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Keywords

– Venture Capital, Networks, Europe, Investment Syndication.

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Syndication networks and company survival: evidence from European venture-capital deals[1]

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We look at syndication in the venture capital industry. Investments conducted by syndicates are believed to have better chances of being successful, measured by the survival probability of portfolio companies or by successful exits. Using a novel and large dataset, covering several countries, our analysis shows that strong network ties of investors are associated with success of portfolio companies in Europe. We also show that there are differences in the association of network centrality with survival between different financing rounds, the former being more important in early-stage investments. Finally, we show a strong association of network ties of investors with sales growth of portfolio companies, before and after the deal.

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JEL classification: G11, G24, M13

1. Introduction

Venture capital (VC) is a form of financing in which investors do not purchase a stake in a going concern but support the creation and development of new companies through investments from the very early stages of business development through the launch of a company. Venture capital investment is associated with high levels of technology diffusion throughout the economy and high employment creation (De la Dehesa, 2002). Starting from the beginning of the 2000s in Europe, venture capital has become one of the most important

[1] This project is accompanied by an online Appendix containing interactive figures and programs used to conduct the analysis. It can be found at https://sites.google.com/view/syndication-networks/home

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policy goals of states. Nevertheless, for various reasons, the development of the venture capital industry in Europe still lags behind the United States.

There are several reasons for why development of venture capital industry has become such an important topic. Firstly, a study by Kortum and Lerner (1998) in the United States demonstrates that a dollar invested in venture capital creates three times more patents than a dollar invested in research and development (De la Dehesa, 2002). This also means that the whole economy benefits from additional productivity and diffusion of technology. Secondly, there is a link between venture capital and job creation. Most of the funds raised go into hiring, which means that dollars invested in new ventures directly translate into new jobs. Finally, as shown by, e.g., Puri and Zarutskie (2012), venture capital financed firms have lower failure rates than non-financed firms, at least in the first five years of existence.

These aspects of venture capital show that it is not only an important research topic but also it has vast policy implications. Understanding how the industry works, and how success of both venture capital firms and their portfolio companies can be achieved is crucial for assuring further development of economies.

The focus of this work is on Europe. While North America has historically dominated the venture capital industry – and research - Europe's overall shares of venture and growth capital have increased recently in line with investors' growing interest in the region. At the same time, research on Europe is still not as prominent as for the American case, to some extent due to the lack of detailed data.

According to 2020 European Venture Report, the volume of VC deals has been on a constant rise. Figure 1 shows the development of the volume of deals over time. While in 2006 the value of European VC deals equaled slightly less than 4 billion Euro, in 2019 it was almost tenfold, at 34 billion. European markets, while still smaller than the US and China, are growing in importance.

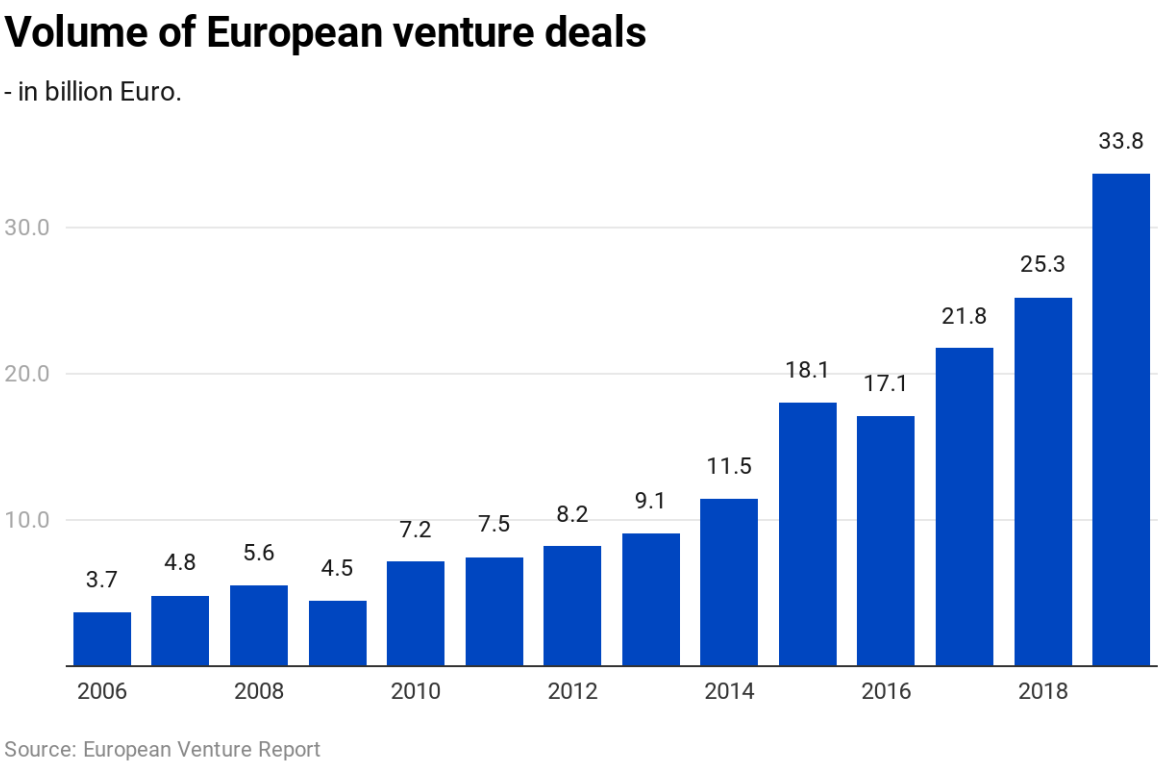


Figure 1: Volume of VC deals in Europe over time.

Source: European Venture Report 2020

In this work, we look at a particular aspect of the venture capital industry, namely syndication. Typically, VC investments are not conducted by a single entity, but by a group of co-investors, a syndicate, led by a leader, usually an investor with vast experience in selecting investment opportunities and then investing in various technology sectors and with deal flow that most investors do not have access to. Investments conducted by syndicates are believed, for various reasons described in this work, to have better chances of being successful. Existing literature has indeed shown, that syndication can lead to more successful investments in the United States and China. For the case of Europe, there is still little evidence that this is true. And while theoretical explanations for the impact of syndication might indeed hold also in the European case, this hypothesis still needs to be tested. Indeed, European markets are quite different from the US ones, and some aspects of syndication might be different here.

There are several novel aspects of the literature addressed in this work, combining results from the finance literature with methodology of social network analysis. Firstly, we provide a rare evidence of how syndication affects performance of companies in Europe, and in particular whether network centrality of a syndicate's central investor positively affects survival of portfolio companies. Secondly, to the best of our

knowledge, we are the first to look at the differences in the impact of centrality of investors on companies' success between early-stage and growth investments. Thirdly, we look at the association between centrality of investors and sales growth of portfolio companies, before and after the deal. Finally, we are one of the few to use the Preqin database in the context of network analysis in venture capital, and the first ones to use Preqin to look at the impact of network features on performance of companies, which allows us, as opposed to most studies, to look at a cross-country sample.

Our main results indeed show that the network centrality is important for the success of portfolio companies in Europe. We find association between network centrality of investors and both probability of survival of portfolio companies and their sales growth. Moreover, we show that there are differences in the impact of centrality on survival between different financing rounds. Syndication and networks of investors are an important correlate of portfolio companies' success in the seed stage, but less so for later financing rounds.

This work is structured as follows: Section 2 provides a brief overview of the literature relevant for this research. Section 3 presents our research questions. Section 4 describes data used in the empirical examination and the methodology. Section 5 presents the main results. Section 6 concludes the paper.

2. Theory and literature overview

Syndication and performance

Jääskeläinen (2012) reviewed aspects of syndication of venture capital firms. He concludes that while the venture-level aspects are relatively well understood, the current literature still lacks an understanding of how and why syndication affects the performance of VC firms. He suggests that more attention should be directed towards syndication as a component of the overall strategy of VC firms.

