Co-investment networks of business angels and the performance of their start-up investments

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Abstract: The venture capital literature has established the positive impact of co-investment networks on the performance of start-up investments. In early stages, however, often angel financing is the primary source of external equity. Using a novel in-depth dataset of US high technology start-ups we investigate the effects of business angel networks. Start-ups of better connected angel investors are more likely to receive subsequent funding by venture capitalists and business angels more often exit successfully. Thereby, angel investors seem to rely on their direct contacts, whereas their network position and possibility to act as information brokers plays a far smaller role.

Keywords: business angel; venture capital; start-up; network; social capital; entrepreneurship.

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1 Introduction

The term business angel characterises a high net-worth individual, often with an entrepreneurial background, who invests in small, private firms on his own account. Angel financing is often the primary source of external equity for high-risk, early stage start-ups (Wetzel, 1987; Freear and Wetze1, 1990). Despite this fact, there is little research on angel financing. Most investigations of angels' decision-making and investment performance are descriptive in nature or based on surveys of limited size. Despite the shortcomings of existing research, one hypothesis to come out of these studies is the pivotal role social networks play in sourcing investment opportunities and adding value to these start-ups (Freear et al., 2002; Mason and Harrison, 2002). However, to date this insight has never been tested empirically.

We build on the existing literature by investigating the exact nature of the business angel's network and its impact on the success of angel financed start-ups using an in-depth dataset. Thereby, we also extend the literature on the role of networks in venture capital financing, typically very often the next financing step in the life-cycle of young, entrepreneurial firms (Heukamp et al., 2006). The importance of networks in venture capital financing is largely undisputed. Networks comprise social capital as they provide access to resources and investment opportunities and facilitate leveraging them in the future. As other researchers have pointed out, the importance of social capital can be summed-up by an often repeated quote: "it's not just what you know, but whom you know" (Zheng, 2004).

In the field of entrepreneurial finance, networks commonly result from former co-investments (syndication). Better networked venture capital firms are found to be better able to overcome informational and geographical boundaries and ultimately achieve higher returns (Hochberg et al., 2007; Stuart and Sorensen, 2001). Surprisingly, despite the fact that informational asymmetries are more pronounced in angel financing, similar studies of the performance impact of business angel networks do not exist. This study begins to close this gap by employing a novel database of high technology start-ups in the USA to derive co-investment networks. We assess the size of each investor's co-investment network as well as his respective position within the overall network of the venture capital industry. Our dataset comprises 1,746 start-ups who received initial funding from business angels.

Our results show that start-ups that are sponsored by better networked business angels find it easier to attract venture capital investors at later stages. They are also more likely to achieve an exit in the form of a trade sale or initial public offering. The analysis also suggests that business angels' success depends on their ability to source information from direct network links, rather than how centrally they are imbedded in the larger venture capital network.

This study is closely related to the venture capital literature to which most efforts in the field of start-up financing have long been confined to. Networks of venture capital firms are shown to be homophilious, i.e., localised, with respect to geography and industry characteristics (Stuart and Sorenson, 2001). Networks can also provide a means of overcoming such boundaries. This may be one of the reasons why better networked venture capitalists are more successful and achieve higher returns (Hochberg et al., 2007). We expect the same to be true for angel investors.

Building on existing studies and theories we identify the specific mechanisms by which networks impact the investment performance of a business angel. First, they promote the ability of angels to source high-quality investment opportunities by making it easier to select the most promising companies (Bygrave, 1988). This is particularly due to facilitated feedback mechanisms with other investors. Second, larger networks grant better access to human, financial and informational resources that can be leveraged to nurture an investment (Deli and Santhanakrishnan, 2010). Third, former connections help overcome the information asymmetry between early and later stage investors (Shane and Cable, 2002). Start-ups sponsored by well-connected angels are thus expected to have better access to financing. These three spheres of influence of social networks make us believe that start-ups sponsored by business angels with extensive networks are more successful.

The following section will provide a brief review of the economic literature on business angels while focusing on the role of co-investment networks. Testable hypotheses are derived from this review. From here, we present the dataset employed in the subsequent empirical analysis. The final section concludes by interpreting the empirical findings. These are put into perspective with existing studies and future research topics are suggested.

