Networks and syndication strategies: Does a venture capitalist need to be in the center?

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Summary. Investing in radical innovation requires specific forms of investment, which have to deal with knightian uncertainty. This paper focuses on the links developed by venture capitalists and start-ups and studies their relationship through social network analysis. We analyze the influence of different proximities on the collaboration among the different actors.

1 Introduction

Many empirical analyses show that venture capitalists form syndicates to finance start-ups. This is usually explained in terms of risk-sharing and information-gathering. According to Brander, Antweiler & Amit (2002), the three main reasons for syndication are: firstly, that venture capitalists cooperate in order to diversify their investment portfolios; secondly, that syndication achieves better screening, and finally, that as each venture capitalist adds value to a start-up, increasing the number of venture-capitalists involved has a positive influence on the outcome.

Syndication favours the emergence of an interaction network between venture capitalists. In this article, we consider networks as interaction structures which can affect market structures and global economic results. We propose to explore the influence of these interactions on the outcome of the financing process through network analysis and econometrics. For this purpose, we study the link between the topological properties of the network and the economic efficiency of the actors. In particular, we show that syndication results from strategies, and we investigate the different determinants. At a local level, the role of the different proximities (spatial, political, industrial) is emphasized. We then consider the robustness of these phenomena at a global level (through analysis of a world data set). Finally, we investigate whether the syndication network favours concentration and local specialization phenomena rather than diffusion of the venture capital activity. The article is organised as follows: section 2 gives a survey of the related literature, the database and methodology are shortly summarized in section 3 and 4, section 5 presents empirical evidence of syndication strategies, section 6 extends the analysis to global network properties, and this is followed by the conclusion.

2 A survey of the literature

Many contributions from social sciences, such as Granovetter (1985) or Cohendet, LLerena, Stahn & Umbhauer (1998), have pointed out the importance of networks in explaining the role of social interactions in various economic fields. Powell, White, Koput & Owen-Smith (2005) study the network of relationships between pharmaceutical firms, start-ups, venture capitalists and universities in the biotechnology industry. They develop and test four alternative logics of attachment to account for both the structure and dynamics of interactions in this particular field. The four possible forms of attachment are "accumulative advantage", "homophily", "follow-the-trend" and "multiconnectivity". These four attachments correspond to four different types of "network strategy", which can be used by agents to access a more central position in the network. As organizations increase the number and diversity of links, cohesive sub-networks appear, which are characterized by multiple independent pathways.

Sorenson & Stuart (2001) have shown that venture capitalists have a strong tendency to invest in nearby start-ups. They investigate both spatial and "industry" proximity. They explain how the intrinsic characteristics of venture capital can justify these tendencies. Because of the high level of uncertainty associated with the financing of new technologies, venture capitalists have to screen the start-ups and then evaluate their expected "quality". For that purpose, they need to gather information about the innovator, future market potential, etc. They then have to monitor and manage the financed enterprise in order to ensure the best exit mode is chosen. Throughout these different steps, being spatially close to the start-up is more practical and keeps costs down. Having what the authors call an "industry" proximity, i.e. having already invested in the same field, helps venture capitalists to evaluate the future product and monitor the firm. But through syndication, the more experienced and better-connected venture capitalists can extend the radius of their activities. Thus, the network can be a vector of diffusion. More recently, Ho & Verspagen (2006) emphasize the influence of national borders on flows of knowledge.

Many analyses show that the production of new and high technologies is strongly spatially concentrated, while the primary production input (knowledge) seems to have very low transport costs. In general, economic literature explains this economic paradox by the positive local interactions between enterprises. As Arthur (1990) or Krugman (1991) observe, there are important geographic spillovers of knowledge across clear boundaries but within small areas. This phenomenon prompts new enterprises to locate near existing firms of the same type, so as to gain early exposure to knowledge produced by these neighbouring firms. This suggests the emergence of a strongly interconnected local network. The search for the most central position could favour spatial concentration.

The literature quoted above suggests that the network has an ambivalent effect, furthering the diffusion of venture capitalists' activities on the one hand and encouraging spatial concentration on the other.

3 Data and Methodology:

3.1 The data

Our empirical results are based on the study of a database provided by Dow Jones - Venture Source. A venture capitalist raises successive funds from institutional investors and invests them in different start-ups. Venture capitalists usually spread their investment in start-ups over successive rounds, following the development of the firm. Venture capitalists also often syndicate their investment, each round usually involving more than one investor. The investors distinguish between five main stages of development, which we group into two main categories, early stages (start-up, product development, product in beta test) and later stages (shipping product, profitability).