There are several channels, which could be responsible for the connection between syndication and performance. The seminal work of Lerner (1994) has put forward three rationales for venture capital syndication:

- Syndicating first-round investments may lead to better decisions regarding investing in firms. Another VC's decision to invest might be a signal to invest, as the "four-eyes principle" applies.
- Overcoming informational asymmetries. Syndication in later venture rounds may arise that is based on informational asymmetries between the initial venture investor and other potential investors. A venture capitalist who is involved in the firm's daily operations may exploit this informational advantage, overstating the proper price for the securities in the next financing round. The only way to avoid this opportunistic behavior

is if the lead venture capitalist maintains a constant share of the firm's equity. This implies that later-round financings must be syndicated (Admati and Pfleiderer, 1994)

· A mechanism through which venture capitalists exploit informational asymmetries and collude to overstate their performance ("window dressing"). Venture capitalists may make investments in the late rounds of promising firms, even if the financial returns are low. This strategy allows them to represent themselves in marketing documents as investors in these firms.

Wilson (1968) followed by e.g., Lockett and Wright (2001) suggest that syndication improves the firms' performance by diversifying their risks. They analyze another three hypothetical channels, for why VC firms syndicate investments:

1. The traditional finance perspective stressing the role of risk-sharing, which combines several rationales.
    - While market risk for listed companies can be more easily overcome trough portfolio diversification, it may prove more difficult in the case of ventures. Evidence suggests that small venture capital funds in particular, i.e. those more likely to invest in early stage deals, find it difficult to achieve optimal diversification (Murray, 1999). In order to achieve portfolio diversification, it may thus be necessary to syndicate investments, in particular, when these are large in comparison to the total size of the VC's portfolio.
    - As a result of illiquidity, it is more difficult in the short term to adjust a VC's portfolio by divesting 'lemons' if the risk of an investment turns out to be greater than initially thought. Hence, syndication provides a means of sharing risk on a deal-by-deal basis that may help to reduce overall portfolio risk (Lockett and Wright, 2001).
    - Finally, syndication may facilitate raising funds in the future. In order to do so, a VC firm may diversify their holdings in the current period.
2. The resource-based approach, stressing reduction of risk and improving selection.
    - At the deal selection stage, syndication has implications for adverse selection in two main ways. Syndication can reduce the potential for adverse selection if it changes the means by which an investment is made because it produces a greater range of analytical skills among investors. This argument goes along the lines of Lerner (1994)'s four-eyes principle for decisions. On the other hand, however, to the extent that syndication increases co-ordination costs and the time scales involved in decision making, risk may be increased if the necessary critical decisions are delayed during times of difficulty.

3. Finally, the deal-flow perspective, notices that it is important for venture capitalists to be in a position to compete for as many deals as possible so that they can make their investment selections from a wide supply of deals. The reciprocation of syndicated deals between VCs may mean that deal flow can be maintained even when an individual venture capital firm may not be the originator of the deal.

Lockett and Wright (2001) find, based on a survey of VC firms, that the finance perspective is the most important, but that the resource-based view can also matter, in particular at early stage investments. Following, they conclude, the reason for syndication, and thus expectation regarding the impact on performance, may differ depending on the stage of investments made.

Additionally, Ferrary (2010) argues that there is an implicit labor division between institutional venture capital investors in which pure venture capital firms are in charge of converting investment uncertainty into risk by funding the seed stage of start-ups. He argues, that this could be seen as a reason why pure VC firms take lead roles within syndications.

Somehow at odds with the view of Lockett and Writgh (2001), Werth (2014) concludes that accessing (complementary) resources appears to be the strongest incentive to syndicate, whereas deal sourcing and especially reciprocity considerations appear relatively weak syndication motives.

Brander et al. (2002) analyze the deal-selection channel, in which a second VC provided a valuable opinion and contrast it with the “value-added hypothesis”, that stresses complementary management skills of additional venture capitalists. According to Brander et al (2001), however, the most promising projects will be conducted as stand-alone investments, as in this case, the need for second opinion is limited. Moderately promising projects, on the other hand, will be syndicated. In contrast, the value-added hypothesis stresses that additional VC bring actual value to the project and raise its profitability. These two mechanisms yield contrasting predictions: if the selection hypothesis is correct, syndicated projects should have lower returns, if the value-added hypothesis is correct syndicated projects should have higher returns than standalone investments. Using Canadian data, the authors find evidence in favor of the second case that is higher returns for syndicated projects. Similarly, Tian (2011) finds improved performance of syndicated investments. First, VC syndication creates product market value for their portfolio firms. Further, VC syndicates nurture innovation of their portfolio firms and help them achieve better post-initial public offering operating performance. Second, VC syndication creates financial market value for their portfolio firms. As a result, VC syndicate-backed firms are more likely to have a successful exit, enjoy a lower initial public offering (IPO) underpricing, and receive a higher IPO market valuation. Das et al (2011) also find improved performance, measured by the investment returns, chances of successful exit, and the time taken to exit, of syndicated

investments. They show that much of the better performance can be ascribed to selection, with the value-addition by monitoring role significantly impacting the likelihood and time of exit. They conclude, therefore, that the two channels (selection and value addition) are complementary.

These results, however, have been countered by Casamatta and Haritchabalet (2007), who argue that while syndication can improve the screening process, it also requires the original VC to show a potentially lucrative deal to another VC, who could become a potential competitor for the deal. They show that having both screening skills and an ability to add value are necessary for syndication to occur in equilibrium, which in turn sheds new light on the argumentation of Brander et al (2001).

Following the deal-flow argument of Lockett and Wright (2001), Cumming (2006), and Sorenson and Stuart (2001) suggest, that syndication grants the VC firms with access to a larger number of investment possibilities. Sorenson and Stuart (2001) find, for instance, that while information about potential investment opportunities circulates within geographic and industry spaces and that the flow of information within these spaces contributes to the geographic- and industry-localization of VC investments, the social networks in the VC community - built up through the industry's extensive use of syndicated investing - diffuse information across boundaries and therefore expand the spatial radius of exchange. This may contribute to increased performance of the firms, through circumventing informational restrictions regarding most promising investments and increasing VC's scope of operations.

Hochberg, Ljungqvist and Lu, (2010) describe yet another mechanism for how syndication may affect performance. They analyze whether strong networks among incumbent venture capitalists in local markets help restrict entry by outside VCs, thus improving incumbents' bargaining power over entrepreneurs. They find that, more densely networked markets indeed experience less entry and that the VC firms benefit from reduced entry by paying lower prices for their deals.

The choice of syndication partners

Whether a VC firm can accomplish the goals of syndication, it matters greatly on what kind of syndication partners a firm is able to attract. A strand of research looked, therefore, not only at whether the VC firms syndicate their investments, but also who the typical syndication partners are. Lerner (1994) was one of the first to notice that top-tier firms tend to syndicate with each other, in particular in early financing rounds.

Du (2011) looked at this issue in more detail, looking at the virtues and vices of heterogeneity of syndication partners. She reasons that too much heterogeneity may be harmful, as it may make communication and coordination less effective (Van den Steen, 2004), resulting in slower actions and responses in the competitive environments (Hambrick, Cho, and Chen, 1996). On the other hand,

heterogeneous groups provide valuable learning opportunities for the group members in the long term. Heterogeneity may encourage group members to collect new information (Van den Steen, 2004), improve the group's problem-solving ability (Hoffman and Maier, 1961), and may lead to increased innovation within groups (Du, 2011). The overall effect is at least theoretically unclear.

She than continues with an empirical analysis and concludes that VCs have strong preferences for syndication partners that are similar to themselves (homophily). Specifically, syndicates are more likely to be formed among VCs with similar levels of experience and performance. Secondly, Du (2011) finds that companies funded by heterogeneous syndicates, in which VCs have different levels of performance, are less likely to have IPOs and sales to other companies, which capture performance of venture capital investments. Finally, and contrarily, she concludes that VCs, whose partners are more heterogeneous, are more likely to make new investments and diversify their investment portfolios, and eventually survive in the future.

At odds with the above logic, Hochberg et al (2011) finds little evidence for preference towards similar firms. They conclude that, there is little evidence of tie formation based on homophily. Rather, consistent with the finding that better networked, broader-scope firms are more likely to have a tie in the network and a larger breadth of ties overall, VC firms appear to link based on cumulative advantage (i.e., forming economic ties with the highest endowed available partner in order to accumulate the highest possible combined levels of resources) motives with respect to access and investment scope. Rather, the authors find clear evidence of resource sharing across linked firms. The quality of a match increases when one partner has more available capital and the other is more experienced, has greater access to deals, or greater investment scope.