2 Hypotheses

Many economic sociologists claim that no part of social and economic life can be properly analysed without understanding how it is fundamentally embedded in networks of social relations (Granovetter, 1990). In the field of entrepreneurial finance the most relevant connections are co-investment networks derived from former syndication. Syndication is a common feature of venture capital contracts. It means that several investors each contribute a portion of capital and take a stake in the company (Lerner, 1994; Podolny, 2001). Once they have invested in the same company they are considered connected.

Earlier contributions in the field of venture capital networks described the structure of these networks and stressed their importance (Bygrave, 1988; Stuart and Sorensen, 2001). Hochberg et al. (2007) investigate the effect of networks on the performance of venture capital funds and argue that social capital inherent to social networks drives investment success.

While organisational theorists stress the importance of social relationships, economists care more about the disclosure of information (Shane and Cable, 2002). Specifically in the case of business angels one may expect co-investment networks to have a positive impact on the performance of portfolio companies. We identify three major fields in which a business angel's network contributes to his own returns and to the success of his portfolio companies: sourcing investment opportunities, adding value and financing growth.

In general, the likelihood of investing in a new venture declines sharply with the geographic and sectoral distance between investor and target. Stuart and Sorensen (2001) show that networks help overcome these boundaries. Pooling location and sector-specific experiences not only allows for portfolio diversification but also increases the set of investment opportunities. Investors can collect signals of other investors in their network in order to reduce uncertainty about the quality of a venture and ultimately choose the best investments (Sah and Stiglitz, 1986). Particularly in early stage and high technology start-up investments, the typical playground of business angels, there is a great need to share information and make use of this method of 'value certification' (Deli and Santhanakrishnan, 2010). Networks ultimately promote the ability to source high-quality investment opportunities by selecting the most promising companies (Bygrave, 1988).

Business angels are typically actively involved in the management and operations of start-ups (Mason and Harrison, 1996; Lengyel and Gulliford, 1997). They typically help tackle weaknesses in the entrepreneurial team (Kaplan and Strömberg, 2004), provide advice on strategic and operational issues (Bygrave and Timmons, 1992) and establish strategic alliances (Lindsey, 2005). Deli and Santhanakrishnan (2010) show that syndication is particularly probable when large human capital investments are needed, suggesting that investors are sensitive to each other's resource. Anecdotal evidence by Stuart and Sorensen (2001) shows that early stage companies also employ network-based recruiting strategies. Angels' networks are likely to facilitate this since they not only offer access to the experience and resources of a larger number of skilled individuals, but also offer relationships with service providers, headhunters, investment banks and the like. Therefore, networks spur the ability to nurture investments.

Once a start-up is nurtured to success, business angels step aside for more professional deep-pocketed investors such as financial or strategic venture capitalists (Gompers, 1995). Their involvement is usually required to finance future growth of the company. Raising funds through venture capitalists becomes a primary responsibility of the business angel. Using the same arguments as above, networks help sourcing and addressing later stage investors, even in the face of sectoral or regional boundaries (Stuart and Sorensen, 2001). These connections also help overcome the information asymmetry between early and later stage investors (Shane and Cable, 2002). These three spheres of influence exerted by social networks lead us to hypothesise that start-ups of business angels with extensive networks should be more successful.

We distinguish two major aspects of a business angel's co-investment network. The first is the size of his network. We assume that knowing more investors enlarges a business angel's scope of action. The second aspect is the central position of a business angel in the overall network of the venture capital industry. The idea is that business angels who are more central within the network can act as brokers to gain information and to attract venture capital investors in the later stages of the start-up (Robinson, 1987).

Therefore, we derive two hypotheses on the effect of networks on the success of a start-up investment. We consider two variables to measure the success of a business angel sponsored start-up. The first is an interim signal of success. As young, entrepreneurial companies in the process of growing need to attain continual funding, we use the binary indicator of whether a venture capitalist invests in the start-up during a later round of financing. The second variable measures whether the start-up was nurtured to success, which we define as the start-up being sold via a trade sale or exited through an initial public offering. The following two hypotheses summarise the testable claims.

Hypothesis 1 Business angels rely on their direct network of co-investors to source high-quality investments and to nurture them. Portfolio companies of business angels with larger networks are thus more successful in receiving external later stage funding and achieving an exit.

Hypothesis 2 Business angels act as information brokers and brokers for financing. Portfolio companies of business angels that have a more central position in the venture capital industry network are thus more likely to receive external later stage funding and achieve an exit.

