. The variables *Same nation*, *Same industry preference,* and *Same size* are, therefore, time invariant.

3.2. *When are connected VC firms more likely to partner in the same syndicate?*

According to Cestone et al. (2006) and Nanda and Rhodes-Kropf (2019), VC firms with different levels of experience are unlikely to have aligned incentives. This suggests a positive association between the experience gap of VC firms and their coordination costs (Casamatta and Haritchabalet, 2007). More generally, Du (2016) argues that co-investments among similar syndicate partners tend to have low coordination costs. If sharing information through social networks reduces coordination costs, we predict that the impact of social networks on the likelihood of VC syndication is more pronounced when the VC pair exhibits a large experience gap. To empirically test this prediction, we estimate the following equation:

$$Syndication_{i,j,t} = \alpha_0 + \beta_t + \theta Social\ ties_{i,j,t-1} + \tau VC\ experience\ gap_{i,j,t-1}$$
$$+ \vartheta Social\ ties_{i,j,t-1} \times VC\ experience\ gap_{i,j,t-1} + \delta' X_{i,j} + \gamma' Y_{i,j,t-1} + \epsilon_{i,j,t} \quad (2)$$

This equation is an extension of Eq. (1) with *VC experience gap* and the interaction terms between *VC experience gap* and social connection measures. We measure *VC experience gap* as the difference between two VC firms in (i) the number of investments that they have conducted since 1990 (*Investment gap),* (ii) the number of their portfolio companies that successfully exit via an IPO or M&A (*Success gap)*, and (iii) the number of their portfolio companies that exit via an IPO (*IPO gap*).

Our variable of interest is the interaction term between *Social ties* and *VC experience gap*, where both are measured at time *t* - 1. Similar to Eq. (1), we estimate Eq. (2) with year fixed effects and standard errors clustered at the VC pair level. Our time-invariant control variables, $X_{i,j}$, include *Same nation*, *Same industry preference,* and *Same size,* to reflect the similarity between the dyad of VC firms in terms of their location, industry preference, as well as capital under management. Meanwhile, $Y_{i,j,t-1}$ takes into account the syndication history of both VC firms. We report the regression results in Table 2.

[Insert Table 2 here]

In all three models of Table 2, we obtain results consistent with our hypothesis. The coefficient ϑ of the interaction term is positive and statistically significant at the 1% level. Interestingly, the standalone social connection measure, *Social ties*, remains positive and significant in column (3), but is insignificant in columns (1) and (2), implying that social connection carries only a small value in fostering syndicate relationships between VC firms that have the same investment experience and the same number of exits.

4. Social network centrality, VC syndication, and investment performance

4.1. Do central VC firms lead VC syndicates?

A VC firm that is central in a social network can identify correlated signals from other VC firms and know more about the quality of other VC firms that potentially become its syndicate partners. Moreover, social networks facilitate effective communication between partnering VC firms, resulting in the more efficient valuation of potential investment opportunities and better investment monitoring. Such information advantages naturally lead to an expectation that central VC firms will play an active role in a VC syndicate, that is, lead the VC syndicate. To examine this conjecture, we rely on the sample of VC investment rounds between 2000 and 2020. We remove non-syndicated rounds and require two or more VC firms in the syndicate to have available information on their social network positions. We define a lead VC firm as the VC firm that has the largest investment in the portfolio company in a particular round. Note that the leading position is dynamic across financing rounds, since existing VC firms might discontinue their investment, or new VC firms might join and lead the syndicate. We run a linear regression to estimate the following equation:

$$Lead\ VC_{i,n,k,r,t} = \alpha_0 + \beta_t + \beta_k + \beta_r + \beta_n + \theta Network\ centrality_{i,t-1} + \delta' X_{i,t} + \epsilon_{i,n,k,r,t} \quad (3)$$

where α_0 denotes a constant and $\beta_t, \beta_k, \beta_r$, and β_n denote year, portfolio company, round, and VC nation fixed effects. We control for VC characteristics, $X_{i,t}$, including capital under management (*VC capital*) and age (*VC age*). An error term is represented by $\epsilon_{i,n,k,r,t}$. We present the results in Table 3.

[Insert Table 3 here]

Out of the four network centrality measures, three, in columns (1), (2), and (4), respectively *Degree*, *Eigenvector,* and *Closeness,* are positive and statistically significant at the 1% level. This indicates that VC firms in a more central network position are more likely to lead the syndicate. The impact of network centrality is also economically meaningful. The point estimates of the three network centrality measures being 0.104, 0.104, and 0.189 with standard deviations of 0.288, 0.312, and 0.149 (see Panel B, Table IA.2) suggests increases of 3% (= 0.104×0.288), 3.24% (= 0.104×0.312), and 2.82% (= 0.189×0.149) in the likelihood of being a lead VC for a one-standard-deviation increase in *Degree*, *Eigenvector,* and *Closeness*, respectively. The measure in column (3), *Betweenness*, while positive, is not significant at conventional significance levels. Since *Betweenness* is a measure based on the frequency of a VC firm being on the shortest-distance paths between all possible pairwise VC firms, its insignificance suggests the trivial role of a VC firm as an intermediary between other VC firms in the market.

4.2. *Social network centrality and VC investment performance*

In this section, we explore the impact of social network centrality on VC investment performance at both the portfolio company and VC fund levels. Since central VC firms benefit from their information and connection with other VC firms in the social network (Cohen et al., 2008, 2010; El-Khatib et al., 2015; Houston et al., 2018), we expect to observe better performance among portfolio companies in which central VC firms invest, as well as better VC fund performance. We test these conjectures in the following sections.

4.2.1.Portfolio company–level analysis

4.2.1.1. Social network centrality and portfolio company survival

We first examine the impact of a lead VC firm's network centrality on the ability of portfolio companies to survive from one round to the next, which signals their interim success. Specifically, we define a company as surviving round R ($R = 1, 2, 3, \ldots$) if it reaches the next round, $R + 1$, or exits through an IPO or M&A. Since a company that survives round $R + 1$ must have survived round R, the number of observations for the analysis at round R will decrease when R increases. In the interest of brevity, we focus on the survival of portfolio companies in the first three rounds. Following Nahata et al.

(2014), we start with a sample of first-round investments by lead VC firms during 2000 to 2020.[14] The sample has 5,027 observations. We then determine whether a given portfolio company in this dataset obtains a second round (2,605 observations) or third round of financing (1,634 observations).[15] We estimate the following regression model:

$$Survival_{i,k,g,t} = \alpha_0 + \beta_t + \beta_g + \theta Network\ centrality_{i,t-1} + \delta' X_{i,t} + \gamma' Y_{k,t} + \epsilon_{i,k,g,t}, \quad (4)$$

where *Survival* includes *First round survival*, *Second round survival,* and *Third round survival,* indicating the portfolio companies survived the first, second, and third rounds, respectively; α_0 is a constant term; β_t and β_g indicate year and portfolio company's industry fixed effects; $X_{i,t}$ is a vector of variables to control for VC firm characteristics, including the VC firm's capital under management and age; and $Y_{k,t}$ is a vector of control variables at the company level, including the round syndication size, company age, and company development stage when the the first round of financing is received.[16] The control variables are defined in Table A.1 of the Appendix. We report the regression results of survival from the first, second, and third rounds in Panels A to C of Table 4, respectively.

[Insert Table 4 here]

[14] We focus on the social network position of the VC firm that has the largest influence on the portfolio company in the earliest financing round.

[15] See summary statistics in Table IA.2 of the Internet Appendix.

[16] The variables *Early stage, Expansion stage,* and *Later stage* are three of four dummies that represent the development stage of the portfolio company in the first round of VC financing. The omitted group represents those portfolio companies that first obtain their VC financing at the seed or start-up stage.

As shown in Panel A of Table 4, the coefficients of all the network centrality measures are positive and statistically significant (at the 1% level in columns (1), (2), and (4), and at the 5% level in column (3)), suggesting that portfolio companies led by VC firms of high centrality in the first financing round are more likely to receive financing in the second round or exit successfully. We continue to document a positive impact of network centrality on the survival likelihood from the second round in Panel B. Specifically, except for the evidence in column (3) when *Betweenness* is used as the main independent variable, the coefficients of the network centrality measures are positive and statistically significant at the 10% level. We observe that the statistical significance of the network centrality measures in Panel C falls significantly, but their signs are generally consistent with the previous results.

Besides, we find a strong positive association between *VC capital* and *Survival* in Panel A of Table 4, suggesting that larger VC firms with greater reputation and resources tend to have a higher survival likelihood. In addition, younger portfolio companies in their first financing round are more likely to survive to the second financing round or exit through an IPO or M&A. Meanwhile, *Expansion stage*, and *Later stage* have negative and statistically significant coefficients, suggesting that, if a company receives its first financing round in a later development stage (i.e., at the expansion, or later stage), it is less likely to succeed than other companies that receive first-round financing at the seed or start-up stage.

4.2.1.2. Social network centrality and portfolio company success

We further explore whether a VC firm's social network centrality affects its portfolio company's ultimate success. We follow the previous literature to consider a successful exit as a proxy of investment success (see, for example, Nahata, 2008; Nahata, Hazarika, and Tandon; 2014). We use the sample of VC investments by lead VC firms in the first financing round as described in Section 4.2.1.1. We identify the corporate status of portfolio companies as of April 2021 and construct a dummy variable, *Success*, that takes the value of one if a portfolio company exits through an IPO or M&A, and zero otherwise. We regress *Success* on social network centrality measures and report the estimation results in Table 5.[17]

$$Success_{i,k,g,t} = \alpha_0 + \beta_t + \beta_g + \theta Network\ centrality_{i,t-1} + \delta' X_{i,t} + \gamma' Y_{k,t} + \epsilon_{i,k,g,t} \quad (5)$$

The point estimate of network centrality is positive in all models and statistically significant in columns (1), (2), and (4) when we use *Degree*, *Eigenvector*, and *Closeness* to measure network centrality. This suggests that portfolio companies benefit from investments by well-connected VC firms. Similar to the earlier findings, the impact of *Betweenness*, a network centrality measure that proxies for the intermediary role of a VC firm in connecting others, though positive, is not statistically significant.