In addition to the argument of Hochberg et al (2011), Manigart et al. (2006) find that portfolio management motives are more important for syndication than individual deal management motives for European companies (in contrast to the US). They further find that risk sharing, portfolio diversification, and access to larger deals are more important than selection and monitoring of deals, independent of being an early or later stage venture capital company.

Finally, Bubna et al (2019), look at the formation of communities. They conclude that VC firms tend to tend to draw from smaller groups of partners they call VC "communities." These communities form according to complex choices, with preferences for similarity on dimensions of functional style and preferences for the dissimilar on dimensions of size and influence. They find that different VC clusters represent different pools of expertise, consistent with syndicates competing through differentiation and specialization in such dimensions such as knowledge of industry and local geographic markets. The logic behind forming smaller communities can be drawn from the literature on learning-by-doing models of VC

investing (Goldfarb, Kirsch, and Miller (2007), Sorensen (2008)). VC investing is skill intensive. While some skills are endowed, others are acquired through learning-by-doing because VC-funded firms tend to have unproven business models. Syndicating with familiar partners can aid learning through better understanding of partners' norms and processes (Gertler (1995); Porter (2000)). Incomplete contracting theories, i.e., stressing the impossibility of foreseeing all possible contingencies, also generate a preference for familiar, trusted partners. In models such as Grossman and Hart (1986) or Hart and Moore (1990), the suspicion that partners will free ride or hold up initial investors (i.e., refraining from a profitable cooperation because of concerns that they may give the other party increased bargaining power, and thereby reduce their own profits), lowers investment. These problems are alleviated when partners know each other. Familiarity can lead to better outcomes by enhancing trust and reciprocity (Guiso, Sapienza, and Zingales (2004), Bottazzi, Da Rin and Hellmann (2011)).

Properties of networks among VC firms

A more sophisticated analysis of the syndication – performance nexus requires a closer look at the actual structure of the syndication networks. To this end, researchers looking at venture capital have started using the standard tools of sociological network analysis.

As mentioned above, Sorenson and Stuart (2001) suggest, that syndication grants the VC firms with access to a larger number of investment possibilities. Yet, it is of vital importance, what the actual position in the network a firm have. They argue, thus, that VCs in pivotal or axial positions within a network manage to invest in more distant companies.

Hochberg et al (2007) construct a measure of network centrality aimed measuring five different aspects of VC firm's influence: the number of VCs with which it has a relationship, as a proxy for the information, deal flow, expertise, contacts, and pools of capital it has access to; the frequency with which it is invited to coinvest in other VCs' deals, thereby expanding its investment opportunity set; its ability to generate such co-investment opportunities in the future by syndicating its own deals today in the hope of future payback from its syndication partners; its access to the best-connected VCs; and its ability to act as an intermediary, bringing together VCs with complementary skills or investment opportunities that lack a direct relationship between them. They conclude that better-networked VC firms experience significantly better fund performance, as measured by the proportion of investments that are successfully exited through an IPO or a sale to another company. Similarly, the portfolio companies of better-networked VCs are significantly more likely to survive to subsequent financing and eventual exit.

3. Research questions

Following these theoretical considerations, we want to address several research hypotheses. Firstly, there is a theoretical reason to believe, that syndication of investments has a positive impact on survival of portfolio companies. We address this question using network analysis as described further on. Secondly, we look at whether significant differences exist between different stages of financing, when it comes to the effects of syndication. Finally, we look at sales growth following the VC deal.

Following the literature, we believe that syndication plays an important role for the success of companies also in Europe. While European markets are less developed than the American ones, and venture capital is less developed here, there is no reason to believe that the structure of the industry should be entirely different.

Hypothesis 1: Network centrality of investors positively affects the survival of portfolio companies.

We have shown in the previous section, that there are various reasons for syndication, and these differ also between early and growth stages. In early stages, it is crucial to have knowledge about the portfolio company's specific characteristics, such as the team and the technology developed, and to foresee a market fit. A strong lead investor in an early stage must be able to evaluate these and should additionally be able to assist the company in business development and operations. Investors of this kind would typically be partners at VC firms with vast experience or business angels. Their role is extremely important, as they provide a lot of knowledge and support, which could be crucial for the success of the company.

Conversely, at growth stages, the entrepreneurs have already proven their capability of building a company and developing a product or a technology, for which there is market demand. Thus, the role of growth-stage investors is generally less crucial. They mainly provide capital for growth, but generally not question the need for the product or existence of market demand. When forming a syndicate at a growth stage, the investment team must be able to provide capital for up to a late stage (i.e., IPO), and thus risk-sharing plays an important role. Growth-stage investors are more like investment bankers. We hypothesize, that the central role of a central investor is of less importance for success compared to the early stage.

Hypothesis 2: Network centrality of investors is more strongly associated to success in early stage compared to growth investments.

Similarly to a measure of survival, we expect network properties of investors to be associated with sales growth. Following argumentation and empirical results for the US of Hochberg et al (2007), we expect portfolio companies to perform better, in terms of sales, if backed by a well-connected investor. Moreover,

drawing upon the literature on selection effects, we expect the differences in performance even before the deal, as the best-connected VCs invest in companies, which have been performing better and have a higher potential for the future.

Hypothesis 3: Network centrality of investors positively correlates with sales growth of portfolio companies.

4. Data and Methods

Network Analysis Methodology

Network analysis aims to describe the structure of networks by focusing on the relationships that exist among a set of economic actors. A key aim is to identify influential actors. Influence is measured by how "central" an actor's network position is, based on the extent of their involvement in relationships with others (Hochberg et al. 2007). Network analysis formalizes the concept of centrality and develops several measures, which help identify key actors in a network. In this work we use two concepts of centrality: eigenvector centrality and betweenness. Although a node that is central by one measure is often central by several other measures, this is not necessarily always the case.

Eigenvector centrality measures the number of relationships a VC firm in the network has. The more ties, the more opportunities for exchange and so the more influential, or central, the actor. It assigns relative scores to all nodes in the network based on the concept that connections to high-scoring nodes contribute more to the score of the node in question than equal connections to low-scoring nodes. Unlike degree centrality, it does not only consider the number of nodes to which one is connected, but also their importance. The main principle is that links from important nodes (as measured by degree centrality) are worth more than links from unimportant nodes. Technically, eigenvector centrality scores correspond to the values of the first eigenvector of the graph adjacency matrix; these scores may, in turn, be interpreted as arising from a reciprocal process in which the centrality of each actor is proportional to the sum of the centralities of those actors to whom he or she is connected. In general, vertices with high eigenvector centralities are those which are connected to many other vertices which are, in turn, connected to many others (and so on). Since the centrality depends on the size of the clique, which in turn, depends on the overall size of the network, which might be changing over time and is different in different countries, the score needs to be normalized.

VCs that have ties to many other VCs may be in an advantageous position. Since they have many ties, they are less dependent on any one VC for information or deal flow. In addition, they may have access to a wider range of expertise, contacts, and pools of capital (Hochberg et al 2007). In the VC context, eigenvector centrality shows not only that a particular investor has many co-investors, but that she has many

important co-investors (co-investors with multiple syndicated partners), who themselves play an important role in a network.

Betweenness, on the other hand, attributes influence to actors on whom many others must rely to make connections within the network. It is roughly defined as the number of shortest paths (geodesics) going through a vertex. Vertices with high betweenness may have considerable influence within a network by virtue of their control over information passing between others. They are also the ones whose removal from the network will most disrupt communications between other vertices because they lie on the largest number of paths taken by messages.

Betweenness measures a degree to which a VC firm may connect or bring together other VCs with complementary skills or bringing together investment opportunities, which otherwise would lack a direct relationship. It also measures a degree to which a particular VC is able to control the information flow between other VCs active in a market. It also needs to be normalized.

