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This study investigates the phenomenon of syndication in the venture capital industry. Investments conducted by syndicates are believed to have a better chance of being successful, which can be 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 investors' strong network ties are associated with the success of portfolio companies in Europe. We also demonstrate differences in the association of network centrality with survival between different financing rounds, with the former being more important in early-stage investments and in the first round of financing. Furthermore, we show a strong association of investors' network ties with the sales growth of portfolio companies before and after the deal, which is consistent in both selection and value-added channels. Finally, we explicitly account for the endogeneity of syndicate formation and show that the results hold if we instrument for venture firms' network properties, as indicated by significant and correspondingly larger coefficients.

Keywords: Venture Capital, Networks, Europe, Investment Syndication

JEL: G11, G24, M13

Syndication networks and company survival: Evidence from European venture capital deals

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

Abstract

This study investigates the phenomenon of syndication in the venture capital industry. Investments conducted by syndicates are believed to have a better chance of being successful, which can be 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 investors' strong network ties are associated with the success of portfolio companies in Europe. We also demonstrate differences in the association of network centrality with survival between different financing rounds, with the former being more important in early-stage investments and in the first round of financing. Furthermore, we show a strong association of investors' network ties with the sales growth of portfolio companies before and after the deal, which is consistent in both selection and value-added channels. Finally, we explicitly account for the endogeneity of syndicate formation and show that the results hold if we instrument for venture firms' network properties, as indicated by significant and correspondingly larger coefficients.

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1. Introduction

In this work, we examine a particular aspect of the venture capital (VC) industry: syndication. Typically, VC investments are not conducted by a single entity but by a group of co-investors (i.e., a syndicate) with a leader at the helm. A leader is usually an investor with vast experience in selecting

[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

investment opportunities and investing in various technology sectors, following the deal flow that most investors do not have access to. For various reasons described in this work, investments conducted by syndicates are believed to have better chances of being successful compared to other investments. The existing literature has shown that syndication can lead to more successful investments in the US and China. However, in the case of Europe, there is still little evidence that this is true. While theoretical explanations for the impact of syndication might indeed hold in the European case, this hypothesis still requires further testing. Indeed, European markets are quite different from US ones, and some aspects of syndication might be different in the latter context. In particular, as shown by Hochberg, Ljungqvist, and Lu (2010), dense networks serve as barriers to entry, thus enabling incumbents to perform better. In comparison, European networks are much less developed (yet), and for this reason, the incumbency effects for central network players might be less pronounced.

Thus, using a dataset of European VC deals, we focus on the question of whether syndication affects the performance of portfolio companies. Following the hypotheses presented in the literature, we are interested in exploring whether the network properties of investors in syndication networks are related to several performance-related outcomes. Finally, we ask the question of whether syndication and network properties affect performance differently in the early and growth stages.

Several novel aspects of the literature are addressed in this work, which combines results from the finance literature with the methodology of social network analysis. First, we provide rare evidence of how VC companies' network properties affect the performance of companies in Europe, and whether the network centrality of a syndicate's central investor positively affects portfolio companies' survival. For reasons spelled out in the study, the relationship between investor networks and the performance of portfolio companies in Europe might be different than in the well-researched US market. Second, to the best of our knowledge, this is the first study to examine differences in the impact of the centrality of investors on companies' success between early-stage and growth investments. Third, we look at the association between the centrality of investors and sales growth of portfolio companies before and after a deal. Fourth, we use instrumental variables to identify the effects of centrality on further outcomes. Finally, we test our hypotheses using Preqin data, which have not yet been used to investigate this particular question. Although the Preqin database has been used in VC research (Kaplan and Kerner 2016; Buchner, Abdulkadir, and Schwienbacher 2017; Gompers and Wang 2017; Nykanen 2018), we are not aware of research using the Preqin database in the context of network analysis in VC, particularly the impact of network features on portfolio companies' performance. Thus, by using such data, we can examine a cross-country sample to address our research question, as opposed to most studies that have conducted single-country comparisons.

Our main results reveal that network centrality is important for the success of portfolio companies in Europe. In particular, we find an association between the network centrality of investors and portfolio companies' probability of survival and sales growth. Moreover, we show the different impacts of centrality on survival between different financing rounds. Investors' network position is an important correlate of portfolio companies' success in the seed stage but less so for later financing rounds. Additional regressions using instrumental variables confirm the analysis and reveal that the coefficients in the base regressions could be underestimated. Furthermore, the actual effect of the investors' centrality is larger.

The rest of the paper is organized as follows: Section 2 provides a brief overview of the literature relevant to this research; Section 3 presents our research questions; Section 4 describes the data used in the empirical examination, along with the methodology employed in this paper; Section 5 presents the main results; and Section 6 concludes the paper.

2. Theory and Related Literature

This work is related to the literature on how the syndication of investments affects the performance of companies, as reviewed by Jääskeläinen (2012), among others. Several channels are responsible for the connection between syndication and performance. Lerner's (1994) seminal work proposed three rationales for VC syndication. The first refers to "the four-eyes principle," which affects the decision to invest. The second rationale is to overcome informational asymmetries, particularly those involving the initial venture investor and other potential investors. It has been argued that the only way to avoid opportunistic behaviors of initial investors is if the lead VC maintains a constant share of the firm's equity. This implies that later-round financing must be syndicated (Admati and Pfleiderer 1994). The third and final rationale is "window dressing," which means that 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.

According to Wilson (1968) and Lockett and Wright (2001), among others, syndication improves firms' performance by diversifying their risks. They analyze three other hypothetical channels for why VC firms syndicate investments: the traditional finance perspective, the resource-based approach, and the deal flow perspective. On the one hand, the traditional finance perspective stresses the role of risk sharing, which combines several rationales: optimizing diversification (Murray 1999); improving liquidity to divest potential "lemons," thus sharing risk on a deal-by-deal basis; and facilitating raising funds in the future. On the other hand, the resource-based approach stresses risk reduction and the improvement of selection. This is based on the notion that syndication can reduce the potential for adverse selection if it changes how an investment is made because it produces a greater range of analytical skills among investors. However, to the extent that syndication increases coordination costs and the time scales involved in decision-making, the risk may be increased if the necessary critical decisions are delayed during times of difficulty. Finally, the deal-flow perspective notes 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 VC firm is not the originator of the deal.

What channel prevails and is the most important has also been the subject of debate. Based on a survey of VC firms, Lockett and Wright (2001) find that, while the finance perspective is the most important, the resource-based view can also matter, particularly at early-stage investments. At odds with the view of Lockett and Wright (2001), Werth (2014) concludes that accessing (complementary) resources appears to be the strongest incentive to syndicate, whereas deal sourcing—especially reciprocity considerations—appear relatively weak syndication motives.

Following the deal-flow argument of Lockett and Wright (2001), Cumming (2006) and Sorenson and Stuart (2001) suggest that syndication grants VC firms access to a larger number of investment possibilities. In particular, while information about potential investment opportunities circulates within geographic and industry spaces and the information flow within these spaces contributes to the geographic- and industry-localization of VC investments, social networks in the VC community, which are established through the industry's extensive use of syndicated investing, diffuse information across boundaries, thus expanding the spatial radius of exchange (Sorenson and Stuart 2001). This may contribute to the increased performance of firms, which is achieved through the circumvention of informational restrictions regarding most promising investments and an increase in the VC's scope of operations.