[Insert Table 5 here]

[17] We obtain similar results when performing probit regressions of *Success* on network centrality (see Table IA.3 in the Internet Appendix).

4.2.2.Fund-level analysis: VC network centrality and fund performance

We next investigate whether a VC firm's network centrality improves its fund performance. We first obtain complete information on global VC funds from the VentureXpert database. We then merge the fund data with the list of 458 VC firms that have information available in the BoardEx dataset. We require the vintage year of these funds to range from 2000 to 2020. To estimate fund performance, we then match this dataset with VentureXpert's round-by-round investment data. We employ an indirect measure of individual fund performance, *Fund performance*, which is the ratio of the number of portfolio companies that exit via an IPO or M&A to the total number of portfolio companies that the fund invests in since its vintage year. The higher the number of successful exits that a fund has, the larger its internal rate of return.

We compute the network centrality measures one year prior to the VC fund's vintage year and use them as proxies for the fund's network position. Our final sample includes 926 funds. We then examine the impact of the VC fund's network centrality on its performance:

$$Fund\ performance_{f,t} = \alpha_0 + \beta_t + \beta_{fn} + \beta_{fs} + \theta Network\ centrality_{i,t-1} + \delta X_{f,t} + \epsilon_{f,t} \quad (6)$$

where α_0 is a constant term; β_t, β_{fn}, and β_{fs} indicate vintage year, fund nation, and fund sequence–type fixed effects; and $X_{f,t}$ is the natural logarithm of fund size. We cluster the standard errors at the vintage year level.

We obtain positive coefficients of all measures of network centrality, as indicated in Panel A of Table 6. The coefficient estimates of *Degree*, *Eigenvector*, *Betweenness,* and

Closeness are 0.092, 0.079, 0.116, and 0.052, respectively. Given their standard deviations of 0.295, 0.324, 0.240, and 0.237, respectively, the estimates translate to increases of 2.71%, 2.56%, 2.78%, and 1.23% in the ratio of the number of successful exits to the total number of portfolio companies.[18] Among the four centrality measures, *Degree, Eigenvector,* and *Betweenness* are statistically significant at the 1% level.

[Insert Table 6 here]

Since VC funds have a typical life cycle of 10 years (Ewens and Farre-Mensa, 2020), we further limit our sample to include only funds that have vintage years no later than 2010 (to allow for at least 10 years of the fund life cycle). Correspondingly, our sample size reduces to 606 observations. We re-estimate Eq. (6) and present the results in Panel B of Table 6. Overall, the results of Panel B are consistent with those in Panel A, emphasizing the positive impact of network centrality on fund performance.

4.3. *How do social networks affect VC investment performance?*

Our earlier results on the superior performance of central VC firms suggest that social networks offer valuable information that enhances VC performance. In this section, we explore mechanisms through which social networks benefit VC firms. Previous literature attributes VC firms' investment success to superior (i) deal access ability (Krishnan et al., 2011) and (ii) ability to add value to their portfolio companies (Hellman and Puri, 2002; Hsu, 2004; Bottazzi, Darin, and Hellmann, 2008; Tian, 2012). We examine

[18] See the summary statistics in panel D, Table IA.2 of the Internet Appendix.

whether a VC firm that holds a central position in social networks has better access to deal flow or adds more value to its portfolio companies.

4.3.1.Deal access of central VC firms

A VC firm can initiate a syndicate and invite other VC firms to co-invest. By doing so, it generates an investment opportunity and offers access to other VC firms. On the other hand, a VC firm can join a syndicate after being invited by other lead VC firms, which expands its access to deal flow or its investment opportunity set. We argue that a central VC firm through its connections with other VC firms is more likely to be invited to join a syndicate. Being central, it can also identify correlated signals from other VC firms, thus has better access to deal flow. To test whether a central VC firm has a higher likelihood of success because of having better access to deal flow, we first proxy its access to deal flow by the number of syndicated investments in which it participates but does not lead. We construct a dummy variable, *High deal flow,* indicating whether the VC firm's deal flow is larger than the median value of all VC firms' deal flow in the same year. If social networks indeed offer a central VC firm better deal access, the impact of network centrality on success should be more (less) pronounced in the group with low (high) access to deal flow. To test this hypothesis, we interact *Network centrality* and *High deal flow* and examine its impact on *Success.* We provide the regression results in Table 7.

[Insert Table 7 here]

We obtain positive and statistically significant coefficients of *Network centrality* in all columns of Table 7, except column (3) where *Network centrality* is proxied by

Betweenness. The results indicate a positive relation between a VC firm's social network centrality and its portfolio company's likelihood of success in the group of VC firms with low access to deal flow. The coefficients of the interaction terms are negative and statistically significant at conventional significance levels, suggesting that the impact of network centrality on the likelihood of success is less pronounced among the group of VC firms with high access to deal flow. This evidence is consistent with our conjecture that VC firms with better inherent deal access benefit relatively less from their social networks. In other words, *Network centrality* , by enhancing a VC firm's deal access, plays a more important role for VC firms with limited deal access. [19]

4.3.2. Value-added services by central VC firms

Central VC firms with superior access to information through social networks can add value to their portfolio companies by improving their companies' human resources policies and senior managers' hiring decisions, assisting with fundraising, as well as introducing them to strategic partners. To empirically identify the value-added services by central VC firms, we use a subsample of second-round deals whose lead VC does not participate in the first round. Because the new lead VC firms in the second round are not involved in the deal origination, this empirical setting is expected to isolate the impact of the value added by central VC firms from the impact of access to deal flow. Using Eq. (4), we re-estimate the survival of the portfolio companies to the third round as a function of

[19] In unreported analyses, we validate our mechanism by examining the effect of *Network centrality* on *Deal flow* and find that network centrality improves a VC firm's access to deal flow. The results of this test are available upon request.

their second-round lead VC firms' network centrality. The estimation results are reported in Table 8.

[Insert Table 8 here]

We document positive coefficients for all network centrality measures in Table 8. Except *Betweenness*, all the centrality measures are statistically significant at the 1% level. Overall, this evidence indicates that the network centrality of the new lead VC in the second round improves the survival likelihood of the portfolio company to the third round. This finding supports the second channel that central VC firms have better ability to add value to their portfolio companies.

5. Social networks versus investment networks

One could be concerned that VC firms' prior investment ties facilitate social interactions across their executives. As VC investment ties leads to better performance (Hochberg et al., 2007), if this is true, our results so far could be driven by investment networks rather than by social networks. We conduct a battery of tests to ascertain that this is unlikely to be the case.

5.1. Educational ties

Investment ties tend to affect professional ties rather than educational ties. VC firms' executives who recently invested together could potentially join the same corporate board or share membership in a club or charity organization. However, it is unlikely for investment ties to drive educational ties, which were most likely formed decades earlier.[20] Therefore, if our findings remain consistent when social connection is measured based on educational ties only, this suggests that our main results are not driven by the existence of a historical investment tie. We check the robustness of our main results by regressing *Syndication* on *Professional ties* and *Educational ties* separately. We report the results in Table 9.

[Insert Table 9 here]

In columns (1) and (2) of Table 9, we use *Professional ties* and *Educational ties* as the main independent variable, respectively, whereas, in column (3), *Professional ties* and *Educational ties* are simultaneously included. We obtain positive and significant coefficients for *Educational ties* in both columns (2) and (3). This evidence suggests that our findings are not driven by historical investment experience. Interestingly, the results also indicate that professional ties have a stronger impact on the likelihood of syndication than educational ties do. It is plausible that the larger magnitude of the coefficient on *Professional ties* implies the greater relevance of recent social ties on the likelihood of syndication, since educational ties tend to be developed much earlier than professional ties.

5.2. Reverse causality

If investment networks drive social networks, our results could be subject to an endogeneity concern that arises from reverse causality. We follow Engelberg et al. (2012)

[20] According to Cohen et al. (2008), the formation of educational ties has often been ex ante and independent of the information transferred in networks.

and Houston et al. (2018) to replace the one-year-lagged measure of social connection by a preexisting pairwise social connection. Specifically, we use (i) educational ties that were formed at least five (ten, twenty) years ago, and/or (ii) professional ties whose formation occurred at least five years earlier. Given that the formation of social connections predates the VC syndication date by years, our new measures are expected to mitigate the reverse causality issue. We find consistent results in Table 10 that preexisting social connections between dyadic VC firms increase their syndication partnership likelihood.

[Insert Table 10 here]

We further construct new social networks based on the preexisting connections between VC firms and measure the network centrality of each VC. We then re-estimate all the tables in Section 4 (i.e., Tables 3 to 8) and obtain consistent results.[21]

5.3. Controlling for investment networks

5.3.1. Controlling for lagged syndication

To provide further evidence that our results are not driven by investment networks, we re-estimate Eq. (1) with a new control variable, *Lagged syndication*, to indicate if the two VC firms co-invested in a portfolio company in the previous year. Table 11 shows that the coefficients of the social connection measures remain positive and statistically significant at the 1% level, suggesting that VC firms that are socially connected have a higher propensity to partner in a syndicate, even after controlling for a

[21] Our tables are available upon request.

prior investment tie. As expected, the coefficient of *Lagged syndication* is positive and statistically significant at the 1% level, indicating VC firms that co-invest in a given year tend to co-invest in the year after.