Figure 2 shows the eigencentrality and betweenness of Austrian VC firms as an example. The colors represent centrality measures, in which red means low centrality and green means high centrality

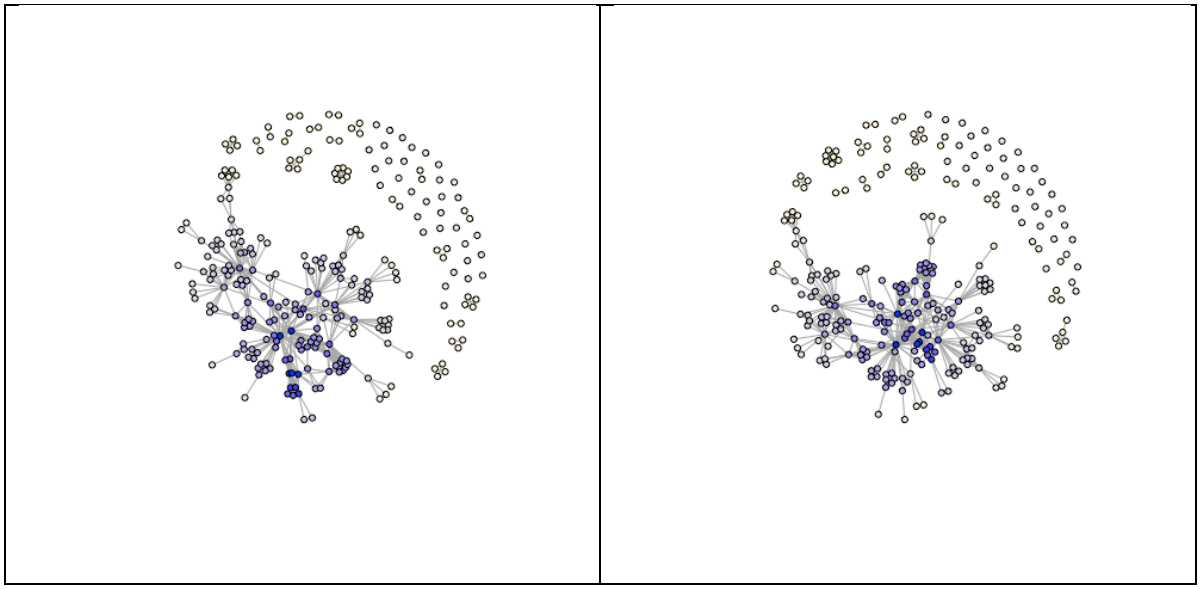


Figure 2: Betweenness (left panel) and eigenvector centrality (right panel) of Austrian VC firms (color scale in square roots for the purpose of visualization).

While the two measures are correlated at 0.66 in the whole sample (at 0.79 for Austria) there are indeed visible differences. Relatively speaking, betweenness is much less equally spread compared to eigencentrality, meaning that only a few VCs control important connections. Regarding eigenvector centrality,

we can see a clear distinction between the “core” and the “periphery”. The core consists of fairly equally connected VCs, and the periphery consists of single investors with no relevant contacts.

Looking back at the theoretical explanation for why syndication is important for VC success, we can connect the network measures with the particular network analysis tools presented. As stressed by Hochberg et al (2008), an ability of a VC to act as an intermediary, bringing together VCs with complementary skills or investment opportunities that lack a direct relationship between them is an important aspect of syndication. This aspect can be captured by the betweenness measure: VCs with high betweenness are the ones, who are in best positions to act as middlemen joining investment partners.

On the other hand, the traditional financial perspective underlines the role of capital pooling and risk sharing, and the deal-flow perspective stresses syndication as a vehicle to get access to best deals; both aspects are determined by the access to the most important and best-connected VCs. This can be captured by eigencentrality, which measures how well connected a particular VC is.

The problem, which remains, is that most network measures, in particular the ones we use, might be highly correlated. While the theoretical distinction of diverse aspects of syndication is straightforward, separate empirical investigation of the two aspects proves difficult, due to above-mentioned correlation. Finding a solution to this issue is beyond the scope of this work and will be addressed in further work.

Data

The main data source is the Preqin database. The Preqin database encompasses comprehensive information about diverse aspects of global venture capital markets. In particular it contains information about 6,300 investors worldwide, more than 110,000 venture capital deals starting from 2007 and more than 50,000 buyout deals. Moreover, it contains detailed information on 10,000 fund managers, in particular about their background, investment criteria, funds raised, and key contacts. Each entry consists of a particular deal, in which the portfolio company is identified together with all investors, who took part in this deal. The size of the deal and total known funding of a portfolio company are also given. Some descriptive statistics about the deals are given in Table 1

Table 1: Descriptive statistics of the main variables in the deal dataset

	N	Mean	Median	St.Dev	Min	Max
Financing Rounds	23423	1.432	1	2.256	0	13
Syndicate Size	23423	3.958	3	3.171	1	24
Deal Size EUR Mio	19731	11.577	5	27.258	.01	660
Known Funding EUR Mio	21378	39.646	12	115.747	.01	1789.62

Syndicated	23423	.795	1	.404	0	1

Portfolio firms survive on average 1.4 financing rounds, with a median of 1. On average about 4 investors are involved in a deal, with a median of 3, showing slight positive skewness. The smallest deals in the sample are of 100.000 EUR while the largest is 660 Million EUR. The latter is the secondary stock purchase of Delivery Hero AG by Naspers Ventures. The largest known funding of a portfolio company of almost 1.8 billion EUR went to Spotify AB, with a largest deal of 466 Million EUR of Series G financing by, among others, the Coca-Cola company and its co-investors. Almost 80% of the deals are syndicated, that is involve more than one investor. The largest syndicate consists of 24 investors.

We use data for the years 2010 to 2016. The number of deals during this period has been on a constant rise, starting with 2406 in year 2010, and rising to 4451 in 2016. The number of deals has almost doubled within six years, which shows that the VC industry is on a steady rise, becoming a relevant factor for the general economic development. The total number of deals in the sample is 24,400.

Preqin data also include information about network characteristics of the investors and syndicates. Here we present some basic descriptive statistics. For visualizations and further information such as programs and interactive figures, please visit the online Appendix at the website of this project (Link).

Table 2: Descriptive Statistics of network measures.

Measure	**Number of Obs**	**Mean**	**Median**	**Std. Dev**
Eigencentrality	7,353	.0002506	.0007747	.0012611
Betweenness	7,353	.0071267	.0000005	.0378612
Eigencentrality (excluding zeroes)	7,009	.0074765	.0009466	.0387455
Betweenness (excluding zeroes	4,289	.0004296	.0000163	.0016278

What is typical for the venture capital scene, is also visible if we look at the network measures. Both measures are characterized by a strong skewness, with a few large investors with many connections, and many small investors who do not have many ties. This is particularly visible, if we exclude the zeroes. For the betweenness measure over 40% of investors have a value of zero, meaning that no shortest path goes through such a node. These nodes connect no other nodes and have therefore no impact on the deal flow

or similar. For eigencentrality, the discrepancy is less visible, with only about 5% of investors not having any connections.

These data are combined with firm information from the Orbis database. We look at the development of sales in the years 2010 to 2019 (or respectively the last available year if the company closed operations). For Western Europe 6347 companies and for Nordic countries 780 companies were found in the database, which have been matched with the deal data. Development of sales is measured as a logarithm of the absolute growth, that is e.g. $log(sales_t)$-$log(sales_{t-1})$. To assess the quality of the deal data from the Preqin database, we compared it to ownership changes after the respective dates and found no large discrepancies.

Methodology of estimation

We look at two aspects of how syndication and centrality of investors affects the performance of companies. First, we analyze whether centrality of investors has an impact on survival of companies, in which we define survival as reaching follow up financing rounds, as described in more detail below. Secondly, we look at the development of companies' sales growth following the VC deals and dependent on centrality of the investors.