3 Dataset

The analysis of networks requires longitudinal data representing multiple individuals, which is rarely to be found. However, CrunchBase, a novel database of high technology start-ups in the USA, provides data to explore the performance effects of networks in this industry. This section presents the CrunchBase database and explains the derivation of the employed variables and network measures.

3.1 The CrunchBase database

On the cover page of its website http://www.CrunchBase.com, CrunchBase is referred to as “the free database of technology companies, people, and investors that anyone can edit”. CrunchBase was developed and is maintained by TechCrunch, the most influential technology blog in the USA. Professionals in the technology community can add information to the database, which then goes through an approval process before being made available online.

Since its launch in 2007, the CrunchBase database has grown enormously. As of September 30, 2011, the reference date for this study, the database includes more than 74,000 technology companies, 7,000 financial companies and 98,000 individuals and investors. At least from 2007, CrunchBase provides almost complete coverage of the US technology start-up market, constituting the reference database for this sub-sector of the venture capital industry. CrunchBase includes information on both new and established companies. Other commercial databases rarely include young start-ups, particularly those that have not been successful. As far as large companies are concerned, we made spot checks using ThomsonONE Private Equity and found no indication of missing or incorrect entries to CrunchBase.

CrunchBase classifies five categories: company, person, financial company, service provider and product. For this analysis, we rely on information gathered on companies and investors (persons). The most critical piece of information provided for each start-up is the funding history. Covering each funding round of the company, it includes the date of funding, amount, investor name and investor type. An investor can be a business angel, a venture capital firm or another corporation. All existing links between investors and start-ups can be reproduced, which makes the calculation of structural and relational network measures possible.

We consider a subset of all funding rounds available in CrunchBase, namely all funding rounds of companies that have received initial investment (‘seed money’) from at least one business angel. A business angel shall be defined as an individual that has made at least one investment into a start-up company. CrunchBase identifies 2,866 business angels who invested in 5,409 funding rounds. The funding rounds span a time period from 1997 to 2011. However, most funding rounds occur after 2007, reflecting the more recent establishment of CrunchBase, and biasing the recordings toward current events.

We filter these 5,409 business angel funding rounds according to two criteria. First, the funding round has to be the company's first funding round, as we are only interested in true seed investments by business angels. Later stage investments are not considered. Second, the initial seed funding for the company has to have taken place no later than September 2009. The time span of two years between September 2009 and September 2011 can be interpreted as the maximum allowed time for the start-up investment to show some sign of success, measured by the successful attaining of later stage financing (see next subsection). In our dataset, the average time between seed investment and this form of later stage financing is 15.2 months for all start-ups that received such funding. Therefore, we neglect seed investments made after September 2009. Since CrunchBase is biased towards recent events, a large number of funding rounds are dropped due to this second criterion, resulting in 1,746 of the 5,409 business angel funding rounds.

3.2 Success measures

This study considers two different dependent variables that measure the success of a start-up: series-A and exit.

In the case of variable series-A we make use of a common feature in venture capital contracts: staging. This refers to the fact that investors provide money in pieces (stages) as the start-up company meets intermediate, pre-defined goals. Gompers (1995) notes that the staging of capital infusions allows investors to gather information and monitor the progress of firms while "maintaining the option to periodically abandon projects". Theoretical studies find that staging is one of the most efficient control mechanism in start-up contracts to mitigate moral hazard (Bergemann and Hege, 1998; Neher, 1999). Staging is particularly common for start-up firms in industries with significant growth opportunities and high research and development intensities (Gompers, 1995). Every high technology start-up in our dataset is stage-financed.

Business angels invest and commonly become actively involved in the early stages, before later stage professional and deep-pocketed investors such as venture capital firms or corporations (corporate venture capitalists) join. Venture capital investment is needed at later stages to finance the future growth of the start-up. Since the investment following the initial seed investment is typically called series-A funding, we refer to the investment by a venture capitalist (venture capital firm or corporation) as series-A.

The value of our series-A variable is set to one if the company into which the business angel invested has received subsequent funding by at least one professional investor, either a venture capital firm or a corporation (corporate venture capital). If the second funding round happens to be a business angel-only round, we check if there is a third funding round. If a professional investor or a strategic investor participates in the third round, the variable is set to one. If the third funding round is also business angel-only, we check whether there is a fourth funding round and set the variable to one if a professional investor or a strategic investor participates in this fourth round. If the portfolio company does not receive funding from another investor in these rounds, the binary indicator remains zero. This encoding mechanism guarantees that a follow-on funding round after the seed investment is not merely a 'bridge financing' by the same or another business angel, but a true series-A investment in the next stage of growth. The successful closing of series-A funding by a start-up is considered a preliminary measure of initial success.