[Insert Table 11 here]

5.3.2. Controlling for investment network centrality

Next, following Hochberg et al. (2007), we construct the investment networks of our sample VC firms based on their previous investment ties. We examine the impact of a lead VC's social network centrality on the likelihood of its portfolio company's successful exit (similar to Table 5) while controlling for its investment network. The regression results in Table 12 confirm the findings from Table 5, that social network centrality improves the portfolio company's likelihood of success after controlling for the VC investment network centrality.

[Insert Table 12 here]

5.3.3. First-time VC syndication

Finally, we construct a sample of first-time pseudo syndication pairs, that is, VC pairs that have no prior investment connection. Specifically, for each year t between 2000 and 2020, we generate all possible investment pairs between VC firms and drop all pairs in which two VC firms have an investment tie with each other in any portfolio company during the period from 1990 to year t - 1. The remaining sample has 411,506 first-time pseudo-investment pairs, among which 2,918 pairs (0.7%) are actual syndicated investments for the first time. We then examine the effect of social connections on the likelihood of first-time syndication using Eq. (1). The results are reported in Table 13.

[Insert Table 13 here]

We obtain positive and statistically significant coefficient estimates for the social connection measures in all specifications. This evidence suggests that social connections between two VC firms with no prior investment relationship increase the likelihood of their first-time syndication. We further decompose *Social ties* into *Professional ties* and *Educational ties* and estimate their impact on the likelihood of first-time syndication and obtain consistent results (see Table IA.4 in the Internet Appendix). Overall, the results strengthen our previous findings on the value of social networks, which are related but not driven by investment networks.

6. Additional analyses

6.1. Syndicate formation by socially connected cross-border VC firms

As shown in Fig. 1, VC networks are geographically concentrated and dominated by VC firms in the United States. One natural question would be whether the role of social connections is driven by within-country syndication formation, especially within the United States, or also pertains to cross-border VC syndication. In this section, we test directly if the pairwise social connections of cross-border VC firms have an impact on the likelihood of cross-border syndication. We re-estimate Eq. (1) using a subsample of possible VC firm pairs that are located in two different countries. Table 14 provides consistent evidence that the coefficients of all social connection measures, including *Social* *ties, Social ties* (*unscaled*), and *Connected,* are positive and statistically significant at the 1% level.

[Insert Table 14 here]

6.2. Robustness checks

6.2.1.Pseudo-analysis

We run additional tests to ascertain our findings. We first conduct pseudo-analyses where we randomly select the value of *Social connection* from the pool of all possible values in our sample. We then re-estimate Eq. (1) to obtain the coefficient θ on *Social connection*. We repeat this process 1,000 times to obtain distributions of the bootstrapped coefficient θ.

[Insert Figure 3 here]

Figure 3 illustrates the distributions of the bootstrapped coefficients of *Social ties* (left panel) and *Connected* (right panel). As shown, the bootstrapped coefficients of *Social ties* and *Connected* are normally distributed, with the mean and standard deviation being -0.0001 and 0.0028, respectively, for *Social ties*, and 0.00002 and 0.0007, respectively, for *Connected.* The coefficients on *Social ties* and *Connected* obtained from the baseline regressions equal 0.273 and 0.060, respectively, which are 98 and 86 standard deviations from the means of the bootstrapped coefficients, suggesting that the results in Table 1 are not obtained by chance.

6.2.2.Difference-in-Differences analysis

The findings from the analyses above suggest that socially connected VC firms tend to co-invest in a VC syndicate. One alternative explanation is that VC firms may hire connected executives to target a desired VC syndicate. Following Fracassi (2017), we use the deaths of VC executives as exogenous shocks to VC social connections. When a VC executive passes away, the executive's social ties with other VC executives in social networks cease to exist, and this causes an exogenous shock to the networks. We obtain data for the year of death of VC executives from the BoardEx database. We conduct a Difference-in Differences (DiD) analysis to address the potential endogeneity concern. Our DiD sample is restricted to all possible VC pairs where there is an executive death during the sample period. Our sample size thus drops from 458,250 observations in Table 1 to 158,610 observations. Our treatment group includes VC pairs that were connected by the deceased executive. We report the results for the DiD analysis in Table 15.

[Insert Table 15 here]

In column (1) of Table 15, we include (i) a dummy variable *Death as connection* to indicate the treatment group, (ii) a dummy variable *After death* that equals one for any period after the death of an executive, and (iii) an interaction term between *Death as connection* and *After death.* In column (2), we control for the common characteristics and preferences of VC firms. In both models, we obtain a negative and significant coefficient on *Death as connection*×*After death.* Economically, after the death of a connected executive, the syndication likelihood between the two VC firms drops by 9.3% and 8.7% as indicated in columns (1) and (2), respectively. Overall, the results suggest that a social connection between the two VC firms has a positive causal effect on the likelihood of syndication.

6.2.3.The social networks of U.S. VC firms

Given the domination of U.S. VC firms in the global VC market, we limit our sample to the sample of investments by U.S. VC firms only and confirm whether our previous findings hold. We re-estimate the analyses in Tables 1 to 3 and 5 and report the results in Table IA.5 of the Internet Appendix. Overall, our results hold in the sample of investments by U.S. VC firms.

7. Conclusion

In this study, we examine the impact of VC social networks built upon the historical social ties of VC executives on VC investment decisions and performance. Constructing the social networks of 458 global VC firms with capital under management of at least $100 million, we document that socially connected VC firms are more likely to join the same VC syndicate. This effect is more pronounced when the experience gap between VC firms is larger, consistent with the hypothesis that social connections mitigate coordination frictions and promote VC syndication. We then investigate the role of VC firms that are in a central position of social networks. We document that well-networked VC firms with greater access to soft information tend to lead VC syndicates. Portfolio companies receive funding from central VC firms have a higher likelihood of survival to subsequent financing rounds and are more likely to exit successfully, either though an IPO or an M&A. Consistently, VC funds under the management of central VC firms experience better performance compared to other VC funds. We identify two channels through which social networks improve investment performance, that is, better access to deal flow and the ability to add value of central VC firms. Our results are robust to alternative measures of social connections and the inclusion of investment networks and withstand endogeneity concerns.

Overall, our results offer evidence that whom you know matters in the VC context. The superior investment performance of central VC firms suggests that VC firms should strategically consider improving their position in social networks. This could start with their human resource decisions, by attracting well-connected executives or promoting networking activities. The results from our study also raise interesting questions. For instance, since social networks help to drive performance success and at the same time, are costly and difficult to replicate, do they contribute to a VC's performance persistence? Is there an optimal level of social network centrality for a VC firm? Given the typical "2 and 20" fee structure of a VC fund, why don't all limited partners allocate their capital into the most central VC firm in a social network? These questions remain open for future research.

Appendix

Table A.1: Definitions of variables

Variable name	Description
Social network variables	
Social ties	The number of social ties between two VC firms, scaled by their average number of executives.
Social ties (*unscaled*)	The natural logarithm of one plus the number of social ties between two VC firms.
Connected	A dummy variable that equals one if two VC firms are socially connected, and zero otherwise.
Professional ties	The number of professional ties between two VC firms, scaled by their average number of executives.
Educational ties	The number of educational ties between two VC firms, scaled by their average number of executives.
Professionally connected	A dummy variable that equals one if two VC firms are professionally connected, and zero otherwise.
Educationally connected	A dummy variable that equals one if two VC firms are educationally connected, and zero otherwise.
Professional ties 5 years	Professional ties between two VC firms formed at least 5 years ago, scaled by their average number of executives.
Educational ties 5 (*10, 20*) *years*	Educational ties between two VC firms formed at least 5 (10, 20) years ago, scaled by their average number of executives.
Degree	VC firm’s degree centrality.
Eigenvector	VC firm’s eigenvector centrality.
Betweenness	VC firm’s betweenness centrality.
Closeness	VC firm’s closeness centrality.
VC characteristics	
VC syndication history	The natural logarithm of one plus the cumulative number of syndicated investments a VC firm participates in from 1990 to a given year.
Same nation	A dummy variable that equals one if two VC firms share the same country location, and zero otherwise.
Same industry preference	A dummy variable that equals one if two VC firms have the same industry preference, and zero otherwise.
Same size	A dummy variable that equals one if two VC firms are in the same tercile based on their capital under management, and zero otherwise.
Age gap	The natural logarithm of one plus the absolute difference of two VC firms’ founding age.
Success gap	The natural logarithm of one plus the absolute difference of two VC firms’ number of successful exits from 1990 to a given year, where successful exits include both IPO and M&A exits.
Investment gap	The natural logarithm of one plus the absolute difference of two VC firms’ number of investments from 1990 to a given year.
IPO gap	The natural logarithm of one plus the absolute difference of two VC firms’ number of IPO exits from 1990 to a given year.
VC capital	The natural logarithm of the VC firm’s capital under management.
VC age	The natural logarithm of one plus the difference between the financing year and a VC firm’s founding year.
Lead VC	A dummy variable that equals one if the VC leads the VC syndicate, and zero otherwise.
VC fund characteristics	

Fund performance	The ratio between the number of exits through an IPO or M&A and the number of portfolio companies that the fund invests in since its vintage year.
Fund size	The natural logarithm of the fund's size.
Company characteristics	
Success	A dummy variable that equals one if a portfolio company exits through an IPO or an M&A, and zero otherwise.
Company age	The natural logarithm of one plus the difference between the financing year and a company's founding year.
Early stage	A dummy variable that equals one if the company is in its early stage when it receives the first financing round, and zero otherwise.
Expansion stage	A dummy variable that equals one if the company is at an expansion stage when it receives the first financing round, and zero otherwise.
Later stage	A dummy variable that equals one if the company is at a later stage when it receives the first financing round, and zero otherwise.
Syndication size	The natural logarithm of the number of VC firms co-investing in a portfolio company.
Total round size	The natural logarithm of the number of investment rounds a portfolio company receives.
Round syndication size	The natural logarithm of the number of VC firms co-investing in a round.
First round survival	A dummy variable that equals one if the company survives after the first round, i.e., either exits through an IPO or an M&A or receives the second financing round, and zero otherwise.
Second round survival	A dummy variable that equals one if the company survives after the second round, i.e., it either exits through an IPO or an M&A or receives the third financing round, and zero otherwise.
Third round survival	A dummy variable that equals one if the company survives after the third round, i.e., either exits through an IPO or an M&A or receives the fourth financing round, and zero otherwise.
High deal flow	A dummy variable that equals one if the VC firm's deal flow is larger than the median value of all VC firms' deal flow in the same year.
Deal characteristics	
Syndication	A dummy variable that equals one if two VC firms co-invest in any company, and zero otherwise.
Lead VC	A dummy variable that equals one if the VC firm leads the VC syndicate, and zero otherwise.
Round	The financing round number. A higher round number indicates a later round.