Survival

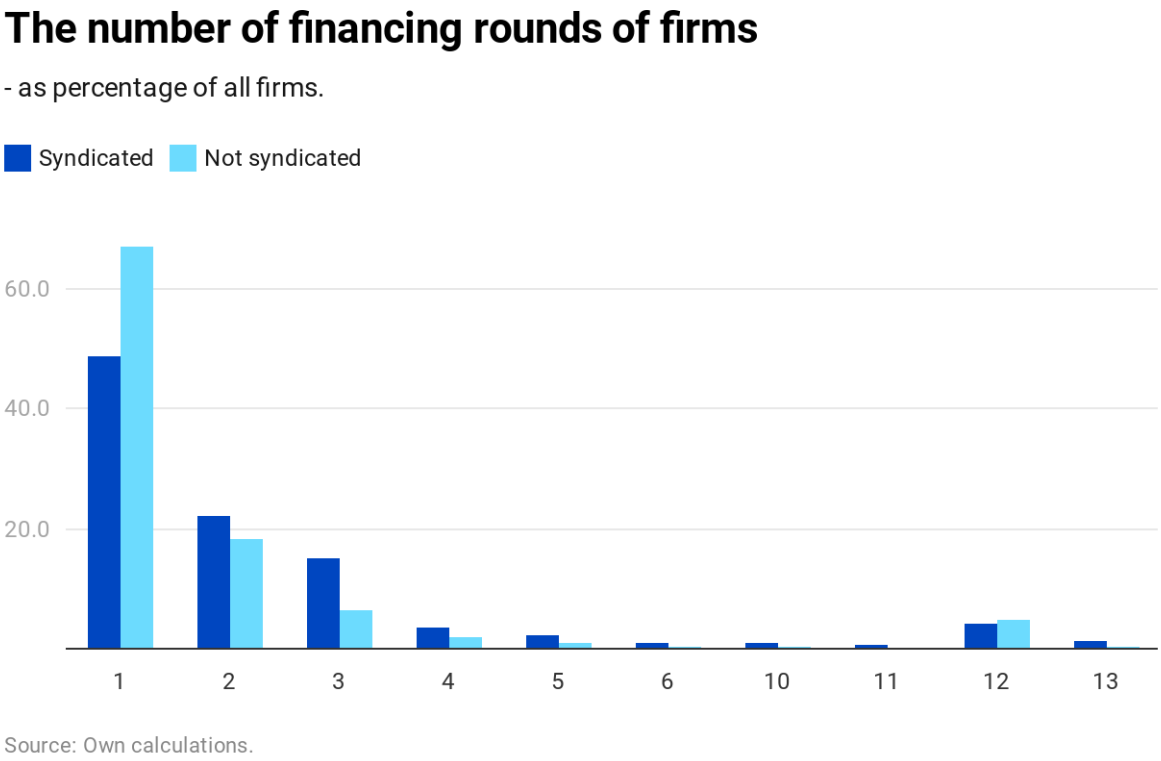
Given the literature linking the performance of funds and companies to networks of VC firms, we shall analyze whether properties of syndicates affect the survival rates of portfolio companies. We define survival of a portfolio company at the probability of obtaining one more round of financing. Our dataset includes information about the following financing rounds: Add-on, Angel, Grant, Growth Capital/Expansion, Merger, PIPE, Pre-IPO, Secondary Stock Purchase, Seed, Series A/Round 1, Series B/Round 2, Series C/Round 3, Series D/Round 4, Series E/Round 5, Series F/Round 6, Series G/Round 7, Series H/Round 8, Series I/Round 9, Series J/Round 10, Series K/Round 11, Unspecified Round, Venture Debt

Most of these can be arranged in a logical fashion, indicating a growth of the portfolio company, with the following exceptions: Add-On and Growth funds can be granted at any stage of the portfolio company's lifecycle; Grant, Venture Debt and Unspecified Round will be excluded. The other financing rounds are arranged as follows:

Angel, Seed, Series A/Round 1, Series B/Round 2, Series C/Round 3,Series D/Round 4, Series E/Round 5, Series F/Round 6, Series G/Round 7, Series H/Round 8, Series I/Round 9, Series J/Round 10, Series K/Round 11

each receiving a value of between 1 (first round) and 13 (second to last round). Finally, any of the events: Merger, PIPE, Pre-IPO, and Secondary Stock Purchase is valued as the ultimate success of a company and given a value of 14. The measure of survival involves a relative number of financing rounds a firm has received. Since some companies receive their first financing round at a later stage than seed (an average portfolio firm in the database starts with a Series A financing), we calculate in each case the number of rounds a company has survived starting from its first round. A histogram of survival is presented in Figure 3.

Figure 3: The number of financing rounds survived by firms



Source: Own calculations.

As can be observed, almost 50% of the portfolio companies receive only one round of financing by syndicated investors. This number is much higher, almost 70% for non-syndicated investments. About 20% survive at least one round, that is receive a second round: 22% of syndicated and 18% of non-syndicated investments. A large difference can be observed for three rounds with more than 15% of syndicated investments receiving three rounds of financing as opposed to only 6 percent of non-syndicated. Subsequently the numbers drop further, with a slight increase in probability of survival of about 12 to 13 rounds, which corresponds to companies with successful exits (e.g. Merger or pre-IPO financing), as defined above. The overall fraction of companies, which survive until the final round is lower than 3 percent, within

the observed time frame. Visually, the probability of surviving financing rounds seems to be higher for syndicated investments, as expected.

There are several ways, in which we can estimate the probability of survival. The easiest way is to define the number of survived rounds per company as a count outcome variable, and estimate a count panel model, such as a panel Poisson regression or a panel negative binomial regression. Parametric models, such as a Poisson model, however, assume a constant hazard rate over time. On the other hand, a Cox's proportional hazards model, which will be used as a robustness check, makes no parametric assumptions about the baseline hazard. Both models assume that the hazards to be proportional for units of observation (in our case portfolio companies) with different values of explanatory variables. Alternatively, similarly to Hochberg et al (2007) we can estimate a (panel) binary outcome model (a probit or a logit model), in which we define as binary variables the fact whether a portfolio company survived to round N, conditional on surviving to round N-1. That is, for first round financing, 1 means surviving the first round, while 0 corresponds to not surviving. This specification will also be used as a robustness check.

A standard Poisson regression takes the form

$$log(E(Y|x))=\theta'x,$$

where x is a vector of independent variables. This corresponds to

$$E(Y|x)=exp(\theta'x),$$

defining the predicted mean of the Poisson distribution. The model can be estimated by numerical maximum likelihood methods. A drawback of Poisson estimation is that the mean is assumed to equal the variance, an assumption which might be too restrictive in case of over-dispersed data. It can be relaxed by estimating a negative binomial model instead. In the panel variant of the Poisson regression, we can use random or fixed effects at a company level, to account for unobservable company characteristics. We also use company level clustering of standard errors, to account for the fact, that investments in each company have correlated characteristics (each partner reveals less additional information about the deal).

The main variables of interest are the measures of network characteristics for each financing round. We use two basic measures of VC firms' centrality as the main variables of interest: the eigenvector centrality and betweenness, both measuring an "importance" of the VC company in the network, as described in the Methodology section.

Alternatively, instead of adding the network characteristics of all syndicated partners, we could concentrate on the "lead" or most central investors. While we do not have detailed information about the initiators of the deals, we approximate a lead position by the highest measure of centrality. Thus, in an

alternative specification, we explain the survival rates by the centrality measures of the syndication partner, with the highest measure only - shortly called “Leader” in the Results section.

Further variables, which might affect the performance of portfolio companies and to which we have access in the database will be added. Firstly, we add the absolute size of the syndication network in each round as an explanatory variable. According to the complementary-skills interpretation, simply a larger number of syndication partners may improve the performance of the portfolio company, which gains access to diverse sources of know-how and management practices. Secondly, specific location and industry of the portfolio company are likely to affect its survival chances. Thus, we add fixed effects for 16 countries and 74 broadly defined industries, e.g., Software, Telecoms, Medical Technologies etc. Finally, the performance of the company is likely to correlate with the overall financing it received, while in this case the causality is likely to run in the opposite direction, as more successful firms receive more financing. The total known funding of a portfolio company is added as a correlate of survival in the model.

Performance

To analyze the development of sales, we employ an event study methodology. For each company, we code as time=0 the event of a deal. In case of subsequent deals, each is coded as 0. Other observations in the data are than coded relative to this event, e.g., sales one year after the deal, two years after the deal etc. Since we are specifically interested in how the structure of the deal – syndication or centrality of partners – affects the development, we interact these measures with the time before and after the event. The estimated equation has the form:

$$log(sales_{t,i}) - log(sales_{t-1,i}) = \sum_{n=-N}^{n=N} \gamma \times I_n + X_{t,i} + YE_t + u_{i,t}$$

where n=1,2,3,… is the index denoting years before or after the deal (year 0 is the normalization year), γ is the measure of centrality, *X* is a vector of further control variables, *YE* are the year effects capturing overall macroeconomic trends affecting the whole sample, and *u* is the error term.

As opposed to the analysis of survival, we need to aggregate the data to match yearly observations on sales and employee growth. This means, that the data now has a panel structure of company-year form. Since the actual deals are given in daily format, we assume a balance sheet reporting day to be the end of the year on all countries. We calculate the number of months between the deal and the reporting day and summarize them into years, whereas anything below 12 months Is the Year 0, 12 to 23 months is Year 1 and so on. For each deal, we look at the centrality or betweenness of the lead investor as the main variable of interest. Additional control variables are country effects (industry effects cannot be added as the sample is

too small), total known funding, and the size of the syndicate for each deal. The models are estimated on an unbalanced panel of about 2,700 observations.