For each venture capitalist, the database provides the successive funds he/she has raised between 1990 and 2005 and the characteristics of the start-ups in which he/she has invested. For each start-up, we know the financing rounds it has received and the venture capitalists involved in each round. We also know the amount of the investment in each round, and the stage of development of the start-up when the round occurs. Finally, we know the industry in which the start-up is operating (Information Technologies (IT), Retail and consumers, (RETAIL) or Health care (HEALTH)) and its current status at the end of the observation time (bankruptcy, private or exit). There are several different types of investors in the database (Venture Capital, Corporate, Investment Bank, Public, Angel Investor). To insure some homogeneity in our analysis, we have chosen to study only the Venture Capital type, which designates independent venture capital firms. They represent 48% of the investors in the database, but 72% of the investments.

Our data set contains 63375 rounds, 4696 venture-capitalists and 25145 start-ups, entailing 81338 edges between venture-capitalists and start-ups. The different agents belong to three main geographical areas: Israel, the United States and Western Europe.

3.2 The methodology:

We focus mainly on the syndication networks between venture capitalists. Most investments in start-ups are syndicated; 63% of all the rounds in our database involve at least two venture capitalists. In our network analysis, we consider that two venture capitalists are linked if they participate in at least one round together. Links are weighted by the number of start-ups in which the two venture capitalists have co-invested. Networks can be restricted to the region of the world in which the venture capitalists have their main office, and/or to a given time period.

We first study the structural properties of the networks, then validate our findings with an econometric analysis of link creation.

The network tools

We use social network tools to analyse a network in which nodes are venture capitalists. We follow the small-world and scale-free network perspective recently developed by Watts & Strogatz (1998), Newman (2001) and Albert & Barabasi (2002), and the recent contributions from social sciences such as Powell et al. (2005) or Moody & Douglas (2003). In order to characterize the structure of the network and to identify syndication strategies, we start by computing network properties including degree distribution, degree assortativity and clustering coefficient for regional, industry-restricted, or world-wide nets.

We choose to use the free software GUESS (Adar 2006) for the visualisation of networks. GUESS is slower and less complete than PAJEK, but it allows for easy manipulation of the networks via a command-line interface and an SQL-oriented manipulation of nodes and edges. The graphic representations are based on the Kamada-Kawai and Fruchterman-Rheingold algorithms. Both are force-directed layout algorithms, i.e. a repulsive force affects all nodes and an attractive force keeps connected nodes next to each other. The Kamada-Kawai algorithm is more efficient, but can be too slow for big networks with GUESS. In this case, we limit ourselves to Fruchterman-Rheingold layouts. We use R (R Development Core Team 2005) and the igraph package to compute the statistical properties of the networks.

The econometric tools

In order to analyse the process of link creation, we follow (Sorenson & Stuart 2001) and use the rare event logit model developed by (King, & Zeng 2001). These authors observe that in a given context (international relations, for example) certain events (such as war or revolution) are very rare, but have a great impact on the outcome of societies. Their model makes it possible to study rare events in an efficient way. Since most of the information comes from the positive but rare events, it is sufficient to consider a restricted set of negative events. The required amount of data is then significantly reduced. Following this methodology, and considering co-investment between two venture capitalists as a rare event, we build a subsample in which we include all cases of funding relations that actually appear in the data. We then create a matched sample of potential ties that did not occur. The rare event logit model provides a correction for the selection bias induced by the sampling of negative events. This is sufficient to provide the real rate of the positive events. Apart from this correction, the model is similar to a usual logit.

4 Local properties of the network: syndication results from strategy

In what follows, we use tools both from social network analysis and from econometrics to see whether the syndication phenomenon results from strategies or from simple random matching. For this purpose, we first compute the connectivity of the network nodes, to determine whether or not the degree distribution follows a well-known distribution.

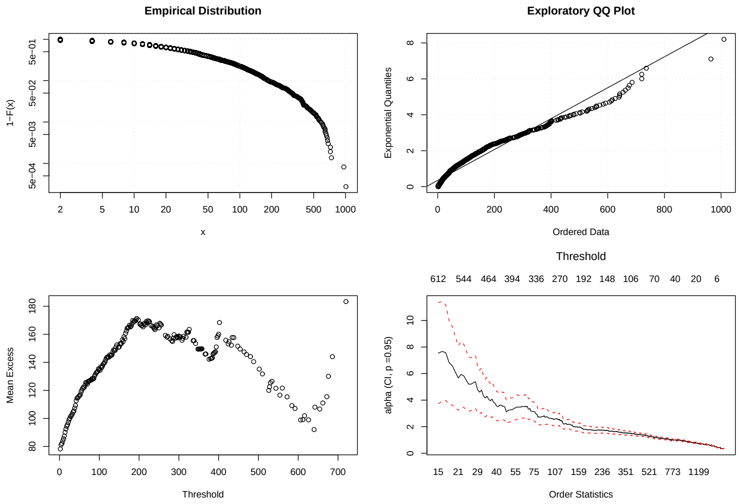


Fig. 1. Degree distribution of the whole set of venture capitalists. The upper left graph is log-log plot of the cumulative degree distribution and the there other plots are tests for various distributions. The cdf is obviously very large, ranging from degree one to seven hundred on a total of 1826 venture capitalists across the world. All test discard the power law distribution hypothesis.