Table A.2: Summary statistics of pairwise connection measures

This table presents the mean of *Social ties*, *Professional ties*, *Educational ties*, and *Connected* from 1999 to 2019. *Social ties*, *Professional ties*, and *Educational ties* are quantified as the number of social ties, professional ties, and educational ties between two VC firms scaled by their average number of executives, respectively. *Connected* is a dummy variable that equals one if two VC firms are socially connected, and zero otherwise.

Year	N	Social ties	Professional ties	Educational ties	Connected
1999	14,878	0.015	0.008	0.008	0.052
2000	18,336	0.015	0.008	0.007	0.056
2001	19,701	0.015	0.008	0.007	0.058
2002	19,503	0.016	0.009	0.008	0.07
2003	21,115	0.018	0.01	0.008	0.075
2004	22,155	0.017	0.009	0.008	0.077
2005	25,651	0.017	0.009	0.008	0.077
2006	26,565	0.019	0.01	0.009	0.089
2007	27,261	0.019	0.011	0.009	0.095
2008	22,791	0.021	0.012	0.01	0.112
2009	25,425	0.021	0.011	0.01	0.109
2010	26,565	0.021	0.012	0.009	0.109
2011	24,531	0.022	0.013	0.009	0.112
2012	24,310	0.025	0.015	0.01	0.132
2013	24,090	0.024	0.015	0.009	0.13
2014	24,753	0.023	0.014	0.009	0.127
2015	19,900	0.024	0.016	0.009	0.135
2016	18,528	0.027	0.018	0.01	0.157
2017	17,766	0.025	0.017	0.008	0.145
2018	17,955	0.026	0.018	0.008	0.159
2019	16,471	0.025	0.018	0.008	0.153

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Figure 1: Social network of venture capital around the world in 2019

This figure depicts the social network of VCs around the world in 2019. The node size is increasing in the VC firm's *Degree centrality*, which is the number of nodes in the network a VC has connection to. Green circles indicate VCs in the U.S., and other colours represent VCs in the rest of the world. Each VC label refers to the node located in the centre of the label. Due to the excessive density when all nodes are shown, we only show nodes where the *Degree centrality* of international VCs are at least 34 and the *Degree centrality* of the U.S. VCs are at least 120.

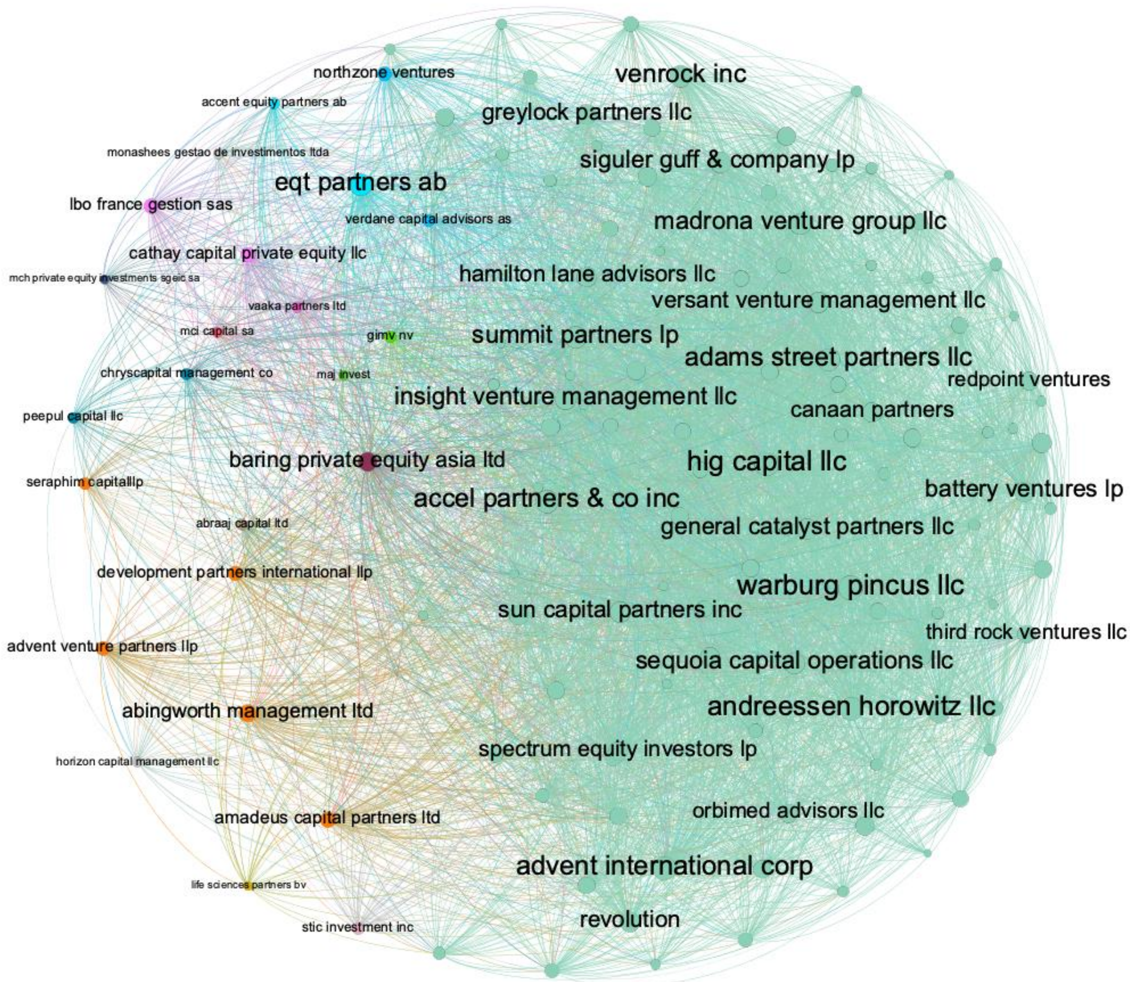

Figure 2: Time trend of pairwise connection measures from 1999 to 2019

This figure displays the time trend of the average of *Social ties*, *Professional ties*, *Educational ties* and *Connected* from 1999 to 2019. *Social ties*, *Professional ties,* and *Educational ties* are measured as the number of social ties, professional ties, and educational ties between two VC firms scaled by their average number of executives, respectively. The left-side y-axis denotes the ratio of binary connections, while the right-side y-axis denotes the measurement of scaled ties.

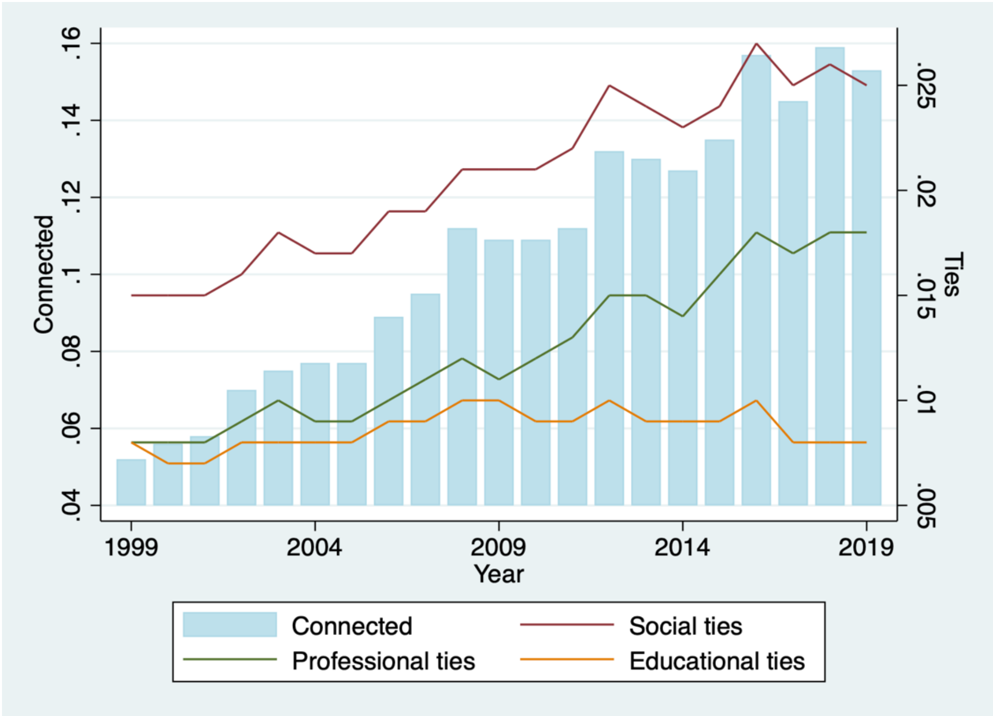

Figure 3: Bootstrapped coefficients

We randomly select the value of *Social connection* from the pool of all possible values in our sample and re-estimate Equation 1 to obtain the coefficient on *Social connection*. We repeat this process 1,000 times to obtain 1,000 bootstrapped coefficients. The graph on the left is the distribution of bootstrapped coefficients of *Social ties* whereas the one on the right is the distribution of bootstrapped coefficient of *Connected*.