Brander, Amit, and Antweiler (2002) analyze the deal-selection channel, in which a second VC provides a valuable opinion. They contrast this with the "value-added hypothesis," which stresses the complementary management skills of additional venture capitalists. On the one hand, the most promising projects will be conducted as stand-alone investments as, in this case, the need for a second opinion is limited. On the other hand, moderately promising projects will be syndicated. In contrast, the value-added hypothesis emphasizes that additional VC brings actual value to the project and raises its profitability. These two mechanisms yield contrasting predictions: If the selection hypothesis is correct, syndicated projects should have lower returns, whereas 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, which is higher returns for syndicated projects, in favor of the value-added hypothesis (Brander, Amit, and Antweiler 2002).

Similarly, Tian (2011) finds that syndication creates product market value for their portfolio firms. Furthermore, VC syndicates nurture innovation among their portfolio firms and help them achieve better operating performance in their post-initial public offerings. At the same time, VC syndication creates financial market value for portfolio firms. Meanwhile, Das, Hoje, and Yongtae

(2011) show that improved performance can be mainly attributed to selection, in which the value-addition of the monitoring role significantly impacts the likelihood and time of exit. They conclude that the two channels (selection and value addition) are complementary.

These results, however, are 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 the ability to add value is necessary for syndication to occur in equilibrium, thus shedding new light on the argumentation of Brander, Amit, and Antweiler (2002). In most cases, a combination of several factors influences the decision to syndicate.

Properties of Networks among VC Firms

The main focus of this work is on a more concrete question. Rather than examining whether syndication affects performance, we want to know whether it matters how the syndication network looks within syndicated investments and how the investors are placed within these networks. The established literature looked at the effects of networks on investment performance in general financial markets (see, e.g., Hong, Jeffrey, and Stein [2004] and Garmaise and Moskowitz [2003]) and in entrepreneurship (Greve and Salaff 2003; Hoang and Yi 2015; Uzzi 1999). In comparison, the topic of how VC investors' network properties affect portfolio firms' performance remains fairly underexplored.

The seminal paper by Hochberg, Ljungqvist, and Lu (2007) sheds light on investors' network properties and portfolio firms' performance. They construct a measure of network centrality that measures five different aspects of a VC firm's influence:

(1) the number of VCs with which it has a relationship as proxies for the information, deal flow, expertise, contacts, and pools of capital it has access to;

(2) the frequency with which it is invited to co-invest in other VCs' deals, thereby expanding its investment opportunity set;

(3) its ability to generate such co-investment opportunities in the future by syndicating its current deals in the hope of future payback from its syndication partners;

(4) its access to the best-connected VCs; and

(5) its ability to function 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 improved fund performance, as measured by the proportion of investments that are successfully exited through an IPO or a sale to another company. Similarly, portfolio companies of better-networked VCs are significantly more likely to survive in the face of subsequent financing and eventual exit.

Hochberg, Ljungqvist, and Lu (2010) also consider performance from the network perspective. Specifically, 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. Their results indicate that more densely networked markets experience less entry, and that VC firms benefit from reduced entry by paying lower prices for their deals.

Braune et al. (2019) study the properties of VC networks from a different perspective by investigating the degree to which incumbent companies capture information from VC networks, with a focus on the IT sector. They find that the R&D investments made by these companies, along with the amount of corporate VC investments made, have strong impacts on both the number of relationships they forge and maintain and on the centrality of their position in VC networks.

Bellavitis, Filatotchev, and Souitaris (2017) look at the relationship between network cohesion and VC performance in the case of UK firms and find that mature and high-status VCs obtain fewer benefits from network cohesion. The authors also show that maturity and status simultaneously determine the performance effects of network cohesion.

3. Research Questions

Following these theoretical considerations, particularly the empirical findings of Hochberg, Ljungqvist, and Lu (2007), we want to address several research hypotheses. First, there is reason to believe that the notion of network properties of VC investors affecting portfolio firms' performance, which has been validated using US and UK data, also holds for the case of European venture deals. To the best of knowledge, we are the first to address this question using European cross-country data. Second, we look at whether significant differences exist between the various stages of financing in terms of the effects of syndication and network properties. While theoretical reasoning can be found in the literature, empirical confirmation for the case of VC investments and their network properties has yet to be presented.

While we believe that the network properties of European investors would also affect the portfolio companies, similar to the situation in the US, there are several differences between these two cases that could affect this relationship. For instance, Schwienbacher (2008) finds significant differences between the behavior of VC investors in Europe and those in the US. In particular, he points out that European investors are less active in monitoring and add less value compared to their US counterparts. Thus, the value added by very centrally located investors is lower as they are typically less involved in active management (e.g., by providing contacts). Moreover, less syndication is found in European markets, which potentially reduces the key role played by centrality, following the argument of Hochberg, Ljungqvist, and Lu (2010). More syndications with governmental partners can be found in Europe compared to the US, and more syndicates are formed in regional proximity. All of these can be explained by less liquid and generally less developed markets in Europe. Given that some evidence (see, e.g., review by Colombo, Cumming, and Vismara [2016]) indicate that governmental VCs (GVCs) perform generally worse than private VCs, a strong position within syndication networks of GVCs in Europe might result in a less clear-cut connection between network properties and performance. Following these results, we expect that the centrality of investors within syndicates might be of lower importance in Europe than in the US.

The question remains: What is the best measure to assess the success of an investment? We can draw upon the literature and assess several measures. First, similar to Hochberg, Ljungqvist, and Lu (2007), we look at the probability of surviving to the next financing round. According to Hochberg, Ljungqvist, and Lu (2007), most venture-backed investments are "staged" in the sense that portfolio companies are periodically reevaluated and receive follow-on funding only if their prospects remain promising (Gompers 1995). Thus, we view survival in another funding round as an interim signal of success. Second, similar to a measure of survival, we expect investors' network properties to be associated with sales growth. Following argumentation and empirical results for the US (Hochberg, Ljungqvist, and Lu 2007), as well as the general literature on the sales performance of VC-backed firms, we expect portfolio companies to perform better in terms of sales, but only if backed by a well-connected investor. Therefore, we expect a positive correlation between investors' network centrality and performance/survival. This leads us to the following hypotheses:

Hypothesis 1a: Investors' network centrality positively correlates with the survival of portfolio companies.

Hypothesis 1b: Investors' network centrality positively correlates with the sales growth of portfolio companies.

Nevertheless, we can be more precise regarding our expectations, especially in terms of portfolio firm's performance before and after the deal. Drawing upon the literature on selection effects, we expect differences in performance even *before* the deal, as the best-connected VCs invest in companies with better performance and greater potential for the future. If only the value-added effect is present, which we hypothesize to be stronger for well-connected VCs, we expect no differences between sales growth before the deal that is dependent on centrality, but only after the syndicate has invested. If both selection and value-added effects are present, we are likely to observe sales growth differences before and after the deal. Thus, the following hypothesis is proposed:

Hypothesis 2: In the presence of the selection effect, sales growth correlates positively with investors' centrality before and after the deal.

We have presented in the previous section the many reasons for syndication and the differences between the early and growth stages. In the early stage, 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 assist the company in business development and operations. Investors of this kind would either be partners at VC firms with vast experience or business angels. Their role is extremely important as they provide a great deal of knowledge and support, which could be crucial for the success of the company.