5. Results

Survival

Table 4 presents four different specification of the panel Poisson regressions: including eigenvector centrality and betweenness of all partners in a round, or of a VC firm with the highest value, respectively. All models include portfolio company random effects and standard errors clustered at company level. Industry and country fixed effects are not reported for the sake of readability but are available upon request.

Table 4: Panel Poisson regressions.

	(1)	(2)	(3)	(4)
Syndicate Size	0.00***	0.00***	0.00***	0.00***
	(2.73)	(2.74)	(2.87)	(2.81)
Total Known Funding (EUR Mio)	0.02***	0.02***	0.02***	0.02***
	(10.82)	(10.82)	(9.30)	(9.39)
Eigenvector	0.00*			
	(1.83)			
Betweenness		0.00**		
		(2.16)		
Leader Eigenvector			0.16***	
			(5.36)	
Leader Betweenness				0.21***
				(5.75)
Constant	-1.15***	-1.15***	-1.21***	-1.24***
	(-2.79)	(-2.79)	(-2.80)	(-2.78)
Observations	18507	18507	18507	18507

Panel Poisson regressions with portfolio-company random effects; not reported: industry and country fixed effects; standard errors clustered at portfolio-company level; Z-statistics in parentheses; significance: * 0.1, ** 0.05, *** 0.01

The results presented in Table 4 suggest that all chosen measures of network centrality are positively associated with survival of portfolio companies. The strongest results are found in Columns 3 and 4, in which we report the estimations including the network measures for the most central partner only. Since the variables are standardized, the results can be interpreted as follows: a one standard deviation increase in the eigenvector centrality of the leader in the syndicate is correlated with an increase in the probability of surviving one more round of financing by exp(0.16).173, that is about 17.3 percent. A one standard deviation increase in the betweenness of the leader s correlated with an increase in the probability of surviving an additional financing round by exp(0.21).233, that is about 23.3 percent. These results are, thus, not only statistically significant but also of high economic significance. While we observe significant correlations also in the first two columns, the size of the coefficients is much smaller in this case.

As expected, both the total known funding and the absolute size of the syndicate positively correlate with the survival chances of portfolio companies. As a first robustness test, we show in the Appendix the results of probit regressions, in which the depend variable is defined as a binary of whether a company has survived at least one round of financing, or conditional on surviving one round, whether it has survived two rounds. The results are presented in Tables 7 and 8 in the Appendix and show consistent significant correlation between the centrality measures of the most central investor and the survival chances of the portfolio companies. They also stress that the most robust results are obtained for the characteristics of the central investment partner, and not necessarily of all partners. The latter result suggests that it is the central role of the leader, as a connecting agent between different VCs, which is crucial for the success of the portfolio company.

Early stage versus Growth Investments

Secondly, we look at the question of whether there is a differential effect of network centrality on the portfolio firm's performance depending on the stage of financing. In this, we split the sample into early-stage vs. growth-stage investments. Early-stage investments are angel and seed rounds, while all other rounds are considered growth-stage investments. We construct an Early dummy equaling 1 if an angel or seed round is considered and we interact this dummy with the network centrality measures. The results of this empirical exercise are reported in Table 5.

Table 5: Interaction between the centrality measures and early-stage investments.

	(1)	(2)	(3)	(4)
Early=1	-0.07**	-0.07**	-0.10***	-0.10***
	(-2.55)	**(-2.56)**	(-2.78)	(-2.88)
Syndicate Size	0.00**	0.00**	0.00*	0.00
	(2.00)	(2.04)	(1.70)	(1.38)
Total Known Funding (EUR Mio)	0.02***	0.02***	0.02***	0.02***
	(10.50)	(10.51)	(9.09)	(9.21)
Eigenvector	0.00			
	(0.17)			
Early=1 # Eigenvector	0.03**			
	(2.17)			
Betweenness		0.00*		
		(1.68)		
Early=1 # Betweenness		0.01		
		(1.41)		
Eigenvector Leader			0.15***	
			(5.01)	
Early=1 # Eigenvector Leader			0.03***	
			(2.82)	
Betweenness Leader				0.20***
				(5.36)
Early=1 # Betweenness Leader				0.03***
				(2.75)
Constant	-1.12***	-1.12***	-1.17***	-1.21***
	(-2.72)	(-2.72)	(-2.72)	(-2.73)
Observations	18507	18507	18507	18507

Panel Poisson regressions with portfolio-company random effects; not reported: country fixed effects; standard errors clustered at portfolio-company level; Z-statistics in parentheses; significance: * 0.1, ** 0.05, *** 0.01

As we can observe, and in accordance with our hypotheses, success of early-stage investments is more strongly associated with the centrality of the investors. While early-stage investments generally have a lower probability of surviving to additional financing rounds (coefficient of -0.07 or -0.10, highly significant) in all specifications, centrality positively correlates with survival, and more so in early-stage. One-standard deviation increase in the eigenvector centrality of the investment leader increases the probability of surviving an additional round by exp(0.015)=16.2% on average. An additional exp(0.03)=3 percentage points are added if we consider early-stage investments only. In three out of four specifications this coefficient is highly statistically significant. While this result is generally consistent with the theoretical consideration about the importance of VC firms at different stages, there is an additional aspect, which needs to be discussed. VC investors reporting the deals to the data provider might have wrong incentives when it comes to classifying a particular deal. Since performance of funds is affected by early-stage deal conversions, later-stage or bridge financing might be classified e.g., as series A. Moreover, generally speaking classification of deals is something, which might be subject to interpretation, and different VC firms might have a different classification in mind. We acknowledge this issue while interpreting our results.

Our data does not allow us to determine, whether are qualitative differences in the importance of the leader. As we described in the Hypotheses section, there are not only quantitative differences between the

importance of centrality in early vs later stages, but that the rationales behind could be different: early-stage networks are more about the need for complementary skills of partners, information flow and value-added, later stage investment syndication is likely more in line with the traditional finance perspective, i.e., risk sharing. The first rationale would be mirrored in importance of betweenness, will the second rather by eigenvector centrality. Unfortunately, as mentioned in the methodology section, without further information, we are not able to distinguish between these within the scope of this work, and we leave this interesting starting point for future research.

Performance

Table 6 presents the development of sales growth dependent on the eigencentrality/betweenness of the lead investor (maximum centrality in the syndicate).

Table 6: Sales growth and maximum centrality measures.

	(1)	(2)	(3)	(4)
Sales at -1	-0.04**	-0.04**	-0.04**	-0.04**
	(-2.36)	(-2.34)	(-2.39)	(-2.39)
(log) Deal Size	0.01	0.02	0.01	0.02
	(0.75)	(0.71)	(0.75)	(0.67)
Syndicate Size	-0.01	-0.01	-0.01	-0.01
	(-0.75)	(-0.56)	(-0.78)	(-0.66)
Total Known Funding	0.00***	0.00*	0.00***	0.00*
	(2.64)	(1.79)	(2.82)	(1.90)
Centrality	-1.17*	-1.17**		
	(-1.94)	(-2.24)		
Year -2=1	-0.20	-0.15	-0.26	-0.20
	(-1.03)	(-0.86)	(-1.23)	(-1.01)
Year -2=1 # Centrality	1.31*	1.24*		
	(1.66)	(1.75)		
Year -1=1	-0.08	-0.09	-0.12	-0.12
	(-0.40)	(-0.50)	(-0.55)	(-0.59)
Year -1=1 # Centrality	0.61	0.69		
	(0.80)	(1.08)		
Year 1=1	-0.42**	-0.41**	-0.51**	-0.50***
	(-2.28)	(-2.42)	(-2.50)	(-2.61)
Year 1=1 # Centrality	1.25**	1.16**		
	(2.06)	(2.17)		
Year 2=1	-0.49***	-0.50***	-0.60***	-0.59***
	(-2.71)	(-2.93)	(-2.94)	(-3.09)
Year 2=1 # Centrality	1.32**	1.27**		
	(2.13)	(2.38)		
Year 3=1	-0.59***	-0.57***	-0.65***	-0.62***
	(-3.09)	(-3.19)	(-3.03)	(-3.03)
Year 3=1 # Centrality	1.07	1.03*		
	(1.63)	(1.76)		
Year 4=1	-0.61***	-0.61***	-0.66***	-0.64***
	(-3.13)	(-3.28)	(-3.05)	(-3.13)