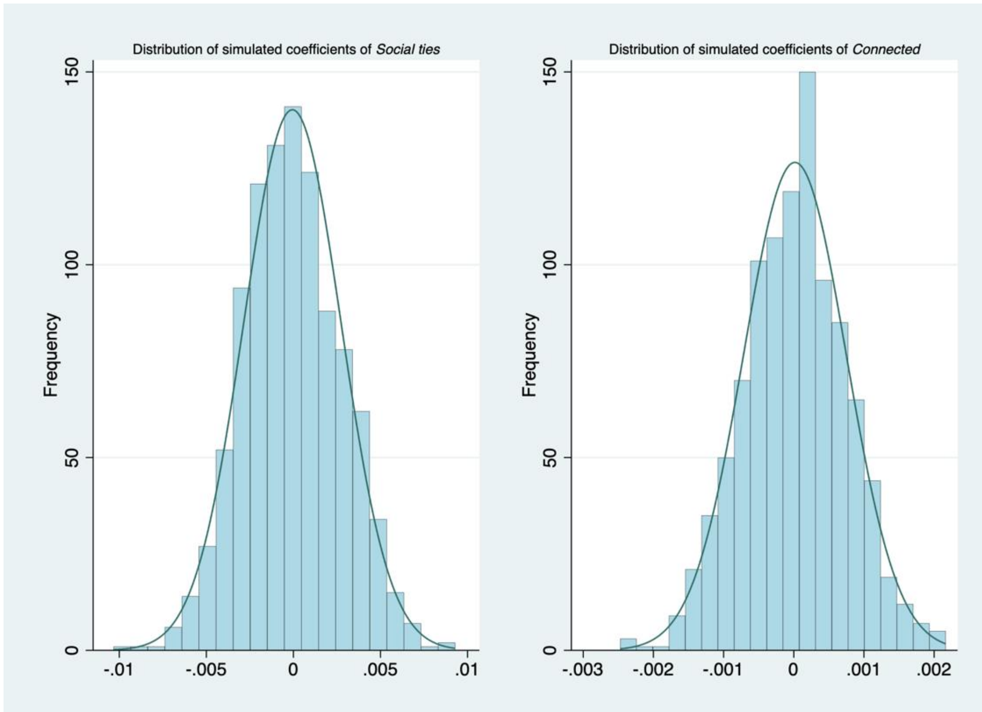

Table 1: Social connection and VC syndication

This table presents the results for regressions of VC syndication on social connection measures. The dependent variable is *Syndication*, measured as a dummy variable equal to one if two VC firms co-invest in any company, and zero otherwise. *Social ties* is the number of social ties between two VC firms, scaled by their average number of executives. *Social ties (unscaled)* is the natural logarithm of one plus the number of social ties between two VC firms. *Connected* is a dummy variable that equals one if two VC firms are socially connected, and zero otherwise. *VC syndication history* is the natural logarithm of one plus the cumulative number of syndicated investments a VC participates in from 1990 to a given year. *Same nation* is a dummy variable that equals one if two VC firms share the same country location, and zero otherwise. *Same industry preference* is a dummy variable that equals one if two VC firms have the same industry preference, and zero otherwise. *Same size* is a dummy variable that equals one if two VC firms are in the same tercile based on their capital under management, and zero otherwise. In model (1), we regress *Syndication* against the lagged value of *Social ties* controlling for *VC syndication history* of both VCs in the pair. Model (2) further extends the set of control variables by including *Same nation*, *Same industry preference*, and *Same size*. The two following models replicate model (2) using *Social ties (unscaled)* (model (3)), and *Connected* (model (4)) as independent variables. Model (5) adds pair fixed effects to model (1). All models include year fixed effects. Standard errors in parentheses are clustered at the VC pair level. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Social ties	0.289***	0.273***			0.030**
	(0.016)	(0.016)			(0.015)
Social ties (unscaled)			0.065***		
			(0.003)		
Connected				0.060***	
				(0.003)	
VC_i syndication history	0.008***	0.008***	0.007***	0.007***	0.010***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
VC_j syndication history	0.004***	0.003***	0.003***	0.003***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Same nation		0.015***	0.014***	0.015***	
		(0.001)	(0.001)	(0.001)	
Same industry preference		0.009***	0.010***	0.009***	
		(0.002)	(0.002)	(0.002)	
Same size		0.010***	0.009***	0.011***	
		(0.001)	(0.001)	(0.001)	
Constant	-0.056***	-0.059***	-0.053***	-0.059***	-0.039***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Year FE	Yes	Yes	Yes	Yes	Yes
VC Pair FE	No	No	No	No	Yes
N	458,250	458,250	458,250	458,250	458,250
Adjusted R-squared	0.0443	0.0476	0.0489	0.0403	0.211

Table 2: VC experience gap, social connection, and VC syndication

This table presents the results for regressions of VC syndication on social connection and VC pair experience gap. In all models, the dependent variable is *Syndication*, measured as a dummy variable equal to one if two VC firms co-invest in any company, and zero otherwise. *Social ties* is the number of social ties between two VC firms, scaled by their average number of executives. VC pair experience gap are proxied by *Investment gap, Success gap,* and *IPO gap*. *Investment gap* is the natural logarithm of one plus the absolute difference of two VC firms' number of investments from 1990 to a given year. *Success gap* is the natural logarithm of one plus the absolute difference of two VC firms' number of successful exits from 1990 to a given year. *IPO gap* is the natural logarithm of one plus the absolute difference of two VC firms' number of IPO exits from 1990 to a given year. *VC syndication history* is the natural logarithm of one plus the cumulative number of syndicated investments a VC participates in from 1990 to a given year. *Same nation* is a dummy variable that equals one if two VC firms share the same country location, and zero otherwise. *Same industry preference* is a dummy variable that equals one if two VC firms have the same industry preference, and zero otherwise. *Same size* is a dummy variable that equals one if two VC firms are in the same tercile based on their capital under management, and zero otherwise. All models include year fixed effects. Standard errors in parentheses are clustered at the VC pair level. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)
Social ties	-0.069	0.019	0.081***
	(0.042)	(0.028)	(0.023)
Investment gap	0.000		
	(0.000)		
Social ties × Investment gap	0.070***		
	(0.009)		
Success gap		0.000	
		(0.000)	
Social ties × Success gap		0.078***	
		(0.009)	
IPO gap			0.001
			(0.000)
Social ties × IPO gap			0.087***
			(0.010)
VC_i syndication history	0.007***	0.007***	0.007***
	(0.000)	(0.000)	(0.000)
VC_j syndication history	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)
Same nation	0.014***	0.014***	0.015***
	(0.001)	(0.001)	(0.001)
Same industry preference	0.009***	0.009***	0.009***
	(0.002)	(0.002)	(0.002)
Same size	0.010***	0.010***	0.010***
	(0.001)	(0.001)	(0.001)
Constant	-0.056***	-0.055***	-0.054***
	(0.002)	(0.002)	(0.002)
Year FE	Yes	Yes	Yes
N	458,250	458,250	458,250
Adjusted R-squared	0.050	0.051	0.051

Table 3: Social network centrality and the role of a VC firm in syndicate formation

This table presents the results for regressions of *Lead VC* on network centrality. In all models, the dependent variable is *Lead VC*, measured as a dummy variable that equals one if a VC firm leads the VC syndicate, and zero otherwise. *Degree* is VC firm's degree centrality. *Eigenvector* is VC firm's eigenvector centrality. *Betweenness* is VC firm's betweenness centrality. *Closeness* is VC firm's closeness centrality. *VC capital* is the natural logarithm of the VC firm's capital under management. *VC age* is the natural logarithm of one plus the difference between the financing year and a VC firm's founding year. All models include firm nation, round, company, and year fixed effects. Robust standard errors are stated in parentheses. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Degree	0.104***			
	(0.032)			
Eigenvector		0.104***		
		(0.030)		
Betweenness			0.043	
			(0.031)	
Closeness				0.189***
				(0.054)
VC capital	0.038***	0.037***	0.048***	0.042***
	(0.008)	(0.008)	(0.008)	(0.008)
VC age	0.008	0.008	0.011	0.010
	(0.010)	(0.010)	(0.010)	(0.010)
Constant	-0.142**	-0.144***	-0.183***	-0.285***
	(0.055)	(0.054)	(0.056)	(0.058)
VC nation FE	Yes	Yes	Yes	Yes
Round FE	Yes	Yes	Yes	Yes
Company FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	16,577	16,577	16,577	16,577
Adjusted R-squared	0.240	0.240	0.238	0.240