Conversely, at the growth stage, entrepreneurs have already proven their capability of building a company and developing a product or technology for which market demand exists. Thus, the role of growth-stage investors is generally less crucial. They provide capital for growth but generally do not question the need for the product or the existence of market demand. When forming a syndicate at the growth stage, the investment team must be able to provide capital for up to a late stage (i.e., IPO); risk sharing plays a key role in this process. Growth-stage investors are more like investment bankers. Hence, we hypothesize that the main role of a central investor is of lower importance for success in the later stages of financing compared to the early stage. Thus, the following hypothesis is proposed:

Hypothesis 3: Investors' network centrality is more strongly associated with success in the early stage compared to growth investments.

Finally, the lead investor in the first round of financing is not necessarily the same lead investor in the final round of financing. Thus, to further understand what drives our results, we test whether the role of centrality is stronger in the *first round of financing* (independent of its stage). We posit that the first lead investor plays an important role in selecting the company before financing and that success in the early stage would be more strongly associated with the network centrality of this investor. Thus, we propose the following hypothesis:

Hypothesis 4: Investors' network centrality is more strongly associated with success in the first round of obtained financing.

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, in which influence is measured by how "central" an actor's network position is based on the extent of his/her involvement in relationships with others (Hochberg, Ljungqvist, and Lu 2007). Network analysis formalizes the concept of centrality and develops several measures that help identify key actors in a network. In the current work, we use two concepts of centrality: eigenvector centrality and betweenness. We argue that although a node that is central by one measure is often central by several other measures, this is not necessarily always the case.

On the one hand, eigenvector centrality measures the number of relationships established by a VC firm within a network. The greater the number of ties, the more opportunities for exchange, and the more influential, or central, the actor becomes. This measure 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, eigenvector centrality not only considers the number of nodes to which one is connected but also their importance.

The main principle to be considered here is that links from important nodes are worth more than those from unimportant nodes. Technically, eigenvector centrality scores correspond to the values of the first eigenvector of the graph adjacency matrix. In turn, these scores may 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 that are connected to many other vertices, which, in turn, are connected to many others (and so on). In this case, the score must be normalized because centrality depends on the size of the clique. The size of the clique depends on the overall size of the network, which, in turn, may also change over time and may vary in different countries.

VCs that have ties to many other VCs may be in advantageous positions. As they have many ties, they are less dependent on any single VC for information or deal flow. In addition, they may have access to a wider range of expertise, contacts, and pools of capital (Hochberg, Ljungqvist, and Lu 2007). In the VC context, eigenvector centrality shows not only that a particular investor has many co-investors but that he/she has many important co-investors (i.e., co-investors with multiple syndicated partners), who themselves play a key role in a network.

On the other hand, betweenness attributes influence actors on whom many others must rely to make connections within a network. This 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 because of their control over information that passes between other vertices. 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 the degree to which a VC firm may connect or bring together other VCs with complementary skills or investment opportunities that would otherwise lack a direct relationship. It also measures the degree to which a particular VC can control the information flow among other active VCs in a market. This also needs to be normalized.

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, Ljungqvist, and Lu (2007), one important aspect of syndication is the VC's ability to act as an intermediary that can bring together VCs with complementary skills or investment opportunities that lack a direct relationship between them. This aspect can be captured by the betweenness measure: VCs with high betweenness are in the best positions to act as middlemen joining investment partners.

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

The problem that remains is that most network measures, particularly those we use, might be highly correlated. While the theoretical distinction of diverse aspects of syndication is straightforward, conducting separate empirical investigations of the two aspects has proven to be difficult due to the abovementioned correlation. Finding a solution to this issue is beyond the scope of this work; hence, it will be addressed in further work.

Data

The main data source for the current study is the Preqin database. This database encompasses comprehensive information about diverse aspects of global VC markets. It contains information about 6,300 investors worldwide, more than 110,000 VC deals, and more than 50,000 buyout deals. Moreover, it contains detailed information on 10,000 fund managers, along with their backgrounds, 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 the total known funding of a portfolio company are also given, although such information is not available for all deals. Some descriptive statistics about the deals are presented in Table 1.

[Table 1 about here]

On average, portfolio firms survive 2.3 financing rounds, with a median of 2. Typically, about four investors are involved in a deal, with a median of 3, showing slight positive skewness. The smallest deals in the sample are 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, almost 1.8 billion EUR, went to Spotify AB, in which the largest deal of 466 million EUR of Series G financing by the Coca-Cola Company and its co-investors, among others. Almost 80 percent of the deals are syndicated and, thus, involve more than one investor. The largest syndicate consists of 24 investors. Successful exits within an industry vary for VCs between 0 and 61.

We use data for deals in Western Europe in the years 2000–2017.[2] The number of deals during this period constantly increased, starting with 452 in 2000, and rising to over 4,600 in 2017. The number of deals has almost doubled within six years, indicating that the VC industry is on a steady rise and is thus becoming a relevant factor for achieving general economic development. The total number of deals in the sample is almost 42,000.

The Preqin data are used to calculate the network characteristics of investors within investment syndicates. In Table 2, we present some basic descriptive statistics. For visualizations and further information, such as programs and interactive figures, please visit the online Appendix on the website of this project (Link).

[Table 2 about here]

What is typical of the VC scene is also visible if we look at the network measures. Both measures are characterized by a strong skewness, with a few large investors having many connections and numerous small investors who do not have many ties. This is particularly visible if we exclude the zeroes. For the betweenness measure, over 40 percent of investors have a value of zero, indicating that no shortest path goes through such a node. These nodes do not connect to other nodes and, therefore, have no impact on the deal flow or similar activities. For eigencentrality, the discrepancy is less visible, with only about 5 percent 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 2010–2019 (or the last available year for each company if it has already closed operations). For Western European and Nordic countries, 6,347 and 780 companies are found in the database, respectively, which are then matched with the deal data. The development of sales is measured as a logarithm of absolute growth (e.g., $log(sales_t)$-$log(sales_{t-1})$). To assess the quality of the deal data from the Preqin database, we compared them with ownership changes after

[2] The countries covered are Austria, Belgium, Denmark, Finland, France, Germany, Iceland, Ireland, Italy, Luxembourg, Malta, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom (including the territories of Gibraltar and Jersey).

the respective dates of deals. The Orbis database registers any changes to company ownership resulting, for instance, from an equity investment. In this case, a new equity investor, such as a venture fund, is listed in the ownership structure of the firm. In this way, we can compare the Preqin data on the deals with changes to ownership found in Orbis. We found no major discrepancies between the two sources.

Furthermore, Crunchbase is used to gain information about exits. Crunchbase keeps track of exits via initial public offerings (IPOs) and mergers and acquisitions (M&As). As of April 2021, Crunchbase has collected records on more than a million companies, 31,687 IPOs, and 115,547 acquisitions. With this information, we can track exits through an IPO or an acquisition of a company as a further measure of performance.

Methodology of Estimation

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

Survival and Exits

Studies have linked the performance of funds and companies to networks of VC firms. Thus, we analyze whether the properties of syndicates affect the survival rates of portfolio companies. We define the survival of a portfolio company as 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, and Venture Debt. The classification of financing rounds comes from the Preqin dataset itself.

Most of these financing rounds can be arranged in an ordered fashion, indicating a growth of the portfolio company, with the following two exceptions: First, Add-On and Growth funds can be granted at any stage of the portfolio company's lifecycle so they cannot be ordered; second, Grant, Venture Debt, and Unspecified Round are excluded on similar grounds. 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 > and Series K/Round 11,

each receiving a value of between 1 (first round) and 13 (second to the last round). Finally, any of the following 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 the relative number of financing rounds received by a firm. Given that some companies receive their first financing round at a later stage than seed (an average portfolio firm in the database starts with Series A financing), we calculate in each case the number of rounds a company has survived, starting from the first round. A histogram of survival is presented in Figure 1.