Our second dependent variable is used to capture ultimate success of the start-up. It has been used for this purpose across numerous studies. For instance, Hochberg et al. (2007) employ this definition of an exit. Again, exit is a binary variable, set to one if the company either achieves an initial public offering or a trade sale. The latter refers to a sale to another company, often a strategic competitor of the start-up. Both exit strategies are ways of 'cashing out' the investment.

While series-A can be seen as a measure of interim success, exit is the prevalent measure of ultimate success. In our dataset, 58.8% of all start-ups that are initially sponsored by a business angel attained series-A funding by a later stage investor, 19.1% achieved an exit. The probability of an exit conditioning on closing series-A funding is 32.5% (334/1,027).

Table 1 Dependent binary variables series-A and exit

		Series-A		
		0	*1*	
Exit	0	719	693	1,412
		(41.2%)	*(39.7%)*	*(80.9%)*
	1	0	334	334
		(0%)	*(19.1%)*	*(19.1%)*
		719	1,027	1,746
		(41.2%)	*(58.8%)*	*(100%)*

3.3 Network measures

The goal of this paper is to quantify the effect of the characteristics of a business angel's network on the success probability of portfolio companies. To this end we first have to define the considered network and then measure the respective position within the network. The use of co-investment networks as first suggested by Bygrave (1988) is commonly employed in entrepreneurial finance research, and so is the application of graph theory as a mathematical representation of networks. It was first applied to real-world social networks in the field of sociology. Wellman (1983) presents an introductory review of the early applications discussing the implications of underlying principles in network formation.

In its most simple form, a social network can be represented by an undirectional graph, i.e., a square matrix A that contains only the elements 0 and 1, where $A(i, j) = 1$ forms an edge in the network between the nodes i and j. For the purpose of this paper, a node represents an investor in CrunchBase, i.e., a business angel, a venture capital firm or a corporation. Edges stand for the fact that two individual investors have both invested into the same company.

This procedure leads to the construction of the network of co-investment relationships within the venture capital community: actors in the market are tied to each other by the investment into the same companies. Since networks evolve across time, a network matrix $A^{m|y}$ for each month m of each year y within the time span of all business angel funding rounds needs to be created. Thus, the network matrix $A^{m|y}$ is based only on past co-investments of two investors, where month m in year y is the dividing line between past and present.

Using the symmetric network matrices, one can establish different measures of network centrality. In essence, we follow the suggestions of Hochberg et al. (2007) combined with the respective implications illustrated in Leydesdorff (2007). We consider first degree, valued degree, betweenness and bonacich centrality.

3.3.1 First degree centrality

One of the most direct measures is first degree centrality. It measures the number of relationships of an actor in the network. The more ties, the more opportunities for exchange exist and so the more influential, or central, the actor. Formally, first degree counts the number of unique ties each business angel has to others. It corresponds to the number of unique investors with which a business angel has co-invested. Let $p_{ij} = 1$ if at least one syndication relationship exists between business angel i and investor j, and zero otherwise. Business angel i's first degree then equals $\Sigma_i p_{ij}$.

Since first degree centrality is a function of network size, which in CrunchBase varies over time due to entry of investors, we consider a normalised version of first degree. The number of edges of an investor is divided by the maximum possible first degree n-1 in an n-actor network. By this, we ensure comparability over time.

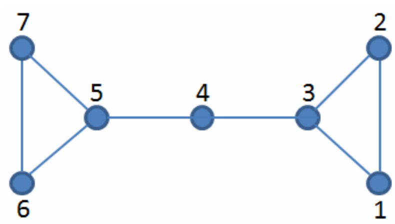
3.3.2 Valued degree centrality

First degree only counts the number of former co-investors and overlooks the information of how often each pair of investors has co-invested. Wasserman and Faust (1997) advocate the use of valued degree centrality which no longer 'undervalues strong links' between individuals. Let q_{ij} be the number of co-investments that a business angel i undertook with an investor j. Business angel i's valued degree is then given by $\Sigma_i q_{ij}$. For any business angel, his valued degree is weakly larger than his first degree. Again, we divide by the maximum possible first degree $n - 1$ in order to normalise this measure.