Table 4: Social network centrality and portfolio company survival

Panel A of this table presents the results for regressions of 5,027 portfolio companies' first-round survival on their lead VCs' network centrality. The dependent variable is *First round survival*, measured as a dummy variable that equals one if the company survives after the first round, i.e., either exits through an IPO or M&A, or receives the second financing round, and zero otherwise. Panel B presents the results for regressions of 2,605 portfolio companies' second-round survival on their lead VCs' network centrality. The dependent variable is *Second round survival*, measured as a dummy variable that equals one if the company survives after the second round, i.e., either exits through an IPO or M&A, or receives the third financing round, and zero otherwise. Panel C presents the results for regressions of 1,634 portfolio companies' third-round survival on their lead VCs' network centrality. The dependent variable is *Third round survival*, measured as a dummy variable that equals one if the company survives after the third round, i.e., either exits through an IPO or M&A, or receives the fourth financing round, and zero otherwise. *Degree* is VC firm's degree centrality. *Eigenvector* is VC firm's eigenvector centrality. *Betweenness* is VC firm's betweenness centrality. *Closeness* is VC firm's closeness centrality. *VC capital* is the natural logarithm of the VC firm's capital under management. *VC age* is the natural logarithm of one plus the difference between the financing year and a VC firm's founding year. *Round syndication size* is the natural logarithm of the number of VCs co-investing in a round. *Company age* is the natural logarithm of one plus the difference between the financing year and a company's founding year. *Early stage* is a dummy variable that equals one if the company is in its early stage when it receives the first financing round, and zero otherwise. *Expansion stage* is a dummy variable that equals one if the company is at an expansion stage when it receives the first financing round, and zero otherwise. *Later stage* is a dummy variable that equals one if the company is at a later stage when it receives the first financing round, and zero otherwise. All models include industry and year fixed effects. Standard errors in parentheses are clustered at the year level. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: VCs' network centrality and Portfolio companies' first-round survival

	(1)	(2)	(3)	(4)
Degree	0.150***			
	(0.024)			
Eigenvector		0.144***		
		(0.021)		
Betweenness			0.080**	
			(0.029)	
Closeness				0.268***
				(0.036)
VC capital	0.014**	0.014*	0.029***	0.013**
	(0.007)	(0.007)	(0.006)	(0.006)
VC age	0.002	0.002	0.003	0.002
	(0.009)	(0.009)	(0.009)	(0.009)
Round syndication size	0.025	0.024	0.026	0.020
	(0.016)	(0.016)	(0.016)	(0.015)
Company age	-0.036**	-0.036**	-0.040**	-0.033**
	(0.014)	(0.014)	(0.014)	(0.014)
Early stage	-0.028	-0.028	-0.025	-0.024
	(0.031)	(0.031)	(0.031)	(0.031)
Expansion stage	-0.076**	-0.076**	-0.076**	-0.064*
	(0.033)	(0.033)	(0.033)	(0.033)
Later stage	-0.121**	-0.121**	-0.122**	-0.119**
	(0.048)	(0.048)	(0.047)	(0.048)
Constant	0.544***	0.539***	0.482***	0.400***

	(0.066)	(0.065)	(0.063)	(0.054)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	5,027	5,027	5,027	5,027
Adjusted R-squared	0.164	0.165	0.160	0.171

Panel B: VCs' network centrality and Portfolio companies' second-round survival

	(1)	(2)	(3)	(4)
Degree	0.092*			
	(0.047)			
Eigenvector		0.077*		
		(0.042)		
Betweenness			0.077	
			(0.045)	
Closeness				0.106*
				(0.047)
Control	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	2,605	2,605	2,605	2,605
Adjusted R-squared	0.129	0.128	0.128	0.128

Panel C: VCs' network centrality and Portfolio companies' third-round survival

	(1)	(2)	(3)	(4)
Degree	0.044			
	(0.040)			
Eigenvector		0.054		
		(0.038)		
Betweenness			-0.021	
			(0.050)	
Closeness				0.033
				(0.059)
Control	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1,634	1,634	1,634	1,634
Adjusted R-squared	0.116	0.116	0.115	0.115

Table 5: Social network centrality and portfolio company success

This table presents the results for regressions of portfolio company success on network centrality. In all models, the dependent variable is *Success*, measured as a dummy variable that equals one if a portfolio company exits through an IPO or an M&A, and zero otherwise. *Degree* is VC firm's degree centrality. *Eigenvector* is VC firm's eigenvector centrality. *Betweenness* is VC firm's betweenness centrality. *Closeness* is VC firm's closeness centrality. *VC capital* is the natural logarithm of the VC firm's capital under management. *VC age* is the natural logarithm of one plus the difference between the financing year and a VC firm's founding year. *Syndication size* is the natural logarithm of the number of VCs co-investing in a portfolio company. *Total round size* is the natural logarithm of the number of investment rounds a portfolio company receives. *Company age* is the natural logarithm of one plus the difference between the financing year and a company's founding year. *Early stage* is a dummy variable that equals one if the company is in its early stage when it receives the first financing round, and zero otherwise. *Expansion stage* is a dummy variable that equals one if the company is at an expansion stage when it receives the first financing round, and zero otherwise. *Later stage* is a dummy variable that equals one if the company is at a later stage when it receives the first financing round, and zero otherwise. All models include industry and year fixed effects. Standard errors in parentheses are clustered at the year level. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Degree	0.070**			
	(0.027)			
Eigenvector		0.075**		
		(0.027)		
Betweenness			0.020	
			(0.019)	
Closeness				0.114***
				(0.033)
VC capital	0.029***	0.028***	0.038***	0.030***
	(0.008)	(0.008)	(0.007)	(0.007)
VC age	-0.016	-0.016	-0.015	-0.015
	(0.009)	(0.009)	(0.009)	(0.009)
Syndication size	0.056***	0.056***	0.056***	0.054***
	(0.014)	(0.014)	(0.014)	(0.014)
Total round size	-0.011	-0.012	-0.011	-0.013
	(0.023)	(0.023)	(0.023)	(0.023)
Company age	0.018	0.018	0.016	0.019
	(0.014)	(0.014)	(0.013)	(0.014)
Early stage	-0.143***	-0.144***	-0.142***	-0.141***
	(0.045)	(0.045)	(0.045)	(0.045)
Expansion stage	-0.148***	-0.148***	-0.147***	-0.142**
	(0.052)	(0.052)	(0.051)	(0.052)
Later stage	-0.118**	-0.118**	-0.118**	-0.117**
	(0.048)	(0.048)	(0.048)	(0.049)
Constant	0.203**	0.207**	0.161**	0.138*
	(0.074)	(0.075)	(0.073)	(0.069)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	5,027	5,027	5,027	5,027
Adjusted R-squared	0.134	0.135	0.133	0.136

Table 6: Social network centrality and VC fund performance

This table presents the results for regressions of 926 VC funds' performance on network centrality. *Fund performance* is the ratio between the number of exits through an IPO or M&A and the number of portfolio companies that the fund invests in since its vintage year. *Degree* is VC firm's degree centrality. *Eigenvector* is VC firm's eigenvector centrality. *Betweenness* is VC firm's betweenness centrality. *Closeness* is VC firm's closeness centrality. *Fund size* is the natural logarithm of the fund's size. All models include year, fund sequence type and fund nation fixed effects. Standard errors in parentheses are clustered at the year level. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Funds with vintage year between 2000 and 2020

	(1)	(2)	(3)	(4)
Degree	0.092***			
	(0.028)			
Eigenvector		0.079***		
		(0.027)		
Betweenness			0.116***	
			(0.040)	
Closeness				0.052
				(0.037)
Fund size	0.007	0.007	0.007	0.009
	(0.008)	(0.008)	(0.008)	(0.007)
Constant	0.305***	0.304***	0.317***	0.284***
	(0.030)	(0.030)	(0.032)	(0.034)
Year FE	Yes	Yes	Yes	Yes
Fund sequence type FE	Yes	Yes	Yes	Yes
Fund nation FE	Yes	Yes	Yes	Yes
N	926	926	926	926
Adjusted R-squared	0.321	0.320	0.322	0.316

Panel B: Funds with vintage year between 2000 and 2010

	(1)	(2)	(3)	(4)
Degree	0.117***			
	(0.034)			
Eigenvector		0.103***		
		(0.031)		
Betweenness			0.156**	
			(0.063)	
Closeness				0.041
				(0.036)
Fund size	-0.003	-0.003	-0.003	-0.001
	(0.009)	(0.009)	(0.009)	(0.009)
Constant	0.455***	0.455***	0.467***	0.451***
	(0.034)	(0.034)	(0.035)	(0.035)
Year FE	Yes	Yes	Yes	Yes
Fund sequence type FE	Yes	Yes	Yes	Yes
Fund nation FE	Yes	Yes	Yes	Yes
N	606	606	606	606
Adjusted R-squared	0.167	0.166	0.170	0.157

Table 7: Social network centrality, access to deal flow, and portfolio company success