[Figure 1 about here]

As can be observed, almost 50 percent of the portfolio companies receive only one round of financing from syndicated investors. This number is much higher, almost 70 percent, for nonsyndicated investments. About 20 percent survive at least one round, meaning they received a second round: 22 percent and 18 percent of syndicated and non-syndicated investments, respectively. A large difference can be observed for three rounds, with more than 15 percent of syndicated investments receiving three rounds of financing as opposed to only six percent of non-syndicated investments. Subsequently, the numbers drop further, with a slight increase in the probability of survival of about 12 to 13 rounds, corresponding to companies with successful exits (e.g., Merger or pre-IPO financing), as defined above. The overall fraction of companies that are able to survive until the final round is lower than three 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 by 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 then estimate a count panel model, such as a panel Poisson regression or a panel negative binomial regression. However, parametric models, such as the Poisson model, assume a constant hazard rate over time. Alternatively, similar to Hochberg, Ljungqvist, and Lu (2007), we can estimate a (panel) binary outcome model (a probit or logit model), in which we define whether a portfolio company survived to round N, conditional on surviving to round N-1, as a binary variable. For first-round financing, 1 means surviving the first round, while 0 corresponds to not surviving. This specification is also used as a robustness check. A standard Poisson regression takes the following form:

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

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

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

which defines the predicted mean of the Poisson distribution. The model can be estimated using numerical maximum likelihood methods. In the panel variant of the Poisson regression, we use random effects at the 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, with each partner revealing less additional information about the deal.

The main variables of interest are the measures of network characteristics for each financing round. Specifically, we use two basic measures of VC firms' centrality as the main variables of interest: eigenvector centrality and betweenness, both measuring the "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 concentrated on the most central investors. As we do not have detailed information about the initiators of the deals, we look instead at investors with the highest measure of centrality—those with greater contributions to the theoretically identified effects of network centrality on performance. Thus, in an alternative specification, we explain the survival rates by the centrality measures of the syndication partner, with the highest measure only (also known as "central investor" in the Results section).

The literature identifies VC firm experience as a further variable that affects investment performance. Several measures of VC experience are possible, such as VC age (Lerner 1994; Gompers 1996; Gompers and Lerner 1999), a cumulative number of investment rounds made by the VC firm (Sorensen 2007), and the VC's aggregate investment in the VC industry (Hochberg, Ljungqvist, and Lu 2007). As a measure, we propose a number of exits backed by the VC firm *in the same industry*. This variable is labeled as *Expertise*. The latter feature is important in differentiating between expertise in different market segments (e.g., deep tech vs. consumer software might require different sets of skills and contacts).

Further variables that might correlate with the performance of portfolio companies and to which we have access to the database are also added. First, we add the absolute size of the syndication network in each round as an explanatory variable. According to the complementary skills interpretation, a larger number of syndication partners may improve the performance of a portfolio company, which gains access to diverse sources of knowledge and management practices. Second, the specific location and industry of a portfolio company are likely to affect its survival chances. Thus, we add fixed effects for 16 countries and 74 broadly defined industries, such as Software, Telecoms, and Medical Technologies, among others. Finally, the performance of the company correlates with the overall financing it has received, but 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. The correlation table of the main variables of interest is presented in Table 3.

[Table 3 about here]

In addition, we run panel probit models for the probability of a successful exit via an IPO or an M&A, in which exit is coded as one. Other variables are defined as above.

Performance

To analyze the development of sales, we employ an event study methodology. We code as *time=0* the event of a deal for each company. In the case of subsequent deals, each deal is coded again as 0. Other observations in the data, e.g., sales one year after the deal, two years after the deal, etc., are also coded relative to this event. As 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 following 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 must aggregate the data to match yearly observations of sales and employee growth. This means that the data now have a panel structure of the company-year form. As the actual deals are given in daily format, we assume a balance sheet reporting day to be the end of the year for all countries. We calculate the number of months between the deal and the reporting day, after which they are summarized into years: anything below 12 months corresponds to Year 0, those below 12–23 months corresponds to Year 1, and so on. For each deal, we look at the centrality of the lead investor's betweenness as the main variable of interest. Additional control variables include country effects (industry effects cannot be added, as the sample is too small), total known funding (in billion USD), mean/maximum expertise in the deal, and the size of the syndicate for each deal. The models are estimated on an unbalanced panel of about 2,600 observations.

5. Results

Survival

Table 4 presents eight different specifications 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. Each model is presented either with portfolio company random effects and multilevel industry and country fixed effects, or as pooled Poisson regression with industry–country fixed effects. Standard errors are clustered at the company level. Industry, country, and industry–country fixed effects are not reported for the sake of brevity but are available upon request.

[Table 4 about here]

The results presented in Table 4 suggest that all the chosen measures of network centrality are positively associated with the survival of portfolio companies. The most significant results are found in the estimations that include the network measures for the most central partner only (Columns 3 and 4, 7, and 8). Given that the variables are standardized, the results can be interpreted as follows (using the specification with company random effects): a one standard deviation increase in the eigenvector centrality of the central investor in the syndicate is correlated with an increase in the probability of surviving one more round of financing by exp(0.12)=0.127, or about 12.7 percent. A one standard deviation increase in the central investor's betweenness is correlated with an increase in the probability of surviving an additional financing round by exp(0.15)=0.162, or about 16.2 percent. Therefore, these results are not only statistically significant, but also of high economic significance. Moreover, as expected, VC firm expertise is significant for the survival chances of portfolio companies but only in the pooled specifications.

We show in the Appendix the results of probit regressions comprising the robustness test. Here, the dependent variable is defined as a binary of whether a company has survived at least one round of financing conditional on surviving one round. The results, presented in Table 11 in the Appendix, show a consistent significant correlation between the centrality measures of the most central investor and the survival chances of the portfolio companies. Furthermore, the most robust results are obtained for the characteristics of the central investment partner and not necessarily for all partners. The latter result suggests that it is the central role of the central investor, which functions as a connecting agent between different VCs, that is crucial for the success of the portfolio company.

Early-stage vs. Growth Investments

We turn to the question of whether there is a differential effect of network centrality on a portfolio firm's performance, depending on the stage of financing. Thus, 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 that is equal to 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 about here]

As we can observe, and following our hypotheses, the success of early-stage investments is more strongly associated with investors' centrality. While early-stage investments generally have a lower probability of surviving additional financing rounds (coefficient of about –0.10 in the random-effects specifications, highly significant), centrality positively correlates with survival and more so in the early stage. A one-standard deviation increase in the central investor's eigenvector centrality increases the probability of surviving an additional round by exp(0.10)=10.5 percent, on average. Additional exp(0.07)=7 percentage points are added if we consider early-stage investments only. Comparing this to the effects shown in Table 4, about half of the effect comes from the importance of investors' network position in the first two rounds of financing (angel and seed). The coefficient for betweenness also shows a similar pattern. This result is generally consistent with the theoretical consideration of the importance of VC firms at various stages.