3.3.3 Betweenness centrality

Degree centrality measures miss many of the interesting aspects of a network. In particular, they do not capture how well-located a node is in the overall network. It might be that a node has relatively few links, but lies in a critical location. Consider for example the network in Figure 1. While nodes 3 and 5 have the highest degree, node 4 is arguably at least as central as nodes 3 and 5. Node 4 is also far more central than nodes 1, 2, 6 and 7. It is central in path-connecting nodes 1, 2 and 3 with nodes 5, 6 and 7, a feature that makes it very important in allowing information transmission.

Figure 1 Illustration of a network (see online version for colours)



Betweenness centrality captures this position across all possible pairs of nodes in the network. Formally, business angel i's betweenness centrality is given by

$$Be_i = \sum_{k \neq j: i \notin \{k,j\}} \frac{P_i(kj) / P(kj)}{(n-1)(n-2)/2}$$

A normalisation by the maximum possible number of shortest paths between two nodes in the network, $(n - 1)(n - 2) / 2$, is undertaken to make the measure comparable at different times. In the context of the above discussed graph the betweenness centrality values of the nodes are 9/15 (node 4), 8/15 (nodes 3, 5) and 0 (nodes 1, 2, 6, 7).

3.3.4 Bonacich centrality

Bonacich centrality is a self-referential prestige measure named after its originator Bonacich (1987). It holds that a node's importance is determined by how important its neighbours are. Presume that the power or prestige of a node is simply a weighted sum of the walks that it has emanating from it. A walk of length 1 is worth a, a walk of length 2 is worth α^2, and so forth, for some parameter $0 < \alpha < 1$. Given the network matrix A, simple graph calculus gives us $A1$ as the number of walks of length 1 that emanate from each node. Here 1 is the $n \times 1$ vector of ones. Generally, A^k1 is the vector where each entry is the total number of walks of length k that emanate from each node. Jackson (2008, p.65) shows that the vector of the prestige of nodes can be written as

$$p^k(A, a) = aA1 + a^2A^21 + a^3A^31 + \cdots = \left(1 + aA + a^2A^2 + \cdots\right) aA1$$

Table 2 Correlation coefficients of the network measures

(n = 1,746)		*D*	*VD*	*Be*	*Bo*
First degree	*D*	1.000			
Valued degree	*VD*	0.989	1.000		
		(0.000)			
Betweenness	*Be*	0.862	0.850	1.000	
		(0.000)	(0.000)		
Bonacich	*Bo*	0.041	0.044	0.083	1.000
		(0.089)	(0.067)	(0.001)	

Note: Significance level for each entry shown in parenthesis.

One way to interpret this measure is to note that one can start by assigning some base value ad_i as prestige to node i, where d_i is the first degree of node i. This is expressed as the vector $aA1$. A given node then gets additional prestige a times the base value of each node that it has a direct link to, plus a^2 times the base value of each node that it has a walk of length 2 to and weighted by the number of walks to the given node, plus a^3 times the base value of each node that it has a walk of length 3 to, and so forth. Bonacich centrality is a generalisation of the prestige measure, because it evaluates walks of length k to other nodes by a factor of b^k times the base value of the end node, allowing b to differ from *a*. *b* captures how the value of being connected to someone decays with distance, while *a* captures the base value on each node. Formally, Bonacich centrality is computed as

$$Bo(A, a, b) = (IbA)^{1} aA1$$

where $a > 0$ and $b > 0$ are scalars and b is sufficiently small such that Bo is well defined. For the subsequent calculations, we set $a = 1$ and $b = 0.8$, following Jackson (2008).

3.4 Further variables

In order to isolate the network effects from others, we follow suggestions made in earlier empirical studies and include a set of control variables (Stuart and Sorensen, 2001; Hochberg et al., 2007). To this end, the regressions include control variables related to the characteristics of investors, the financing rounds and the start-ups themselves.

3.4.1 Experience

Success of a start-up in closing follow-on funding and achieving an exit is naturally not only influenced by the network size and position of a business angel. Experienced business angels can be expected to better add substantive value to the company which then makes raising additional financing easier and an exit more likely. To the extent that the network of a business angel grows with experience, it is merely a proxy for the experience of the business angel.