Year 4=1 # Centrality	1.14	1.13*		
	(1.52)	(1.74)		
Year 5=1	-0.72***	-0.71***	-0.80***	-0.79***
	(-3.28)	(-3.30)	(-3.23)	(-3.22)
Year 5=1 # Centrality	1.08	1.06*		
	(1.56)	(1.72)		
Betweenness			-36.45**	-33.31**
			(-2.21)	(-2.14)
Year -2=1 # Betweenness			34.65*	30.21
			(1.77)	(1.60)
Year -1=1 # Betweenness			22.46	20.96
			(1.18)	(1.18)
Year 1=1 # Betweenness			40.14**	36.84**
			(2.37)	(2.32)
Year 2=1 # Betweenness			42.71**	39.20**
			(2.50)	(2.43)
Year 3=1 # Betweenness			31.17*	26.85
			(1.75)	(1.58)
Year 4=1 # Betweenness			30.24	26.58
			(1.58)	(1.50)
Year 5=1 # Betweenness			35.84*	33.47*
			(1.87)	(1.84)
Constant	0.74***	0.78***	0.82***	0.85***
	(2.97)	(2.96)	(3.09)	(3.06)
Observations	2570	2570	2570	2570
Model	OLS	RE	OLS	RE
Country Effects	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes

Due to the multiple interaction terms, it is difficult to recognize the effect of centrality. Therefore, we present the marginal effects at different levels of centrality and at different years in Tables 7 and 8 and Figure 4.

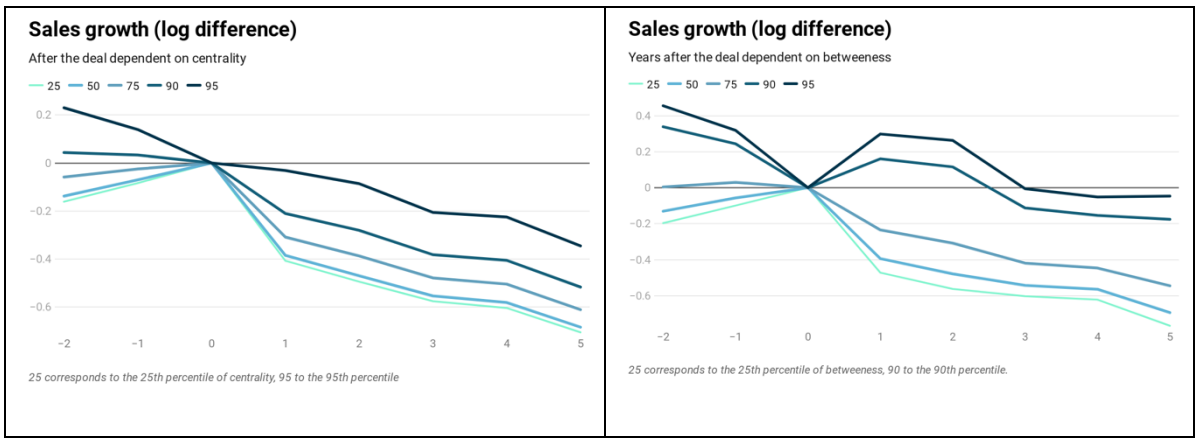
Table 7: Growth of sales dependent on maximum centrality (marginal effects)

	Year	25	50	75	90	95
b	-2	-0,16119	-0,13780	-0,05861	0,04366	0,22992
se	-2	*0,02872*	*0,02661*	*0,02176*	*0,02070*	*0,03390*
b	-1	-0,08344	-0,07010	-0,02502	0,03322	0,13930
se	-1	*0,02872*	*0,02649*	*0,02091*	*0,01824*	*0,02650*
b	1	-0,40705	-0,38458	-0,30848	-0,21019	-0,03121
se	1	*0,02723*	*0,02536*	*0,02052*	*0,01770*	*0,02254*
b	2	-0,49407	-0,46966	-0,38705	-0,28034	-0,08602
se	2	*0,02691*	*0,02505*	*0,02027*	*0,01753*	*0,02250*
b	3	-0,57565	-0,55352	-0,47862	-0,38187	-0,20569
se	3	*0,03000*	*0,02777*	*0,02197*	*0,01843*	*0,02350*
b	4	-0,60377	-0,58110	-0,50438	-0,40529	-0,22484
se	4	*0,03235*	*0,03019*	*0,02512*	*0,02365*	*0,03572*
b	5	-0,70514	-0,68362	-0,61075	-0,51663	-0,34524
se	5	*0,04337*	*0,04032*	*0,03201*	*0,02585*	*0,02791*

Table 8: Growth of sales dependent on maximum betweenness (marginal effects)

	Year	25	50	75	90	95
B	-2	0,19659	0,13056	0,00422	0,33850	0,45496
se	*-2*	*0,03448*	*0,02643*	*0,02060*	*0,06761*	*0,10456*
B	-1	0,09920	0,05686	0,02957	0,24395	0,31863
se	*-1*	*0,03541*	*0,02683*	*0,01871*	*0,05296*	*0,08310*
B	1	-0,47185	-0,39383	-0,23455	0,16048	0,29811
se	*1*	*0,03270*	*0,02538*	*0,01789*	*0,04258*	*0,06565*
B	2	-0,56215	-0,47855	-0,30787	0,11542	0,26290
se	*2*	*0,03225*	*0,02501*	*0,01790*	*0,04482*	*0,06911*
B	3	-0,60267	-0,54221	-0,41876	-0,11262	-0,00595
se	*3*	*0,03675*	*0,02812*	*0,01901*	*0,04577*	*0,07162*
B	4	-0,62169	-0,56395	-0,44606	-0,15369	-0,05183
se	*4*	*0,03786*	*0,02988*	*0,02289*	*0,05960*	*0,09047*
B	5	-0,76661	-0,69367	-0,54474	-0,17541	-0,04673
se	*5*	*0,05403*	*0,04226*	*0,02794*	*0,04873*	*0,07482*

Figure 4: Sales growth after the deal dependent on maximum centrality (left panel) and betweenness (right panel)



Several observations can be made. Firstly, sales generally grow in the years 1 to 5 more slowly than before the deal and in the deal year. This is a bit surprising but can be explained with organizational growth and less focus on pure sales as in the very early day of a venture. Secondly, the growth of sales depends on the centrality or betweenness of the lead investor. Starting from year one after the deal, sales grow more slowly when the betweenness is below the 90th percentile, while for the cases when the investor is at the top 10%

of betweenness, sales grow more quickly than in the deal year, and the growth rate does not drop over time - in contrast quicker growth can be observed in one and two years after the deal has taken place. Thirdly, quicker growth can be observed for the deals with investors who have high centrality even before the deal. This suggests that selection of deals is an important aspect of good performance of those portfolio companies.

The results suggest the following: The main driver for good investments is a selection effect rather than a value-added effect. Good VCs choose good companies or vice versa. Well-connected VCs not only choose better performing companies but also simply have access to more good deals because of their strong network. The effect of a strong VC firm adding more value could still be there, but our results do not show this.

Similarly, we can look at the network properties of the whole syndicate, in which we take the average measures of centrality of the members of the syndicate as a variable of interest. Results are presented in Tables 11 to 13 and Figure 5 in the Appendix and mainly serve as a robustness check for the main specification, since it is less prone to effects of outliers. Results are very similar and qualitatively comparable.

5. Conclusions

Summarizing our main results, three conclusions can be reached. Network characteristics of syndicate leaders are an important driver of success of portfolio companies. While our empirical methodology does not allow any causal statements, the theoretical considerations strongly suggest that the correlation indeed masks a causal channel. We find that both betweenness and eigenvector centrality correlate significantly with the success of portfolio companies. Secondly, centrality seems to be a more important factor of success at an early investment stage rather than later on. This tells us that the level of trust in the central investor is a much more important factor of success for early-stage investments rather than those in later rounds.

Regarding, the performance of companies, we see that investors with a better network create better companies than others. While according to literature, this could be due several reasons (selection, adding value, etc.), our results suggest that the main driver for this is the selection effect rather than value-added effect.