Exits

As an alternative measure of success, we look at exits through M&As or IPOs, and the results are reported in Table 6. We conclude that the central investors' centrality and betweenness is positively and significantly associated with an exit through an M&A, but the correlation in the case of an IPO is insignificant. The latter fact can be attributed to a phenomenon explained by a fairly small variation in the data (i.e., only less than four percent of deals in the data result in IPOs), and is also consistent with the notion that investors' centrality is more important at the earlier stages of financing. While M&As can happen at an earlier stage, IPOs are usually reserved for mature companies, which, at this stage, do not necessarily require further assistance from investors beyond the provision of financial resources. This is also reflected in the seemingly paradoxical correlation coefficient for total funding being negative for the case of M&As but positive for IPOs. This likely reflects the fact that M&As happen at a much earlier stage of venture financing compared to IPOs.

[Table 6 about here]

Finally, Table 7 presents the results of regressions in which we interact the centrality of the investors (or the main investor, respectively) and the first financing round. We can see that, similar to investments in the early stage, the interaction between the first round of financing and centrality measures is positive and significant. This confirms the hypothesis that investors in the first round of financing play a particularly important role in the performance of companies (Hypothesis 4).

[Table 7 about here]

Performance

Table 8 presents the development of sales growth based on the eigencentrality/betweenness of the central investor (maximum centrality in the syndicate).

[Table 8 about here]

Due to the use of multiple interaction terms, recognizing the effect of centrality is difficult. Therefore, we present the marginal effects at various levels of centrality and at different years in Tables 9 and 10 and Figure 2, respectively.

[Table 9 about here]

[Table 10 about here]

[Figure 2 about here]

Several observations can be made. First, sales generally grow more slowly in years one to five than before the deal and in the actual deal year. Although this is surprising, it can be explained by organizational growth and less focus on pure sales compared to the very early days of a venture. Second, 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. For the cases when the investor is at the top 10 percent of betweenness, sales grow more quickly than in the deal year, and the growth rate does not drop over time. In comparison, quicker growth can be observed one and two years after the deal has taken place. Third, quicker growth can be observed for deals whose investors have high centrality before initiating transactions. This suggests that the selection of deals is an important aspect of the good performance of portfolio companies.

The results further suggest that the main driver of good investments is a selection effect rather than a value-added effect. Good VCs choose good companies, or vice versa. At the same time, well-connected VCs not only choose better-performing companies, but also have access to better deals owing to their strong network. The effect of a strong VC firm adding more value could still be present, but our estimation does not allow for disentangling the effects. However, as described in the theoretical section, this is in line with the findings for Europe, which suggest that investors play a less important role in adding value to the company compared to those in the US markets.

Similarly, we can look at the network properties of the entire syndicate in which we take the average measures of the centrality of the members of the syndicate as a variable of interest. Our results are presented in Tables 12–14 and Figure 3 in the Appendix, and mainly serve as a robustness check for the main specification, as it is less prone to the effects of outliers. The results are highly similar and qualitatively comparable.

Endogeneity of Syndicate Formation

The process of finding syndication partners is affected by certain characteristics of VC firms, which might also affect the performance of portfolio companies. Whether a VC firm can accomplish the goals of syndication greatly influences the kind of syndication partners a firm can attract. Related to this, a strand of research examined whether VC firms syndicate their investments and who the typical syndication partners are. Lerner (1994) was one of the first to notice that top-tier firms tended to syndicate with each other, particularly during early financing rounds. In addition, Hochberg et al. (2011) find evidence of resource sharing across linked firms, which is likely to positively affect the performance of companies. This problem makes it difficult to form causal conclusions regarding the impact of syndication on performance. When a positive correlation exists between the unobserved factors that affect how successful an investor is at forming syndicates and their value-adding impact on firms, then coefficients from our regressions are underestimated and the true coefficient becomes larger.

Therefore, there is a need to find an instrument that affects an investor's network position but does not simultaneously affect companies' performance in a meaningful way. To do so, we exploit the fact that certain investments require an additional small ticket to be completed when some amounts are missing. In such cases, additional investors are likely to join the syndicate but only with a small ticket; furthermore, they are not expected to take an active role in the management of the company. Often, these investors do not specialize in this particular industry or a particular stage of investment but join in many syndicates with smaller tickets, thus resulting in better positions within the investors' networks. In this study, we refer to this fact and construct an index of how often particular investors invest outside of their regular scope of business. We achieve this by calculating the index of variation of the investment stage in which they usually invest. For example, if a firm specializes in Series A tickets and does not often enter syndicates in other rounds, this index would be low. If it enters many syndicates through different stages, both the index and the network position will be higher, irrespective of other skills. Moreover, as mentioned at the beginning of the paragraph, these complimentary tickets do not involve the active management of companies. Thus, almost by definition, the exclusion restriction of no direct effect on portfolio firms is satisfied.

As previously stated, all regressions are performed with a set of fixed country and industry effects; thus, to obtain consistent results in the Poisson model, we use the control function approach proposed by Lin and Wooldridge (2019). The first-stage estimates are reported in the Appendix. Coincidentally, the robust statistics on the first-stage standard errors constitute an endogeneity test.

[Table 15 about here]

As we can observe in Table 15, our suspicions about the endogeneity of the centrality measures turned out to be true. The significance of the first-stage residuals is high in three out of four cases, thus confirming the endogeneity of the instrumented variables. While no standard procedure exists for testing the strength of instruments in a non-linear context, the KP Wald statistics from an equivalent linear model suggest that the chosen instrument is very strong. As expected, the results of the IV regressions point to a much higher coefficient of centrality, along with our expectations that the standard Poisson coefficients, would be underestimated. In particular, the corrected coefficients for the centrality and betweenness of the most central investor are 0.22 and 0.26, respectively. This means that their role increases the probability of an additional financing round by 25% to 30%, respectively. Table 16 presents the results of the interaction models and confirms the main results.

[Table 16 about here]

Finally, in Tables 17 and 18 in the Appendix, we report the results of IV regressions of sales[3] and confirm the main results. However, due to weaker instruments, some results are insignificant.

5. Conclusion

In summarizing our main results, three conclusions can be reached. The network characteristics of a syndicate's central investor are important correlates of portfolio companies' success. We find that both betweenness and eigenvector centrality correlate significantly with the success of portfolio companies. Second, centrality seems to be a more crucial factor in succeeding at an early investment stage rather than later on. This indicates that the level of trust in the central investor is a much more important factor of success for early-stage investments than for those in later rounds. We confirm

[3] The IV models are the same as in the main specification besides instrumenting for the centrality measures and their interactions. Full results available upon request.

these correlational observations by running instrumental variable regressions, which allow us to be even more confident in a causal interpretation of our results.

Regarding the performance of companies, we see that investors with better networks are able to create better companies than others. While this could be due to several reasons (selection, adding value, etc.), according to the literature, our results suggest that the drivers for this include both the selection effect and the value-added effect. This is in line with the theoretical expectations about the differences between the behaviors of European and US investors, with the latter being more active in management and providing more value.

Several questions remain open. First, with our data, we are unable 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. Given that these measures correlate strongly, we cannot distinguish among them solely based on our data and without further information. Second, differences between the early-stage and growth phases should be addressed using surveys among funds and companies, as this can shed light on the qualitative differences in investor decisions at various stages of syndicated investments. Finally, more research is needed to examine the kind of selection effect taking place when well-connected VC firms invest in well-performing companies. Future studies may explore the issue of whether well-connected VC firms are also better at choosing the best possible deals from the pool available or because a strong network increases the deal flow. Finally, a particular aspect of European markets is the high availability of public VC, which is driven by different incentive structures compared to private funds. This topic remains to be addressed in further research.