To avoid the spurious correlation we construct two proxy variables for the investment experience of a business angel as it is reflected in the database. It may still not capture experience that remains unreflected in CrunchBase. The first experience proxy, Ninvestments, gives the number of prior investments undertaken by each respective business angel. The variable Nmonths gives the number of months since his first ever start-up investment.

3.4.2 Funding experiment

Other aspects that influence the probability of raising a series-A are due to market conditions and cannot be attributed to the business angel. If the venture capital business is cyclical, then a company that raises its seed investment in a boom market may find it more difficult to attain series-A funding in the next period when venture capital is scarcer and more start-ups from a previous boom cycle compete for the available capital. We hence control for the funding environment by including in the regression the cumulated amount of all CrunchBase venture capital investments in the year of the business angel funding round. As this variable is highly skewed, we use its natural logarithm.

3.4.3 Industry indicators

The business angel investment rounds span 16 different industries. Within each of these industries the importance of network relationships and the general probabilities of success might differ. Therefore, we include a set of industry dummies in the regression.

Table 3 Distribution of the 1,746 start-ups over all industries

Industry	*Share*	*Industry*	*Share*
Advertising	6.70	Network hosting	4.41
Bio-tech	0.46	Public relations	2.75
Clean-tech	1.26	Search	3.72
Consulting	0.46	Security	0.34
E-commerce	6.99	Semiconductor	0.11
Games	7.90	Software	7.39
Hardware	2.00	Web	39.29
Mobile	5.61	Others	4.47
Not available	1.49		

3.4.4 Year indicators

The funding rounds of business angels that we consider span a time period from 1997 to 2007. In order to account for year specific effects we include an indicator for each year.

Table 4 Summary statistics

	Obs.	*Mean*	*Std. dev.*	*Min*	*Max*
Exit	1,746	0.191	0.393	0	1
Series-A	1,746	0.588	0.492	0	1
Nmonths	1,746	13.40	27.47	0	125
Ninvestments	1,746	2.799	7.766	0	65
Funding environment	1,746	23.88	0.954	11.74	24.33
First degree D*	603	0.068	0.077	0.002	0.337
Valued degree VD*	603	0.087	0.107	0.002	0.482
Betweenness Be*	409	0.075	0.122	0.000	0.934
Bonacich Bo*	336	203.3	798.6	0.058	9013

Note: * Distribution for all non-zero entries

4 Empirical analysis

The empirical analysis tackles the two hypotheses that postulate a positive effect of a business angel's network on the performance of his start-up investments. We consider the successful closing of a series-A funding by an external venture capital investor as sign of interim success and an attained trade sale or IPO as ultimate success. As both variables are binary, we need to estimate a limited dependent variable model. For estimation we apply standard multivariate probit procedures of the form

$$\Pr(Y = 1 \mid X) = \Phi(X'\beta)$$

where Pr denotes probability, and Φ is the cumulative distribution function of the standard normal distribution. All models are estimated using probit maximum likelihood estimation.

Table 5 Regression results for dependent variable series-A

Series-A	*5.1*	*5.2*	*5.3*	*5.4*	*5.5*
First degree D	1.411**				6.183**
	(0.607)				(2.253)
Valued degree VD		0.902*			–3.008
		(0.517)			(1.955)
Betweenness Be			–0.233		–1.325**
			(0.331)		(0.453)
Bonacich Bo				0.000	0.000
				(0.001)	(0.001)
Ninvestments	yes	yes	yes	yes	yes
Nmonths	yes	yes	yes	yes	yes
Industry dummies	yes	yes	yes	yes	yes
Funding environment	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes
Pseudo-R^2	8.1%	8.0%	7.9%	7.9%	8.7%

Notes: Standard deviations in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Table 6 Regression results for dependent variable exit

Exit	*6.1*	*6.2*	*6.3*	*6.4*	*6.5*
First degree D	0.652**				2.591**
	(0.323)				(1.280)
Valued degree VD		0.453			–1.488
		(0.284)			(1.116)
Betweenness Be			0.107		–0.263
			(0.187)		(0.256)
Bonacich Bo				0.000	0.000
				(0.001)	(0.001)
Ninvestments	yes	yes	yes	yes	yes
Nmonths	yes	yes	yes	yes	yes
Industry dummies	yes	yes	yes	yes	yes
Funding environment	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes
Pseudo-R^2	13.7%	13.6%	13.4%	13.4%	13.9%

Notes: Standard deviations in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Tables 5 and 6 present the regression results for either dependent variable. We each perform five regressions where the first two include network measures for the size of a business angel's network and the next two contain measures that capture the centrality of the position within the network. The fifth regressions each contain all four measures at once. Regression tables state estimated marginal effects evaluated at the respective distributional means.