This table shows the impact of network centrality on portfolio company success conditional on VC firm's access to deal flow. In all regression models, the dependent variable is *Success*, measured as a dummy variable that equals one if a portfolio company exits through an IPO or an M&A, and zero otherwise. *High deal flow* is a dummy variable that equals one if the VC firm's deal flow is larger than the median value, and zero otherwise. Deal flow is measured by the number of syndicated investments that the VC firm joins but does not lead. *Degree* is VC firm's degree centrality. *Eigenvector* is VC firm's eigenvector centrality. *Betweenness* is VC firm's betweenness centrality. *Closeness* is VC firm's closeness centrality. *Syndication size* is the natural logarithm of the number of VCs co-investing in a portfolio company. *Total round size* is the natural logarithm of the number of investment rounds a portfolio company receives. *Company age* is the natural logarithm of one plus the difference between the financing year and a company's founding year. *Early stage* is a dummy variable that equals one if the company is in its early stage when it receives the first financing round, and zero otherwise. *Expansion stage* is a dummy variable that equals one if the company is at an expansion stage when it receives the first financing round, and zero otherwise. *Later stage* is a dummy variable that equals one if the company is at a later stage when it receives the first financing round, and zero otherwise. All models include industry and year fixed effects. Standard errors in parentheses are clustered at the year level. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
High deal flow	0.064**	0.065**	0.023	0.197***
	(0.031)	(0.031)	(0.023)	(0.052)
Degree	0.185***			
	(0.053)			
Degree × High deal flow	-0.195***			
	(0.064)			
Eigenvector		0.165***		
		(0.045)		
Eigenvector × High deal flow		-0.170***		
		(0.054)		
Betweenness			0.141	
			(0.087)	
Betweenness × High deal flow			-0.165	
			(0.101)	
Closeness				0.178***
				(0.052)
Closeness × High deal flow				-0.259***
				(0.063)
VC capital	0.023**	0.023**	0.031***	0.031***
	(0.009)	(0.009)	(0.008)	(0.009)
VC age	-0.017	-0.017	-0.016	-0.016
	(0.010)	(0.010)	(0.010)	(0.010)
Syndication size	0.061***	0.060***	0.062***	0.059***
	(0.015)	(0.015)	(0.015)	(0.015)
Total round size	-0.015	-0.015	-0.013	-0.015
	(0.024)	(0.025)	(0.024)	(0.025)
Company age	0.017	0.017	0.015	0.017
	(0.014)	(0.014)	(0.014)	(0.014)
Early stage	-0.149***	-0.150***	-0.147***	-0.145***
	(0.048)	(0.048)	(0.046)	(0.047)
Expansion stage	-0.151***	-0.151***	-0.149***	-0.143***
	(0.049)	(0.049)	(0.048)	(0.049)
Later stage	-0.128**	-0.128**	-0.125**	-0.126**
	(0.051)	(0.051)	(0.050)	(0.050)
Constant	0.227***	0.219***	0.202**	0.094

	(0.074)	(0.073)	(0.082)	(0.058)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	4,698	4,698	4,698	4,698
Adjusted R-squared	0.138	0.139	0.136	0.138

Table 8: Social network centrality, value-added services, and portfolio company success

This table presents the results for regressions of *Survival* on network centrality using a subsample of 2,112 second-round deals, the lead VC firms of which do not participate in the first round. In all models, the dependent variable is *Second round survival,* measured as a dummy variable that equals one if the company survives after the second round, i.e., either exits through an IPO or M&A, or receives the third financing round, and zero otherwise. *Degree* is VC firm's degree centrality. *Eigenvector* is VC firm's eigenvector centrality. *Betweenness* is VC firm's betweenness centrality. *Closeness* is VC firm's closeness centrality. *VC capital* is the natural logarithm of the VC firm's capital under management. *VC age* is the natural logarithm of one plus the difference between the financing year and a VC firm's founding year. *Round syndication size* is the natural logarithm of the number of VCs co-investing in a round. *Company age* is the natural logarithm of one plus the difference between the financing year and a company's founding year. *Early stage* is a dummy variable that equals one if the company is in its early stage when it receives the first financing round, and zero otherwise. *Expansion stage* is a dummy variable that equals one if the company is at an expansion stage when it receives the first financing round, and zero otherwise. *Later stage* is a dummy variable that equals one if the company is at a later stage when it receives the first financing round, and zero otherwise. All models include industry and year fixed effects. Standard errors in parentheses are clustered at the year level. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Degree	0.103***			
	(0.031)			
Eigenvector		0.114***		
		(0.026)		
Betweenness			0.012	
			(0.052)	
Closeness				0.127***
				(0.042)
VC capital	0.028**	0.026**	0.041***	0.032***
	(0.010)	(0.009)	(0.012)	(0.009)
VC age	0.010	0.009	0.013	0.012
	(0.015)	(0.015)	(0.015)	(0.015)
Round syndication size	0.018	0.018	0.019	0.016
	(0.021)	(0.021)	(0.021)	(0.021)
Company age	-0.043	-0.041	-0.045	-0.040
	(0.029)	(0.029)	(0.029)	(0.029)
Early stage	-0.180***	-0.181***	-0.175***	-0.174***
	(0.056)	(0.056)	(0.055)	(0.056)
Expansion stage	-0.172***	-0.173***	-0.167***	-0.165***
	(0.048)	(0.048)	(0.047)	(0.047)
Later stage	-0.165**	-0.166**	-0.164**	-0.163**
	(0.059)	(0.059)	(0.059)	(0.060)
Constant	0.560***	0.567***	0.492***	0.463***
	(0.101)	(0.102)	(0.101)	(0.102)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	2,112	2,112	2,112	2,112
Adjusted R-squared	0.159	0.160	0.157	0.159

Table 9: Professional ties, educational ties, and VC syndication

This table presents the results for regressions of VC syndication on professional and educational connection. In all models, the dependent variable is *Syndication*, measured as a dummy variable that equals one if two VC firms co-invest in any company, and zero otherwise. *Professional ties* is the number of professional ties between two VC firms scaled by their average number of executives. *Educational ties* is the number of educational ties between two VC firms scaled by their average number of executives. *VC syndication history* is the natural logarithm of one plus the cumulative number of syndicated investments a VC participates in from 1990 to a given year. *Same nation* is a dummy variable that equals one if two VC firms share the same country location, and zero otherwise. *Same industry* preference is a dummy variable that equals one if two VC firms have the same industry preference, and zero otherwise. *Same size* is a dummy variable that equals one if two VC firms are in the same tercile based on their capital under management, and zero otherwise. All models include year fixed effects. Standard errors in parentheses are clustered at the VC pair level. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)
Professional ties	0.371***		0.316***
	(0.023)		(0.020)
Educational ties		0.101***	0.054***
		(0.015)	(0.013)
VC_i syndication history	0.008***	0.009***	0.009***
	(0.000)	(0.000)	(0.000)
VC_j syndication history	0.003***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)
Same nation	0.016***	0.037***	0.031***
	(0.001)	(0.002)	(0.002)
Same industry preference	0.009***	0.012***	0.011***
	(0.002)	(0.002)	(0.002)
Same size	0.011***	0.014***	0.012***
	(0.001)	(0.001)	(0.001)
Constant	-0.060***	-0.060***	-0.060***
	(0.002)	(0.003)	(0.003)
Year FE	Yes	Yes	Yes
N	458,250	458,250	458,250
Adjusted R-squared	0.050	0.065	0.081

Table 10: The effect of pre-existing social ties on VC syndication

This table presents the results for regressions of VC syndication on pre-existing social connections. In all models, the dependent variable is *Syndication*, measured as a dummy variable that equals one if two VC firms co-invest in any company, and zero otherwise. *Professional (Education) ties 5 (10, 20) years* is professional (educational) ties between two VC firms formed at least 5 (10, 20) years ago, scaled by their average number of executives. *VC syndication history* is the natural logarithm of one plus the cumulative number of syndicated investments a VC firm participates in from 1990 to a given year. *Same nation* is a dummy variable that equals one if two VC firms share the same country location, and zero otherwise. *Same industry* preference is a dummy variable that equals one if two VC firms have the same industry preference, and zero otherwise. *Same size* is a dummy variable that equals one if two VC firms are in the same tercile based on their capital under management, and zero otherwise. All models include year fixed effects. Standard errors in parentheses are clustered at the VC pair level. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Educational ties 5 years	0.176***					
	(0.018)					
Educational ties 10 years		0.180***				
		(0.019)				
Educational ties 20 years			0.186***			
			(0.023)			
Professional ties 5 years				0.338***		
				(0.031)		
Professional ties 5 years & Educational ties 5 years					0.226***	
					(0.017)	
Professional ties 5 years & Educational ties 10 years						0.231***
						(0.018)
VC_i syndication history	0.009***	0.009***	0.009***	0.008***	0.008***	0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
VC_j syndication history	0.004***	0.004***	0.004***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Same nation	0.019***	0.020***	0.020***	0.019***	0.017***	0.017***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Same industry preference	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Same size	0.013***	0.013***	0.013***	0.012***	0.012***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Constant	-0.067***	-0.067***	-0.068***	-0.065***	-0.064***	-0.064***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	458,250	458,250	458,250	458,250	458,250	458,250
Adjusted R-squared	0.029	0.029	0.028	0.036	0.036	0.036

Table 11: Pre-existing investment tie, social connection, and VC syndication

This table presents the results for regressions of VC syndication on social connection measures while controlling for lagged syndication. In all models, the dependent variable is *Syndication*, measured as a dummy variable that equals one if two VC firms co-invest in any company, and zero otherwise. *Lagged syndication* is a dummy variable that equals one if two VC firms co-invest in a portfolio company last year, and zero otherwise. *Social ties* is the number of social ties between two VC firms, scaled by their average number of executives. *Social ties (unscaled)* is the natural logarithm of one plus the number of social ties between two VC firms. *Connected* is a dummy variable that equals one if two VC firms are socially connected, and zero otherwise. *VC syndication history* is the natural logarithm of one plus the cumulative number of syndicated investments a VC participates in from 1990 to a given year. *Same nation* is a dummy variable that equals one if two VC firms share the same country location, and zero otherwise. *Same industry preference* is a dummy variable that equals one if two VC firms have the same industry preference, and zero otherwise. *Same size* is a dummy variable that equals one if two VC firms are in the same tercile based on their capital under management, and zero otherwise. All models include year fixed effects. Standard errors in parentheses are clustered at the pair level. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)
Social ties	0.166***		
	(0.010)		
Social ties (unscaled)		0.040***	
		(0.002)	
Connected			0.037***
			(0.002)
Lagged syndication	0.374***	0.373***	0.379***
	(0.006)	(0.006)	(0.006)
VC_i syndication history	0.005***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)
VC_j syndication history	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)
Same nation	0.010***	0.009***	0.010***
	(0.000)	(0.000)	(0.000)
Same industry preference	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)
Same size	0.007***	0.006***	0.007***
	(0.001)	(0.001)	(0.001)
Constant	-0.036***	-0.032***	-0.035***
	(0.001)	(0.001)	(0.001)
Year FE	Yes	Yes	Yes
N	458,250	458,250	458,250
Adjusted R-squared	0.173	0.174	0.170