Declaration of Interest Statement

We wish to confirm that there are no known conflicts of interest associated with this publication and that there has been no significant financial support for this work that could have influenced its outcome.

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Appendix: Additional Tables and Figures

Table 11: Probit model for the probability of surviving at least one round.

	(1)	**(2)**	**(3)**	**(4)**
Expertise	0.01	0.01***	0.01**	0.01***
	(0.89)	(2.70)	(2.08)	(3.45)
Syndicate Size	0.14	0.13	0.23***	0.22***
	(1.53)	(1.35)	(7.60)	(7.95)
Total Known Funding (EUR) Mio	0.03***	0.03***	0.03***	0.02***
	(6.67)	(5.39)	(6.00)	(2.92)
Centrality	0.13***			
	(4.50)			
Betweeness		0.04*		
		(1.85)		
Centrality Central Investor			0.51***	
			(6.53)	
Betweenness Central Investor				0.28***
				(5.94)
Constant	−1.81	−1.74	−1.75***	−1.72***
	(−0.59)	(−0.78)	(−3.08)	(−4.45)

Observations	26042	26042	26042	26042

*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 12: Sales growth and mean centrality/betweenness

	(1)	(2)	(3)	(4)
Sales at −1	−0.04**	−0.04**	−0.04**	−0.04**
	(−2.33)	(−2.33)	(−2.36)	(−2.37)
(log) Deal Size	0.01	0.01	0.01	0.01
	(0.69)	(0.59)	(0.66)	(0.53)
Syndicate Size	−0.01	−0.01	−0.01	−0.01
	(−0.75)	(−0.64)	(−0.99)	(−0.92)
Max Expertise	0.00	0.00	0.00	0.00
	(0.24)	(0.56)	(0.14)	(0.43)
Total known funding	0.70**	0.79*	0.71***	0.83*
	(2.56)	(1.73)	(2.63)	(1.80)
Mean Centrality	−0.49**	−0.46***		
	(−2.44)	(−2.65)		
Year −2=1	−0.05	−0.02	−0.06	−0.02
	(−0.28)	(−0.11)	(−0.34)	(−0.14)
Year −2=1 # Mean Centrality	0.53**	0.48**		
	(2.47)	(2.55)		
Year −1=1	0.01	−0.00	0.01	0.00

	(0.05)	(−0.03)	(0.08)	(0.01)
Year −1=1 # Mean Centrality	0.35	0.34*		
	(1.61)	(1.90)		
Year 1=1	−0.28*	−0.29**	−0.28*	−0.29**
	(−1.75)	(−1.99)	(−1.78)	(−1.97)
Year 1=1 # Mean Centrality	0.48**	0.44**		
	(2.36)	(2.51)		
Year 2=1	−0.34**	−0.36**	−0.35**	−0.36**
	(−2.15)	(−2.46)	(−2.21)	(−2.46)
Year 2=1 # Mean Centrality	0.54***	0.51***		
	(2.64)	(2.89)		
Year 3=1	−0.46***	−0.47***	−0.47***	−0.47***
	(−2.85)	(−3.09)	(−2.88)	(−3.07)
Year 3=1 # Mean Centrality	0.47**	0.43**		
	(2.22)	(2.34)		
Year 4=1	−0.48***	−0.49***	−0.48***	−0.49***
	(−2.82)	(−3.06)	(−2.85)	(−3.04)
Year 4=1 # Mean Centrality	0.47**	0.44**		
	(2.10)	(2.30)		

Year 5=1	−0.59***	−0.60***	−0.60***	−0.60***
	(−3.17)	(−3.30)	(−3.18)	(−3.27)
Year 5=1 # Mean Centrality	0.46**	0.43**		
	(2.17)	(2.33)		
Mean Betweeness			−0.39**	−0.37**
			(−2.20)	(−2.11)
Year −2=1 # Mean Betweeness			0.42**	0.38**
			(2.12)	(1.97)
Year −1=1 # Mean Betweeness			0.23	0.22
			(1.19)	(1.18)
Year 1=1 # Mean Betweeness			0.40**	0.38**
			(2.14)	(2.13)
Year 2=1 # Mean Betweeness			0.43**	0.41**
			(2.31)	(2.30)
Year 3=1 # Mean Betweeness			0.33*	0.30
			(1.71)	(1.59)
Year 4=1 # Mean Betweeness			0.37*	0.34*
			(1.95)	(1.86)
Year 5=1 # Mean Betweeness			0.36*	0.33*

			(1.76)	(1.72)
Constant	0.61***	0.66***	0.63***	0.68***
	(2.67)	(2.71)	(2.73)	(2.76)
Observations	2563	2563	2563	2563
Model	OLS	RE	OLS	RE
Country Effects	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes

*Pooled OLS and panel regressions with portfolio-company random effects; not reported: country fixed effects and year effects; standard errors clustered at portfolio-company level; t-statistics in parentheses; significance: * 0.1, ** 0.05, *** 0.01.*

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

	Year\Percentile	25	50	75	90	95
b	−2	−0.23	−0.17	−0.01	0.29	0.51
se	−2	(0.03)	(0.03)	(0.02)	(0.03)	(0.05)
b	−1	−0.15	−0.11	0	0.21	0.37
se	−1	(0.03)	(0.03)	(0.02)	(0.03)	(0.04)
b	1	−0.48	−0.43	−0.29	0	0.2
se	1	(0.03)	(0.03)	(0.02)	(0.03)	(0.05)
b	2	−0.58	−0.52	−0.35	−0.03	0.2
se	2	(0.03)	(0.03)	(0.02)	(0.03)	(0.04)
b	3	−0.66	−0.6	−0.46	−0.19	0.01
se	3	(0.04)	(0.03)	(0.02)	(0.03)	(0.05)
b	4	−0.68	−0.63	−0.49	−0.2	−0.01
se	4	(0.04)	(0.03)	(0.03)	(0.03)	(0.06)
b	5	−0.79	−0.73	−0.59	−0.32	−0.12
se	5	(0.05)	(0.04)	(0.03)	(0.03)	(0.05)

Table 14: Growth of sales dependent on mean betweenness (marginal effects)

	Year\Percentile	25	50	75	90	95
b	−2	−0.22	−0.14	0.04	0.35	0.73
se	−2	(0.04)	(0.03)	(0.02)	(0.06)	(0.16)
b	−1	−0.11	−0.07	0.04	0.22	0.44
se	−1	(0.04)	(0.03)	(0.02)	(0.05)	(0.15)
b	1	−0.49	−0.41	−0.23	0.08	0.46
se	1	(0.03)	(0.03)	(0.02)	(0.05)	(0.14)
b	2	−0.57	−0.49	−0.3	0.04	0.45
se	2	(0.03)	(0.03)	(0.02)	(0.05)	(0.14)
b	3	−0.62	−0.56	−0.42	−0.18	0.11
se	3	(0.04)	(0.03)	(0.02)	(0.05)	(0.14)
b	4	−0.67	−0.6	−0.44	−0.16	0.18
se	4	(0.04)	(0.03)	(0.03)	(0.06)	(0.15)
b	5	−0.77	−0.7	−0.55	−0.28	0.05
se	5	(0.05)	(0.04)	(0.03)	(0.05)	(0.14)

Table 17: Growth of sales dependent on maximum centrality from the IV regressions (marginal effects)