The estimated coefficient for first degree is the only one that is significantly different from zero at the 5% level. All other network measures are insignificant, particularly the two that capture the business angel's position in the network. It is counter-intuitive that the network coefficient in 5.3 is negative even without including further network measures. However, when single controls are included, the estimated coefficient is positive as one would expect.

Once all measures are included in the regression (regressions 5.5 and 6.5), some coefficients become negative while the estimated coefficient of first degree is much higher. While point estimates cannot be trusted in this regression due to the prevalent multicollinearity of the explanatory variables, these results further highlight the importance of first degree. Despite controlling for further network measures, the coefficient of first degree remains positive and statistically significant.

In order to verify the economic relevance of the estimated coefficient of first degree, we hold the included control variables constant at their respective means and measure the effect that changes in the network have on the dependent variable. A one standard deviation increase in the network measure, holding all other variables constant at their respective means, is associated with a 10.89% increase of the probability of receiving series-A funding. At the same time the probability of an exit increases by 5.03%. A 5.03% increase in the exit probability appears particularly profound since overall just about 19% of the angel financed start-ups in the sample achieved an IPO or trade sale.

Valued degree captures the level to which an investor repeatedly co-invests. As the coefficient for valued degree is insignificant, one cannot show a statistically significant effect of more profound contacts. These results suggest that business angels rely on their immediate contacts, not on their network position and ability to act as a broker between others.

Our models explain approximately 8% of the variation of whether a start-up receives external later stage funding, and over 13% of the variation in the ultimate success measure. Our model fit values are largely in line with the ones reported in Hochberg et al. (2007). In the case of the dependent variable exit, our reported model fit values surpass the ones reported there. We assume that the effects of business angels' networks are more profound than is true for later stage venture capital investors.

Since one can only establish a positive effect of first degree, we will examine it more closely. We include either group of control variables separately in a regression with first degree. As Table 7 shows, first degree continues to have a significant positive effect on the success variables, irrespective of the kind of control. In fact, controlling for either other variable even increases the estimated coefficient of first degree. It may first seem counter-intuitive that the estimated coefficient in 7.4 and 7.9 is higher than in the base scenarios 7.1 and 7.6, which can only be explained by the collinearity of experience and network measures.

Table 7 Closer look at the role of first degree D

Series-A	*7.1*	*7.2*	*7.3*	*7.4*	*7.5*
First degree D	1.416**	2.134**	1.569**	1.421**	1.411**
	(0.240)	(0.517)	(0.248)	(0.246)	(0.607)
Ninvestments		yes			yes
Nmonths		yes			yes
Industry dummies			yes		yes
Funding environment			yes		yes
Year dummies				yes	yes
Pseudo-R^2	1.6%	2.0%	3.2%	5.8%	8.1%
Exit	*7.6*	*7.7*	*7.8*	*7.9*	*7.10*
First degree D	0.446***	1.233***	0.420***	0.506***	0.652**
	(0.157)	(0.313)	(0.155)	(0.155)	(0.323)
Ninvestments		yes			yes
Nmonths		yes			yes
Industry dummies			yes		yes
Funding environment			yes		yes
Year dummies				yes	yes
Pseudo-R^2	0.5%	1.0%	4.5%	8.2%	13.7%

Notes: Standard deviations in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

The unique structure of our dataset allows for an interesting robustness check. The regressions thus far neglect possibly important unobserved effects. Business angels differ with respect to their attitude towards risks and decision-making as well as in their general ability to source investments and to connect with others. These investor-specific characteristics may have a positive effect on the performance of their respective portfolio companies. If they are also positively correlated with the observed co-investment network, we will overestimate the effect of the network.

As a robustness check to the earlier findings and to verify the importance of the direct contacts, we apply fixed effects estimation. The dataset includes more than 600 business angels that made at least two investments. In the case of the dependent variable series-A, this is sufficient to estimate a model with fixed effects for business angels and still control for the same variables as above. Using the dependent variable exit, in order to have sufficient variation in the variables we have to drop industry and time effects. The regression results in Table 8 again emphasise the significance of the variable first degree. Even when controlling for investor-specific effects, the network measure remains positive and significant.