4.1 Connectivity: the evidence of strategy

Let us first measure the degree distribution of the network nodes, when the degree of a node is given by the number of links. The interest in doing so is that random nets, where the strategy of actors plays no part in establishing links, are represented by Poisson degree distributions, while scale-free networks often have power law distributions.

The following set of data and figures establishes that the distribution is not Poissonian, that it is large, but it is not a power law as observed and discussed on the web.

Power law distributions based, for example, on the preferential attachment algorithm entail that newcomers systematically prefer well-linked nodes and establish links with a probability proportional to the previous number of links already attached to the target node. The preferential attachment algorithm presupposes a passive role of the target, or at least a constant acceptation rate of the target.

When the statistics of degree distributions are taken on smaller more specific sets, such as Region and Industry, the same distribution of degree distribution is observed. Figure 1 displays the equivalent statistics.

region	industry	nodes	edges	density	degree assort.	clustering
Israel	Retail	22	19	0.0822	-0.195	0.409
Israel	Healthcare	52	179	0.135	0.262	0.398
Israel	Information Tech.	67	330	0.149	0.246	0.401
Israel	All Industries	78	464	0.154	0.210	0.389
West. Europe	Retail	252	410	0.0130	0.340	0.296
West. Europe	Healthcare	239	865	0.0304	0.275	0.294
West. Europe	Information Tech.	413	1178	0.0138	0.409	0.208
West. Europe	All Industries	518	2262	0.0169	0.424	0.222
United States	Retail	779	4998	0.0165	0.280	0.209
United States	Healthcare	692	8355	0.0349	0.190	0.295
United States	Information Tech.	1049	18292	0.0333	0.276	0.289
United States	All Industries	1198	27796	0.0388	0.276	0.285
All Regions	Retail	1104	5899	0.00969	0.303	0.199
All Regions	Healthcare	1018	10652	0.0205	0.254	0.278
All Regions	Information Tech.	1570	22370	0.0182	0.328	0.268
All Regions	All Industries	1825	34565	0.0207	0.330	0.263

Table 1. Descriptive statistics for Regional and/or Industrial restricted networks. All networks display a significant positive degree assortativity (except for Israel Retail). All have clustering coefficients much larger than link density.

4.2 Assortativity: the role of the different proximities

Are links established randomly, or do they obey some strategy? *A priori*, we might suppose that co-investment strategies are not random, if only because they result from the initial choice by the same partner, the start-up company looking for supporting funds.

Assortativity answers a related question: it measures the similarity between connected nodes, and then partially answers the issue of strategy, because some choices based on trust would lead to similarity (on a technical or geographical basis), while the need for complementarity in abilities and knowledge would lead to diversity. The level of popularity of a certain venture-capitalist, as measured by large connectivity or centrality, can be related to either trust or the search for market-related, technical or geographical information. In other words, we could say that in the absence of objective institutional information signals, a central place in the network could be seen as a signal of high reputation.

Let us meanwhile check the results of assortativity tests done on several node properties.

- Degree assortativity. Although hardly noticeable on $[k, k']$ plots, statistics on the set of venture capitalists conclude that there is positive assortativity: well-connected venture capitalists connect preferentially to well-connected venture capitalists. (Table 1).

- Geographical assortativity. Are co-investing venture capitalists located in their geographical neighborhood? Positive assortativity could imply that trust based on local reputation is more important in choosing partners than other reasons, such as conquering new markets in different locations. It could also imply that the information on the different actors does not circulate very well between the different countries or states. The measurements are made on Kamada-Kawai plots of the networks, on American and European data. In the Kamada-Kawai, the proximity of nodes on the graph relates to the existence of strong links. The colour indicates the venture capitalist country or the state.
  In Europe, co-investment practices generally take place within the same country (with an exception for Switzerland). In the United States, there is more state dispersion in the choice of partners. We believe here that the barriers between the different venture capitalists are more influenced by the differences between cultural, legal and/ or social norms (quite significant between different European countries) than by geographical distances.
- Industry assortativity.
  Do venture capitalists choose partners in the same industries (according to their previous experience) or in a different industry? Investing in a same industry (or a similar one) would signify that syndication is a meaning of reinforcing the links between some subgroup of people, specialized in certain fields. Diversified strategies (co-investment between people specialized in different industrial fields) could suggest that syndication is a meaning of getting more information on a "new" field. In what follows, we perform an individual measurement and a global one.
  The measurements of individual firms and links are again Kamada-Kawai plots. For each venture capitalist, we define a portfolio measuring the fraction of his/her investment in Information Technologies (IT, coded in red), Health (coded in green) and Retail (coded in blue). Each venture capitalist is represented on the figures by a coloured circle, coded according to the RGB (red green blue) representation of the portfolio.
  We observe for Europe a large degree of specialization: most of the venture capitalists have a focused portfolio. Only a few nodes have mixed colours, such as violet (a venture capitalist investing in the sector of information and technologies and in the retail sector) or