	Year\Percentile	25	50	75	90	95
b	−2	−1.35	−0.65	0.78	4.12	5.64
se	−2	(2.70)	(0.46)	(2.02)	(37.37)	(68.32)
b	−1	−0.58	−0.33	0.17	1.35	1.89
se	−1	(0.77)	(0.20)	(0.38)	(7.80)	(14.45)
b	1	−1.01	−0.68	0	1.58	2.3
se	1	(0.43)	(0.15)	(0.12)	(2.83)	(5.36)
b	2	−1.44	−0.9	0.19	2.74	3.9
se	2	(0.74)	(0.22)	(0.27)	(6.06)	(11.37)
b	3	−1.48	−1	−0.01	2.26	3.31
se	3	(0.64)	(0.21)	(0.20)	(4.69)	(8.84)
b	4	−0.45	−0.44	−0.42	−0.36	−0.33
se	4	(0.54)	(0.20)	(0.15)	(3.37)	(6.40)
b	5	−1.71	−1.22	−0.21	2.13	3.2
se	5	(0.71)	(0.29)	(0.15)	(3.48)	(6.70)

Table 18: Growth of sales dependent on maximum betweenness from the IV regressions (marginal effects)

	Year\Percentile	25	50	75	90	95
b	−2	−1.54	−0.79	0.73	4.28	5.9
se	−2	(1.34)	(0.38)	(0.47)	(11.27)	(21.16)
b	−1	−1.19	−0.6	0.61	3.42	4.71
se	−1	(1.28)	(0.38)	(0.41)	(10.19)	(19.18)
b	1	−1.29	−0.76	0.33	2.87	4.03
se	1	(1.09)	(0.37)	(0.34)	(7.78)	(14.68)
b	2	−1.43	−0.92	0.14	2.59	3.71
se	2	(1.17)	(0.38)	(0.31)	(8.02)	(15.22)
b	3	−1.66	−1.1	0.03	2.67	3.87
se	3	(1.52)	(0.52)	(0.31)	(9.29)	(17.79)
b	4	−0.14	−0.12	−0.1	−0.04	−0.01
se	4	(4.06)	(1.66)	(0.35)	(15.94)	(31.75)
b	5	−2.36	−1.63	−0.15	3.28	4.85
se	5	(1.46)	(0.54)	(0.29)	(8.17)	(15.71)

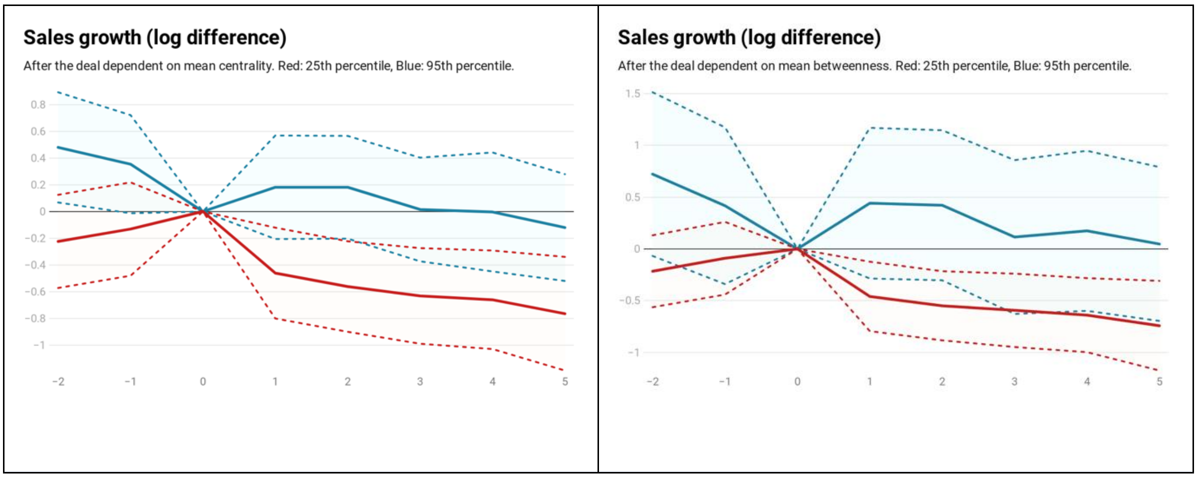


Figure 3: Differences between investors' high and low average centrality or betweenness on the paths of growth of portfolio companies.

Tables

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

	N	Mean	Median	St.Dev	Min	Max
Financing Rounds	29136	2.43	2	2.23	1	14
Syndicate Size	41909	3.48	3	2.4	1	26
Deal Size EUR Mio	31703	11.4	5	26.8	0.01	660
Known Funding EUR Mio	33713	39.2	12	116	0.01	1790
Expertise	41938	3.34	1	6.94	0	61
Syndicated	41938	0.802	1	0.399	0	1

Table 2: Descriptive statistics of network characteristics.

Measure	Number of Obs	Mean	Median	Std. Dev
Eigencentrality	7.353	0.0002506	0.0007747	0.0012611
Betweenness	7.353	0.0071267	0.0000005	0.0378612
Eigencentrality (excluding zeroes)	7.009	0.0074765	0.0009466	0.0387455
Betweenness (excluding zeroes)	4.289	0.0004296	0.0000163	0.0016278

Table 3: Correlation matrix

	Number of financing rounds	At least one round	Expertise	Betweeness central investor	Eigencentrality central investor	Centrality	Betweeness	Syndicate size	Total known funding
Total known funding									1
Syndicate size								1	0.2548
Betweeness							1	0.0077	0.0102
Centrality						1	0.6313	0.0504	0.1753
Eigencentrality central investor					1	0.6254	0.3338	0.1918	0.2672
Betweeness central investor				1	0.5837	0.3854	0.5564	0.2233	0.0869
Expertise			1	0.2201	0.3003	0.4585	0.3863	0.0575	0.1397
At least one round		1	0.1263	0.1706	0.2134	0.1168	0.0573	0.2080	0.1880
Number of financing rounds	1	0.5583	0.1420	0.1192	0.2010	0.1110	0.0229	0.2271	0.3961

Table 4: Poisson regressions: Number of financing rounds.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expertise	0.01***	0.01***	0.01***	0.01***	0.00	0.00	0.00	0.00
	(5.79)	(5.72)	(4.91)	(5.29)	(1.31)	(1.30)	(1.37)	(1.29)
Syndicate Size	0.03***	0.03***	0.02***	0.02***	0.01	0.01	0.01*	0.01*
	(4.33)	(4.28)	(3.66)	(3.22)	(1.38)	(1.37)	(1.77)	(1.75)
Total Known Funding (EUR mn)	0.00***	0.00***	0.00***	0.00***	0.01***	0.01***	0.00***	0.00***
	(7.31)	(7.57)	(6.41)	(7.56)	(6.24)	(6.31)	(5.49)	(6.28)
Centrality	0.03**				0.01			
	(2.33)				(1.25)			
Betweeness		0.02**				0.01		
		(2.31)				(1.39)		
Central Investor Centrality			0.14***				0.12***	
			(5.93)				(4.63)	

Central Investor Betweeness				0.12***				0.15***
				(5.71)				(7.26)
Constant	0.69***	0.68***	0.73***	0.72***	0.30**	0.30**	0.32***	0.34***
	(23.93)	(23.43)	(24.39)	(24.16)	(2.37)	(2.37)	(2.64)	(2.79)
Country	NO	NO	NO	NO	YES	YES	YES	YES
Industry	NO	NO	NO	NO	YES	YES	YES	YES
Industry-Country	YES	YES	YES	YES	NO	NO	NO	NO
Observations	26046	26046	26046	26046	26048	26048	26048	26048