Several questions remain open. Firstly, with our data, we are not able to distinguish between potentially different rationales for the empirical regularities. Both betweenness and eigencentrality seem to correlate with the success of companies, and both can be linked to theoretical considerations. Since these measures correlate strongly, we cannot distinguish between them solely on the basis of our data and without further information. Secondly, differences between early-stage and growth phases should be addressed using surveys among funds and companies, to shed more light on the qualitative differences of investor decisions at different stages of syndicated investments. Finally, more research is needed to look at the kind of selection effect taking place when well-connected VC firms invest in well-performing companies. Are well-connected VC firms also better a choosing the best possible deals from the pool available or is it because a strong network increases the deal flow?

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Appendix: Additional Tables and Figures

Table 9: Probit model for the probability of surviving at least one round.

	(1)	(2)	(3)	(4)
Syndicate Size	0.05	0.15***	0.18***	0.13***
	(1.11)	(5.14)	(5.97)	(4.10)
Total Known Funding (EUR Mio)	0.02***	0.02***	0.03***	0.02***
	(26.30)	(24.39)	(36.77)	(30.72)
Eigenvector	0.08			
	(0.97)			
Betweenness		0.08		
		(1.27)		
Leader Eigenvector			0.55***	
			(6.78)	
Leader Betweenness				0.60***
				(11.26)
Constant	-7.98***	-2.99*	-2.43***	-2.55***
	(-6.39)	(-1.83)	(-2.67)	(-2.71)
Observations	19300	19300	19300	19300

Panel Probit regressions with portfolio-company random effects; not reported: industry and country fixed effects; Z-statistics in parentheses; significance: * 0.1, ** 0.05, *** 0.01

Table 10: Probit model for the probability of surviving at least two rounds.

	(1)	(2)	(3)	(4)
Syndicate Size	-0.16***	-0.19***	0.00	-0.01
	(-4.07)	(-5.30)	(0.01)	(-0.23)
Total Known Funding (EUR Mio)	0.04***	0.04***	0.03***	0.02***
	(56.70)	(46.74)	(32.43)	(21.94)
Eigenvector	0.07			
	(0.75)			
Betweenness		0.03		
		(0.38)		
Leader Eigenvector			0.36***	
			(6.58)	
Leader Betweenness				0.29***
				(6.05)
Constant	-5.12***	-5.52***	-5.19***	-3.91**
	(-5.43)	(-5.04)	(-4.86)	(-2.00)
Observations	19293	19293	19293	19293

Panel Probit regressions with portfolio-company random effects; not reported: industry and country fixed effects; Z-statistics in parentheses; significance: * 0.1, ** 0.05, *** 0.01

Table 11: Performance of companies and mean centrality/betweenness of syndicate members.

	(1)	(2)	(3)	(4)
Sales at -1	-0.04**	-0.04**	-0.04**	-0.04**
	(-2.36)	(-2.36)	(-2.39)	(-2.40)
(log) Deal Size	0.01	0.02	0.01	0.01
	(0.74)	(0.67)	(0.71)	(0.61)
Syndicate Size	-0.01	-0.01	-0.01	-0.01
	(-0.76)	(-0.63)	(-1.00)	(-0.90)
Total Known Funding	0.00***	0.00*	0.00***	0.00*
	(2.59)	(1.75)	(2.65)	(1.83)
Centrality	-4.27**	-3.95**		
	(-2.41)	(-2.56)		
Year -2=1	-0.28	-0.22	-0.29	-0.22
	(-1.39)	(-1.19)	(-1.40)	(-1.18)
Year -2=1 # Centrality	4.67**	4.20**		
	(2.45)	(2.52)		
Year -1=1	-0.14	-0.14	-0.10	-0.11
	(-0.70)	(-0.76)	(-0.51)	(-0.56)
Year -1=1 # Centrality	3.06	2.91*		
	(1.56)	(1.85)		
Year 1=1	-0.49**	-0.47***	-0.49**	-0.49***
	(-2.50)	(-2.62)	(-2.51)	(-2.68)
Year 1=1 # Centrality	4.22**	3.88**		
	(2.33)	(2.47)		
Year 2=1	-0.58***	-0.57***	-0.58***	-0.57***
	(-2.99)	(-3.18)	(-2.97)	(-3.16)
Year 2=1 # Centrality	4.75***	4.47***		
	(2.62)	(2.86)		
Year 3=1	-0.66***	-0.64***	-0.64***	-0.61***
	(-3.30)	(-3.35)	(-3.14)	(-3.17)
Year 3=1 # Centrality	4.11**	3.79**		
	(2.20)	(2.31)		
Year 4=1	-0.68***	-0.68***	-0.68***	-0.66***
	(-3.32)	(-3.44)	(-3.35)	(-3.44)
Year 4=1 # Centrality	4.16**	3.91**		
	(2.07)	(2.26)		
Year 5=1	-0.80***	-0.78***	-0.78***	-0.76***
	(-3.45)	(-3.45)	(-3.28)	(-3.28)
Year 5=1 # Centrality	4.11**	3.84**		
	(2.16)	(2.31)		
Betweenness			-61.03**	-56.74**
			(-2.19)	(-2.08)
Year -2=1 # Betweenness			67.17**	60.97**
			(2.13)	(1.98)
Year -1=1 # Betweenness			36.02	34.61
			(1.16)	(1.15)
Year 1=1 # Betweenness			62.36**	60.29**
			(2.14)	(2.12)
Year 2=1 # Betweenness			66.47**	64.00**
			(2.28)	(2.26)
Year 3=1 # Betweenness			51.19*	46.03
			(1.68)	(1.56)
Year 4=1 # Betweenness			58.81*	53.85*

			(1.93)	(1.83)
Year 5=1 # Betweenness			56.07*	52.14*
			(1.75)	(1.69)
Constant	0.82***	0.85***	0.82***	0.85***
	(3.18)	(3.14)	(3.18)	(3.13)
Observations	2570	2570	2570	2570
Model	OLS	RE	OLS	RE
Country Effects	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes

Table 12: Growth of sales dependent on mean centrality (marginal effects)

	Year	25	50	75	90	95
B	-2	-0,22365	-0,16298	-0,00761	0,27198	0,47943
Se	-2	0,03156	0,02704	0,02030	0,02567	0,04419
B	-1	-0,13124	-0,08940	0,01778	0,21064	0,35374
Se	-1	0,03172	0,02701	0,01927	0,02091	0,03508
B	1	-0,46048	-0,40513	-0,26335	-0,00822	0,18107
Se	1	0,03003	0,02573	0,01908	0,02296	0,03901
B	2	-0,56127	-0,49721	-0,33313	-0,03787	0,18120
Se	2	0,02981	0,02547	0,01873	0,02246	0,03839
B	3	-0,63141	-0,57564	-0,43281	-0,17579	0,01492
Se	3	0,03327	0,02825	0,02015	0,02282	0,03912
B	4	-0,66024	-0,60359	-0,45848	-0,19735	-0,00360
Se	4	0,03531	0,03052	0,02359	0,03042	0,05152
B	5	-0,76429	-0,70871	-0,56636	-0,31020	-0,12014
Se	5	0,04703	0,04086	0,02996	0,02811	0,04149

Table 13: Growth of sales dependent on mean betweenness (marginal effects)

	Year	25	50	75	90	95
B	-2	-0,21573	-0,13575	0,03985	0,35440	0,72190
Se	-2	0,03137	0,02490	0,02223	0,05712	0,16239
B	-1	-0,08995	-0,04674	0,04813	0,21807	0,41662
Se	-1	0,03199	0,02513	0,02109	0,05168	0,14894
B	1	-0,45869	-0,38190	-0,21329	0,08872	0,44158
Se	1	0,02920	0,02330	0,02027	0,04889	0,13770
B	2	-0,54905	-0,46631	-0,28464	0,04078	0,42097
Se	2	0,02896	0,02311	0,02010	0,04846	0,13648

B	3	-0,59292	-0,53258	-0,40007	-0,16273	0,11458
Se	3	0,03264	0,02578	0,02139	0,05016	0,14335
B	4	-0,63938	-0,56995	-0,41750	-0,14442	0,17462
Se	4	0,03321	0,02741	0,02530	0,05794	0,15533
B	5	-0,74109	-0,67385	-0,52622	-0,26178	0,04717
Se	5	0,04876	0,03928	0,02995	0,05270	0,14344

Figure 5: differences between high and low average centrality or betweenness of investors on the paths of growth of portfolio companies.