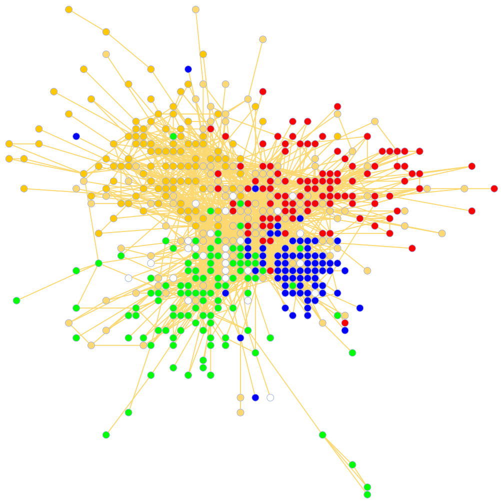


Fig. 2. "Country labeled" Fruchterman-Rheingold representation of the venture capitalist network of Western Europe (main component). Closeness on the graph relates to strong links. The color reflect countries of the venture capitalist: red for United Kingdom, blue for France, green for Germany, orange for Scandinavia and white for Switzerland.

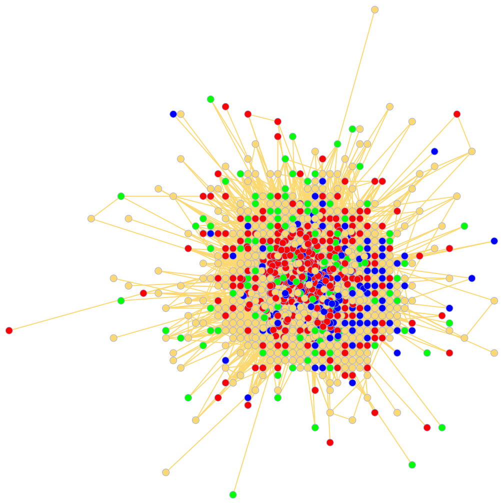


Fig. 3. "States labeled" Fruchterman-Rheingold representation of the venture capitalists network of the United States (main component). Closeness on the graph relates to strong links. The color reflects the state of the venture capitalists: red for California, blue for Massachusset, green for New-York.

brown (a venture capitalist investing in Information and Technologies and in Health). This result is more surprising than the previous one (which indicated that there exists strong barriers between different European countries) but it could results from the fact that the venture capital in Europe is not as developed as it is in United States and that it is quite a new activity (venture capital appears in Europe around 1985).

The American pattern of co-investment is more diversified. Many nodes are violet or brown, which indicates diversified portfolios. We still observe clusters of specialized venture capitalists, but also the existence of intermediate zones populated by diversified venture capitalists.

The measure of the industry assortativity

The integrated measurement of industry assortativity is based on a finer definition of industries. We start from a finer definition of industries, based on a three-level hierarchical classification.

The distance d_{ij} between two industries i and j is one plus the height of their lower common ancestor.

A portfolio of a VC is now defined as a vector whose components are the sum invested in the different specific industries in the 3-digit classification. A possible overlap between two portfolios would consist in directly taking the normalized scalar product of the portfolios. But such a measure would then miss the opportunities for co-investment based on experience between similar but different industries: those corresponding to small distances such as one. We therefore use the following definition of portfolio overlap, which takes into account relative similarities among industries:

$$O(\mu,\nu) = \sum_{i,j} q_i^{\mu} q_j^{\nu} exp(-\alpha d_{i,j}) \tag{1}$$

$$RO(\mu,\nu) = \frac{O(\mu,\nu)}{\sqrt{O(\mu,\mu)O(\nu,\nu)}} \tag{2}$$

Where indices μ and ν refer to the two portfolios, and indices j and j refer to the industries. α is an adjustable parameter: $\alpha = 0$ would give the direct overlap of portfolio based on the fine structure of industries, and a large α would give large overlaps based on coarse graining of the industry structure, only making differences between IT and Health, for instance. We usually take $\alpha = 1$ and re-scale the overlap by taking the ratio of $O(\mu,\nu)$ with respect to the product of the square roots of self overlaps of both portfolios.