All these results support the first hypothesis: business angels make use of their immediate network of former co-investors to source investments and to nurture them. The large network of a business angel is indeed a means of promoting the success of start-up investments. However, we find no evidence for the second hypothesis, business angels do not seem to act as brokers. Central positions in the network and second-order links are hardly used to create more successful start-ups.

Table 8 Employing business angel fixed effects

Series-A	*8.1*	*8.2*	*8.3*	*8.4*	*8.5*
First degree D	2.532**	6.281***	4.110***	3.215*	5.571***
	(1.236)	(1.882)	(1.219)	(1.256)	(2.086)
Investor fixed effects	yes	yes	yes	yes	yes
Ninvestments		yes			yes
Nmonths		yes			yes
Year dummies			yes		yes
Industry dummies				yes	yes
Exit	*8.6*	*8.7*			
First degree D	1.652***	4.463***			
	(0.614)	(1.168)			
Investor fixed effects	yes	yes			
Ninvestments		yes			
Nmonths		yes			

Notes: Standard deviations in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

5 Conclusions

Business angels are high net-worth individuals who invest in young start-up companies, where they commonly become actively involved in company management and operations. For high technology start-ups in the USA, angel financing is often the primary source of external equity. The next financing step in the life-time of young entrepreneurial firms after angel investment is usually the attainment of later stage venture capital financing. The venture capital literature has established the positive relation of co-investment networks and portfolio company performance. However, despite the fact that information asymmetries and uncertainty about the success perspectives are more pronounced in the field of early stage start-up investments, similar studies of business angel networks do not exist.

We build on the existing venture capital literature by investigating the nature of the performance effects of business angel networks using a comprehensive dataset of 1,746 US high technology start-ups. Thereby, we also extend the literature on the role of networks as we identify three spheres of influence: first, sourcing high-quality investment opportunities, second, nurturing companies by drawing from a better pool of resources and third, better attracting later stage venture capital investors. In order to capture the characteristics of the co-investment network, we employ four network measures that comprise different aspects of an investor's network.

Controlling for known and available determinants of investment performance, our empirical analysis reveals one key characteristic of an investor's network: its size. The number of former co-investors (measured by the first degree of an investor's network) is the only network variable that is empirically significant across our analyses.

When holding all further controls constant at their respective means, a one standard deviation increase in the first degree network measure indicates a 10.89% higher probability that the start-up receives later stage funding by a venture capitalist. It would also be associated with a 5.03% higher probability of achieving an exit via trade sale or initial public offering. Considering that merely 19.1% of the angel financed start-ups in the dataset achieved an exit (58.8% received later stage funding), this can explain more than one forth (one sixth) of the variation of the success measures.

While first degree has a significant, positive effect on the start-up's performance, no significant effect is found for valued degree, which measures how often investors co-invested. The centrality measures that capture the business angel's position in the overall venture capital network are also insignificant. Neither the connectedness of his co-investors (Bonacich centrality), nor the likelihood of being the connecting investor between two others (betweenness centrality) have a statistically significant impact. These results suggest that indirect relationships, which require intermediation, play a lesser role for business angels. The same is true for the ability to act as a broker between other investors, as captured by betweenness centrality. Hochberg et al. (2007) also find that betweenness centrality provides the least economic significance in the case of venture capitalists.

These findings suggest that business angels rely on their immediate network to source investment opportunities and nurture them. Indirect relationships play a far lesser role. This finding corresponds to insider statements in previous studies. "Angels have one-degree of separation from people in their professional network – not two, or three, or four. But because angels tend to be operational types, the business relationships they bring to the table are personal, not transactional" (Rob Convey, business angel; see Wong et al., 2009).

This raises the question around how investors become networked in the first place and how they nurture and extend their networks. There remains much to investigate about networks in entrepreneurial finance. For instance, it would be interesting to know about the comparative value of network links with different types of investors, business angels, venture capital firms and corporate venture capitalists.

Our findings manifest the important role of networks in entrepreneurial finance. Co-investment networks are only part of the extensive networks investors have at their disposal, but they are also the most formalised. Business angels in particular benefit from such networks and thus they rely on these direct contacts to source investment opportunities and nurture them.

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