Table 12: Social network centrality, investment network centrality, and on portfolio company success

This table presents the results for regressions of portfolio company success on social network centrality while controlling for VC *Investment network eigenvector*. In all models, the dependent variable is *Success*, measured as a dummy variable that equals one if a portfolio company exits through an IPO or an M&A, and zero otherwise. *Degree* is VC firm's degree centrality. *Eigenvector* is VC firm's eigenvector centrality. *Betweenness* is VC firm's betweenness centrality. *Closeness* is VC firm's closeness centrality. *Investment network eigenvector* is VC firm's eigenvector centrality of the investment network. *Syndication size* is the natural logarithm of the number of VC firms co-investing in a portfolio company. *Total round size* is the natural logarithm of the number of investment rounds a portfolio company receives. *Company age* is the natural logarithm of one plus the difference between the financing year and a company's founding year. *Early stage* is a dummy variable that equals one if the company is in its early stage when it receives the first financing round, and zero otherwise. *Expansion stage* is a dummy variable that equals one if the company is at an expansion stage when it receives the first financing round, and zero otherwise. *Later stage* is a dummy variable that equals one if the company is at a later stage when it receives the first financing round, and zero otherwise. All models include industry and year fixed effects. Standard errors in parentheses are clustered at the year level. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Degree	0.076**			
	(0.032)			
Eigenvector		0.082**		
		(0.032)		
Betweenness			0.017	
			(0.020)	
Closeness				0.119***
				(0.037)
Investment network eigenvector	-0.012	-0.017	0.008	-0.008
	(0.026)	(0.027)	(0.024)	(0.023)
VC capital	0.031***	0.030***	0.039***	0.032***
	(0.008)	(0.008)	(0.008)	(0.008)
VC age	-0.016	-0.016	-0.018*	-0.017
	(0.010)	(0.010)	(0.010)	(0.010)
Syndication size	0.054***	0.054***	0.053***	0.052***
	(0.014)	(0.014)	(0.014)	(0.014)
Total round size	-0.009	-0.009	-0.008	-0.010
	(0.023)	(0.023)	(0.023)	(0.023)
Company age	0.019	0.020	0.018	0.021
	(0.013)	(0.013)	(0.013)	(0.013)
Early stage	-0.138***	-0.138***	-0.138***	-0.136***
	(0.044)	(0.045)	(0.044)	(0.045)
Expansion stage	-0.149***	-0.149***	-0.150***	-0.143***
	(0.049)	(0.049)	(0.049)	(0.049)
Later stage	-0.113**	-0.113**	-0.114**	-0.112**
	(0.050)	(0.050)	(0.049)	(0.050)
Constant	0.189**	0.190**	0.158**	0.122*
	(0.074)	(0.074)	(0.073)	(0.069)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	4,926	4,926	4,926	4,926
Adjusted R-squared	0.135	0.135	0.134	0.136

Table 13: Social connection and first-time VC syndication

This table presents the results for regressions of first-time VC syndication on various measures of pairwise social connections. The dependent variable is *Syndication*, measured as a dummy variable equal to one if two VC firms co-invest in any company, and zero otherwise. *Social ties* is the number of social ties between two VC firms, scaled by their average number of executives. *Social ties (unscaled)* is the natural logarithm of one plus the number of social ties between two VC firms. *Connected* is a dummy variable that equals one if two VC firms are socially connected, and zero otherwise. *VC syndication history* is the natural logarithm of one plus the cumulative number of syndicated investments a VC participates in from 1990 to a given year. *Same nation* is a dummy variable that equals one if two VC firms share the same country location, and zero otherwise. *Same industry preference* is a dummy variable that equals one if two VC firms have the same industry preference, and zero otherwise. *Same size* is a dummy variable that equals one if two VC firms are in the same tercile based on their capital under management, and zero otherwise. In model (1), we regress *Syndication* against the lagged value of *Social ties* while controlling for *VC syndication history* of both VCs in the pair. Model (2) further extends control variables by including *Same nation*, *Same industry preference*, and *Same size*. The two following models replicate model (2) using *Social ties (unscaled)* (model (3)), and *Connected* (model (4)) as an independent variable. In model (5), we further include pair fixed effects to model (1). All models include year fixed effects. Model (5) includes both year and pair fixed effects. Standard errors in parentheses are clustered at the VC pair level. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Social ties	0.047***	0.041***			0.027***
	(0.004)	(0.004)			(0.007)
Social ties (unscaled)			0.011***		
			(0.001)		
Connected				0.011***	
				(0.001)	
VC_i syndication history	0.002***	0.001***	0.001***	0.001***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
VC_j syndication history	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Same nation		0.006***	0.006***	0.006***	
		(0.000)	(0.000)	(0.000)	
Same industry preference		0.002***	0.002***	0.002***	
		(0.001)	(0.001)	(0.001)	
Same size		0.001***	0.001***	0.001***	
		(0.000)	(0.000)	(0.000)	
Constant	-0.008***	-0.009***	-0.008***	-0.008***	-0.020***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year FE	Yes	Yes	Yes	Yes	Yes
VC Pair FE	No	No	No	No	Yes
N	411,506	411,506	411,506	411,506	411,506
Adjusted R-squared	0.005	0.006	0.006	0.006	0.264

Table 14: Social connection and cross-border VC syndication

This table presents the results for regressions of cross-border VC syndication on various measures of pairwise social connections. Our sample includes all possible VC pairs in which two VC firms are located in different countries. The dependent variable is *Syndication*, measured as a dummy variable equal to one if two VC firms co-invest in any company, and zero otherwise. *Social ties* is the number of social ties between two VC firms, scaled by their average number of executives. *Social ties (unscaled)* is the natural logarithm of one plus the number of social ties between two VC firms. *Connected* is a dummy variable that equals one if two VC firms are socially connected, and zero otherwise. *VC syndication history* is the natural logarithm of one plus the cumulative number of syndicated investments a VC participates in from 1990 to a given year. *Same industry preference* is a dummy variable that equals one if two VC firms have the same industry preference, and zero otherwise. *Same size* is a dummy variable that equals one if two VC firms are in the same tercile based on their capital under management, and zero otherwise. In model (1), we regress *Syndication* against the lagged value of *Social ties* controlling for *VC syndication history* for both VC firms in the pair. Model (2) further extends control variables by including *Same industry preference* and *Same size*. The two following models replicate model (2) using *Social ties (unscaled)* (model (3)), and *Connected* (model (4)) as an independent variable. All models include year fixed effects. Standard errors in parentheses are clustered at the VC pair level. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Social ties	0.067***	0.067***		
	(0.011)	(0.011)		
Social ties (unscaled)			0.023***	
			(0.003)	
Connected				0.022***
				(0.003)
VC_i syndication history	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
VC_j syndication history	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Same industry preference		0.002	0.002	0.002
		(0.002)	(0.002)	(0.002)
Same size		0.002***	0.002***	0.002***
		(0.001)	(0.001)	(0.001)
Constant	-0.016***	-0.017***	-0.017***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.001)
Year FE	Yes	Yes	Yes	Yes
N	217,397	217,397	217,397	217,397
Adjusted R-squared	0.007	0.007	0.009	0.009

Table 15: Difference-in-differences analysis

This table presents the results for the difference-in-differences analysis. The sample restricts to all possible VC pairs where there is an executive death during the sample period. The dependent variable is *Syndication*, measured as a dummy variable equal to one if two VC firms co-invest in any company, and zero otherwise. *Death as connection* is a dummy variable indicating the treatment group, i.e., VC pairs that were connected by the deceased executive. *After death* is a dummy variable that equals one for any period after the death of an executive. *VC syndication history* is the natural logarithm of one plus the cumulative number of syndicated investments a VC firm participates in from 1990 to a given year. *Same nation* is a dummy variable that equals one if two VC firms share the same country location, and zero otherwise. *Same industry preference* is a dummy variable that equals one if two VC firms have the same industry preference, and zero otherwise. *Same size* is a dummy variable that equals one if two VC firms are in the same tercile based on their capital under management, and zero otherwise. In model (1), we regress *Syndication* against *Death as connection, After death* and the interaction term *Death as connection* × *After death*. Model (2) further controls for *VC syndication history*, *Same nation*, *Same industry preference* and *Same size*. Both models include year fixed effects. Standard errors in parentheses are clustered at the VC pair level. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)
Death as connection	0.084**	0.055
	(0.039)	(0.036)
After death	0.001	-0.007**
	(0.004)	(0.003)
Death as connection × After death	-0.093**	-0.087**
	(0.042)	(0.040)
VC_i syndication history		0.014***
		(0.001)
VC_j syndication history		0.007***
		(0.001)
Same nation		0.035***
		(0.003)
Same industry preference		0.020**
		(0.010)
Same size		0.024***
		(0.008)
Constant	0.042***	-0.132***
	(0.002)	(0.011)
Year FE	Yes	Yes
N	158,610	158,610
Adjusted R-squared	0.012	0.049