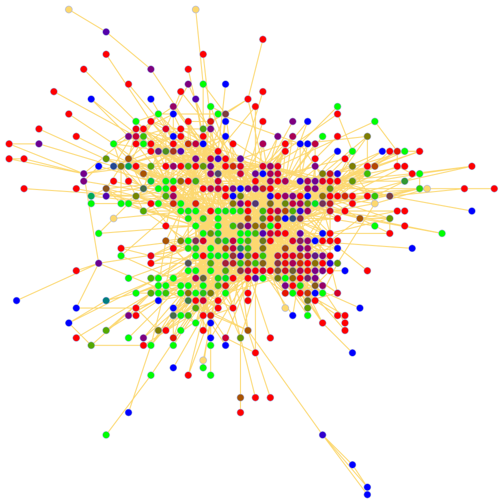


Fig. 4. "Industry labeled" Fruchterman-Rheingold representation of the VC network of Western Europe (main component). Each VC node is colored according to the RGB code of its portfolio. The pure colors code industries: IT, coded in red, Health in green and Retail in blue. Closeness on the graph relates to strong links.

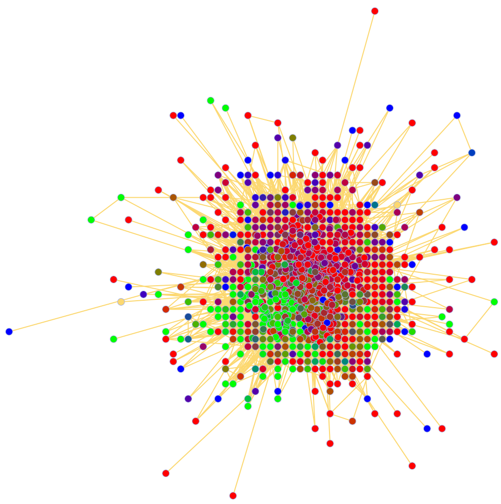


Fig. 5. "Industry labeled" Fruchterman-Rheingold representation of the venture capital network of the United States (main component). Closeness on the graph relates to strong links. The color code is the same as for Western Europe.

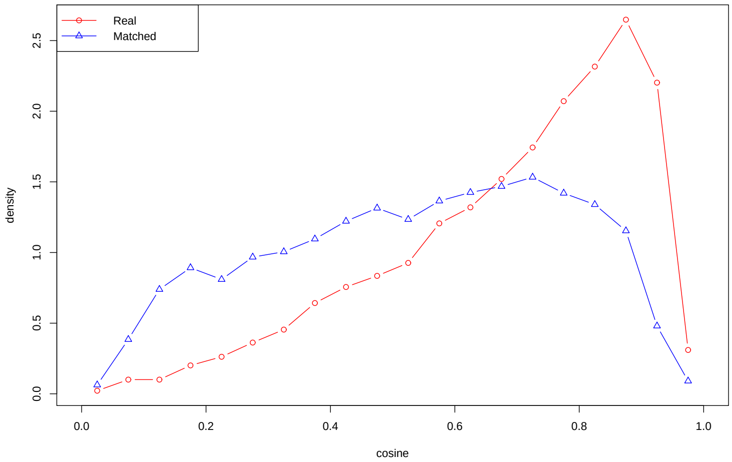


Fig. 6. Histogram of overlap in portfolio of VCs. The red line correspond to empirical data and the blue line to the null hypothesis.

The graph 6 displays the histogram of global industry overlap. It clearly indicates a positive assortativity according to industries, especially when compared to the zero hypothesis of random co-investments among the venture capitalists who did invest.

- Experience assortativity. Do experienced VCs prefer to associate with other experienced VCs or with newcomers? A correlation on our data test gives a positive and significant coefficient of 0.15. This indicates that experienced venture capitalists tend to invest with partners of a similar level of experience.

4.3 Clustering coefficient

The clustering coefficient represents the tendency of venture capitalists connected to the same venture capitalists to be connected among themselves. If the probability of such connections is larger than in a random net, we can infer that the process of establishing new links is favoured by the pre-existence of common partners. Venture capitalists nets usually have a clustering coefficient ten times higher than their density (the ratio of the actual number of edges to the number of edges of the fully-connected network), while random nets have equal figures for both.

Large clustering coefficients correspond to an over-representation of the 3-loop motif.

5 Econometric analysis: the determinants of link creation

In order to study the determinants of the creation of links, i.e the determinants of the choice of a syndication partner, we run on yearly data a rare event logit model as described above. For each year, we build the past syndication networks using only the rounds that took place before. We then analyze the links generated by the rounds that occur during that year. In our data, the proportion of positive events is $\tau = 0.01689$.

In order to generate the sample set of negative events, we use the following matching procedure. For each link we create two matched links, one for each venture capitalist in the actual link. To create a negative event, we select, from among all the active venture capitalists, one who did not syndicate with the venture capitalist of the real link.

We use data about the rounds made in our three regions ('United States', 'Western Europe', 'Israel') over a time period ranging from 1990 to 2000. Out of the 39734 links created during this ten year period, we sample 5000 links and match them with 10000 pairs of venture capitalists with no syndication link. This gives us 15000 potential links, with one third of effective links. For each potential link we compute the following characteristics.

We use a dummy variable ('repeated') whose value is 1 if the two venture capitalists have already invested together in a previous year and 0 if they have not. This allows us to measure the propensity of venture capitalists to make new investments with trusted partners. On the basis of this dummy variable we can also independently study new and repeated syndication links.

We use another dummy variable ('country.diff'), which takes the value 1 when the two venture capitalists are located in different countries and 0 if they are in the same country.

We measure the total experience of the pair ('experience'), i.e. the sum of all the previous investments made by each venture capitalist. We also compute the similarity between the experience of the two venture capitalists ('exp.sim') as the ratio of the smallest value to the greatest. This allows us to test whether the venture capitalists syndicate to increase their total experience, and whether venture capitalists tend to syndicate with others of the same experience.

Finally, we compute the industrial proximity between the previous investment portfolios of the two venture capitalists ('ind.prox'), according to equation 2. This can only be computed if both venture capitalists have some experience. So we use a dummy variable ('no.prox.ind') to

	Real links	Matched links
exp	110.7 (98.16)	74.85 (75.55)
exp.sim	0.3251 (0.2908)	0.2499 (0.2856)
prox.ind	0.6704 (0.2071)	0.5419 (0.2322)
repeated = FALSE	0.6156	0.89468
repeated = TRUE	0.3844	0.10532
country.diff = FALSE	0.906	0.72252
country.diff = TRUE	0.094	0.27748
year = 2000	0.2708	0.27087
year = 1999	0.1956	0.19601
year = 1998	0.1046	0.10452
year = 1997	0.0696	0.069546
year = 1990	0.0696	0.069446
year = 1991	0.0574	0.05722
year = 1996	0.0556	0.055416
year = 1995	0.054	0.054114
year = 1992	0.0492	0.049203
year = 1993	0.041	0.041086
year = 1994	0.0326	0.032568
N =	5000	9979

Table 2. Descriptive statistics for real and matched links

control for the case where one of the venture capitalist has no experience. In this case, the dummy variable is set to 1 and the industrial proximity to 0.

Descriptive statistics for these variables are given in Table 2 for each subgroup, the real links and the matched ones. A first comparison between the two columns indicates a clear relationship between the two dummy variables 'repeated' and 'country.diff' and the formation of links. The proportion of links between two previous partners and between partners in the same country is indeed significantly greater in the real links than in the matched ones. The other variables 'exp', 'exp.sim' and 'prox.ind' also display significant differences between the two groups. To evaluate the effect of each variable with respect to the others, we ran a multivariate analysis.

Table 3 gives the results of the estimation of the rare event logit model. The most explanatory variable is the 'repeated' dummy. Having already invested together before multiplies the probability of syn-

Link creation						
	All		New		Repeated	
(Intercept)	-4.5928	***	-4.3334	***	-3.6955	***
repeated	1.2863	***				
country.diff	-1.1303	***	-1.2395	***	0.058892	
exp	-0.00016247		0.00016191		0.00015881	
exp.sim	0.0011622		0.020674		0.30548	.
no.prox.ind	0.34589	***	0.42945	***		
prox.ind	1.4397	***	1.5915	***	0.19507	
1990	-0.85012	***	-1.1426	***	-0.62131	***
1991	-0.92466	***	-1.1275	***	-0.84966	***
1992	-0.81348	***	-0.79567	***	-0.96477	***
1993	-0.79583	***	-0.55235	***	-1.2855	***
1994	-0.8104	***	-0.65699	***	-1.1519	***
1995	-0.70331	***	-0.57078	***	-1.0513	***
1996	-0.43989	***	-0.29576	**	-0.933	***
1997	-0.3331	***	-0.28854	**	-0.57882	**
1998	-0.23758	***	-0.2144	**	-0.42974	*
1999	-0.054802		-0.014367		-0.32377	*
N	14979		12006		2973	
null deviance	19078		13668		3862.5	
deviance	16649		12774		3757	
pseudo R^2	0.12733		0.065405		0.027306	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 3. Determinants of link creation. Rare event logit model run on a data set of 5000 effective syndication links between venture capitalists and 10000 matched pair of venture capitalists with no syndication links. First column contains the model run on all the data, the second and the third one are run respectively only on the new and the repeated links.

dication by 3.34. Trusted partners are the first choice for making new investments.

Country difference is also very influential. Being in the same country multiplies the probability of syndication by 3.06. This confirms the result found before, that venture capitalists tend to invest with partners in the same country.

Neither of the experience variables are significant. Experience seems have no influence on the choice of syndication partner. Venture capitalists do not seem to syndicate to compensate for their lack of experience, nor to prefer equally experienced partners.

Industrial proximity, on the contrary, has a clear positive effect. Moving up from the first quartile of industrial proximity $q_1 = 0.41$ to the third $q_3 = 0.78$, the probability of syndication is multiplied by 1.67. This also confirms the previous result of industrial assortativity.

Finally, we ran the model on two subsets, one with only new syndication partners, and one with only repeated interactions ('repeated' is false for the first subset, and true for the second). All our informative variables keep their effect in the case of new syndication links, but not for the repeated interactions. This means that we have found determinants for the choice of new partners, i.e. the creation of new links in the syndication networks, not for the choice of continuing to co-invest with a previous partner, i.e the reinforcement of the syndication link. For this latter case, other variables should be considered, related to the success of the collaboration between the two partners.

6 Global structures: is the venture capitalist community strongly connected?

The first question about global structures concerns the existence of a giant component, i.e. the existence of a robust core of strongly connected individuals: are most nodes reachable from any node according to a path across network edges? By contrast, some might not be so connected, and belong to isolated clusters.

At first glance, we do observe giant components. Most of the venture capitalists belong to the connected giant component, but how robust is the central component with respect to edge deletion? Building k-components may provide an answer to this question. The idea is to check how many nodes become disconnected from the giant component when one removes k nodes. Since the result depends on which nodes are removed, the worst case is considered. Acccording to Moody and White, a network is $k - connected$ when it is invulnerable to disconnection by the removal of fewer than k nodes; a $k - component$ is the maximal sub-graph which is $k - connected$.

Detecting a k-component can be very computationally intensive for big networks. A useful weaker definition of communities is the k-core. A k-core is a connected sub-network where all the nodes have a degree of at least k. A k-component is always a k-core but the opposite is not necessarily true. However, if the k-core detection never reveals more than one connected component, as is the case for our syndication, it is a good indication that the network is built around a unique community.

A sufficient condition for a k-core to be a k-component is that its connectivity is equal to k, i.e. that the sub-network remains connected even if $k - 1$ nodes are removed. In our case, this is verified for the main core, a 59-core, and for the intermediate k-cores. Venture capital syndication networks seem to form a unique worldwide community.

Figure 7 display the size of the $k - cores$ of US and Western Europe syndication networks as a function of k. The absence of any sharp decrease as a function of k tells us that the $k - components$ is never disrupted in smaller clusters by the erosion of the nodes. This robustness up to large values of k is also directly verified on GUESS plots.

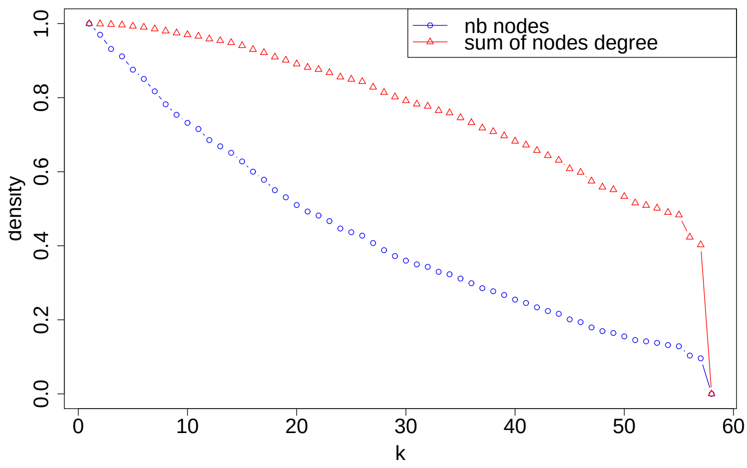
The extreme robustness of the $k - core$ with k until complete collapse is a surprising property, which calls for interpretation in terms of VC strategy. Why do VC make systematic efforts to belong to the center? Why is complete connectivity achieved in the $k - core$ at the onset of collapse?

Restricting the network to its $k - core$ allows easier visualisation. Figure 8, for instance, displays the $10 - core$ of the Western Europe VC network, coloured by country. Among the many features displayed, we can check that the $10 - core$ is connected, that all countries have nodes in the $10 - core$, roughly in proportion to the original national figures, and that the positive country assortativity is roughly preserved.

The relatively faithful representation by $k - core$ of the whole network is observed for all VC networks that we tested.

7 Conclusion

Through syndication venture capitalists build an international social network. The statistical analysis suggests that this network is not a random one, and that co-investment can result from strategic behavior. A number of features of venture capital network emerge from our measurements. The most important and less a priori obvious results are that the degree distribution is large but not power law (which means that the connections are not purely determined by preferential attachment), positive assortativity is observed for different features such as geography, industry and to a lesser extent degree distribution. The network remains extremely robust to link deletion as measured by the evolution of the $k - core$ with k. Observing the coincidence of the two last properties appears counter-intuitive: if the dominant rule was that venture capitalists are doing connection according strictly to similarity, the network should end in distinct separated communities after a small



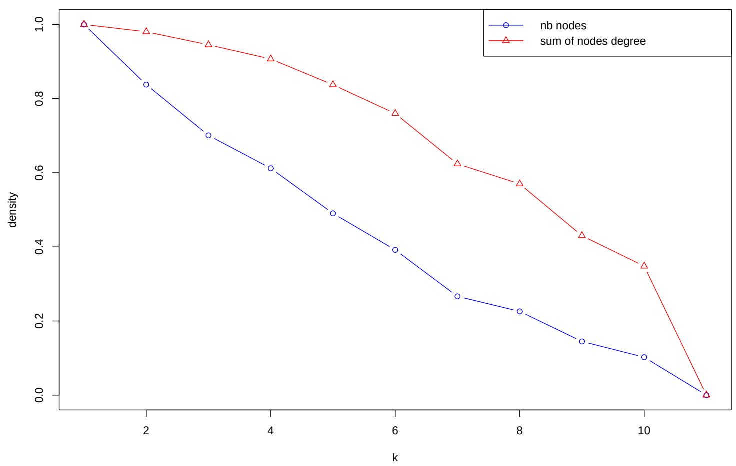


Fig. 7. Variation of the weight of the $k - cores$ of US and Western Europe VC-VC networks with the number of removed nodes k. This curve reflects the robustness of the network connectivity with respect to node deletion. The red points correspond to the number of links, the blue points to the number of nodes.

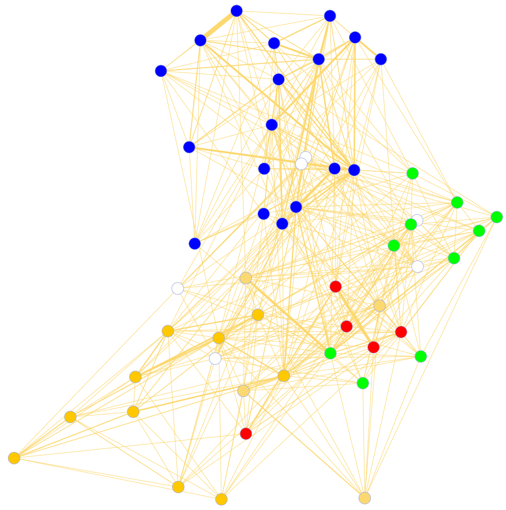


Fig. 8. "Industry labeled" Fruchterman-Rheingold representation of the $10-$ *core* of the VC network of Western Europe. This figure maintains most of the traits observed for the complete network.

number of deletions. Such a behaviour was described about the robustness of Internet networks against focused attacks (Albert, Jeong & Barabàsi 2000). But this is not what we here report: the $k-core$ remains connected up to large values of k. According to what we know, there exists no article in the literature which could account for our empirical observations, except maybe the observation by (Powell et al. 2005) that venture capitalists try to get connected to a central core. Still, we can already point to the specificity of the venture capital challenges and practices directly linked to the radical uncertainty. One of the main activity of venture capitalist is to finance new products for whom there exists very few signals of quality. The network structure reflects the need for alternative information sources.

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Group	Segment	Code	Count
Inform. Tech.	Software	Business Application Software	1668
		Connectivity/Communications Tools	1656
		(...)	
		Total	7029
	Communications	Connectivity Products	617
		Fiberoptic Equipment; Photonics	479
		(...)	
		Total	2542
	(...)		
	Total		14669
Retail	Cons/Bus Services	Business Services	2848
		Financial Institutions and Services	573
		(...)	
		Total	4073
	Retailers	Speciality Retails	486
		Electronic Commerce	82
		(...)	
		Total	810
	(...)		
	Total		5617
Healthcare	Biopharmaceuticals	Biotechnology	964
		Drug Discovery	580
		(...)	
		Total	2088
	Medical Devices	Surgical Devices	286
		Therapeutic Devices-Impleantable	237
		(...)	
		Total	1577
	(...)		
	Total		4879
Other			859
Total			26024

Table 4. Industry classification