*Pooled Poisson regressions (Columns 1–4) and panel Poisson regressions with portfolio-company random effects (Columns 5–8); 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.*

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expertise	0.01***	0.01***	0.01***	0.01***	0.00	0.00	0.00	0.00
	(5.02)	(4.97)	(4.15)	(4.52)	(1.40)	(1.39)	(1.42)	(1.36)
Syndicate Size	0.02***	0.02***	0.02***	0.02***	0.01	0.01	0.00*	0.00*
	(3.69)	(3.66)	(3.07)	(2.69)	(1.29)	(1.29)	(1.72)	(1.67)
Total Known Funding (EUR mn)	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(7.29)	(7.53)	(6.44)	(7.54)	(5.57)	(5.60)	(5.03)	(5.70)
Early=1	−0.32***	−0.33***	−0.29***	−0.30***	−0.11**	−0.11**	−0.10**	−0.10**
	(−11.20)	(−11.33)	(−9.56)	(−9.66)	(−2.06)	(−2.07)	(−2.20)	(−2.13)
Centrality	0.02				0.00			
	(1.61)				(0.87)			
Early=1 # Centrality	0.02				0.02**			
	(0.88)				(2.10)			
Betweeness		0.01				0.00		
		(1.05)				(1.10)		

Early=1 # Betweeneness		0.03				0.01		
		(1.13)				(1.58)		
Central Investor Centrality			0.11***				0.10***	
			(4.58)				(4.75)	
Early=1 # Central Investor Centrality			0.09**				0.07***	
			(1.99)				(3.66)	
Central Investor Betweeneness				0.11***				0.13***
				(4.50)				(6.29)
Early=1 # Central Investor Betweeneness				0.06				0.06***
				(1.40)				(3.24)
Constant	0.78***	0.78***	0.81***	0.80***	0.33***	0.33***	0.36***	0.38***
	(25.35)	(24.94)	(25.84)	(25.56)	(2.60)	(2.61)	(2.86)	(3.01)
Country	NO	NO	NO	NO	YES	YES	YES	YES
Industry	NO	NO	NO	NO	YES	YES	YES	YES
Industry-Country	YES	YES	YES	YES	NO	NO	NO	NO
Observations	25872	25872	25872	25872	25874	25874	25872	25872

*Pooled Poisson regressions (Columns 1–4) and panel Poisson regressions with portfolio-company random effects (Columns 5–8); 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.*

Table 6: Probit model for the probability of a successful exit by M&As (Columns (1) and (2)) or IPOs (Columns (3) and (4)).

	(1)	**(2)**	**(3)**	**(4)**
Expertise	0.04***	0.04***	0.02***	0.03***
	(12.76)	(12.81)	(9.48)	(9.12)
Centrality Central Investor	0.07**		0.03	
	(2.28)		(0.42)	
Syndicate Size	0.05***	0.05***	0.03**	0.03**
	(5.65)	(5.54)	(2.21)	(2.40)
Total Known Funding (EUR) Mrd	−1.19***	−1.07***	2.48***	2.52***
	(−3.28)	(−3.06)	(4.72)	(4.80)
Betweenness Central Investor		0.06**		−0.01
		(2.43)		(−0.29)
Constant	−1.02***	−1.02***	−2.09***	−2.10***
	(−3.21)	(−3.19)	(−4.41)	(−4.44)
Observations	33209	33209	31543	31543

*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 7: Interaction between the centrality measures and the first round of financing.

	(1)	(2)	(3)	(4)
Expertise	0.00	0.00	0.00	0.00
	(1.24)	(1.26)	(1.25)	(1.21)
Syndicate Size	0.01	0.01	0.01	0.01
	(1.26)	(1.27)	(1.30)	(1.31)
Total Known Funding (EUR) Mrd	4.86***	4.86***	4.78***	4.82***
	(4.51)	(4.51)	(4.38)	(4.52)
First=1	−0.13	−0.13	−0.13	−0.13
	(−1.45)	(−1.45)	(−1.43)	(−1.46)
Centrality	−0.00			
	(−0.05)			
First=1 # Centrality	0.01**			
	(1.97)			
Betweeness		−0.00		
		(−1.11)		
First=1 # Betweeness		0.01		
		(1.52)		
Centrality Central Investor			0.02	

			(1.38)	
First=1 # Centrality Central Investor			0.03***	
			(3.54)	
Betweenness Central Investor				0.01
				(1.56)
First=1 # Betweenness Central Investor				0.02***
				(2.77)
Constant	0.50***	0.50***	0.50***	0.50***
	(5.67)	(5.69)	(5.70)	(5.70)
Observations	25968	25968	25968	25968

*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.*

Table 8: Sales growth and maximum centrality/betweeness.

	(1)	(2)	(3)	(4)
Sales at −1	−0.04**	−0.04**	−0.04**	−0.04**
	(−2.33)	(−2.32)	(−2.36)	(−2.37)
(log) Deal Size	0.01	0.02	0.01	0.01
	(0.73)	(0.66)	(0.71)	(0.61)
Syndicate Size	−0.01	−0.01	−0.01	−0.01
	(−0.73)	(−0.51)	(−0.76)	(−0.65)
Max Expertise	0.00	0.00	0.00	0.00
	(0.05)	(0.60)	(0.14)	(0.52)
Total known funding	0.70***	0.79*	0.73***	0.82*
	(2.62)	(1.76)	(2.82)	(1.88)
Max Centrality	−0.13*	−0.14**		
	(−1.93)	(−2.36)		
Year −2=1	−0.14	−0.10	−0.15	−0.11
	(−0.78)	(−0.63)	(−0.84)	(−0.66)
Year −2=1 # Max Centrality	0.15*	0.14*		
	(1.69)	(1.77)		

Year -1=1	−0.05	−0.07	−0.05	−0.06
	(−0.31)	(−0.42)	(−0.28)	(−0.37)
Year −1=1 # Max Centrality	0.07	0.08		
	(0.83)	(1.08)		
Year 1=1	−0.36**	−0.37**	−0.38**	−0.39**
	(−2.12)	(−2.34)	(−2.22)	(−2.43)
Year 1=1 # Max Centrality	0.14**	0.13**		
	(2.09)	(2.19)		
Year 2=1	−0.43**	−0.45***	−0.46***	−0.47***
	(−2.54)	(−2.84)	(−2.66)	(−2.92)
Year 2=1 # Max Centrality	0.15**	0.14**		
	(2.14)	(2.36)		
Year 3=1	−0.54***	−0.54***	−0.55***	−0.54***
	(−3.08)	(−3.29)	(−3.09)	(−3.25)
Year 3=1 # Max Centrality	0.12*	0.12*		
	(1.67)	(1.76)		
Year 4=1	−0.56***	−0.57***	−0.56***	−0.57***
	(−3.08)	(−3.31)	(−3.08)	(−3.28)

Year 4=1 # Max Centrality	0.13	0.13*		
	(1.56)	(1.75)		
Year 5=1	−0.67***	−0.67***	−0.69***	−0.69***
	(−3.32)	(−3.43)	(−3.32)	(−3.40)
Year 5=1 # Max Centrality	0.12	0.12*		
	(1.58)	(1.71)		
Max Betweeness			−0.24**	−0.22**
			(−2.24)	(−2.24)
Year -2=1 # Max Betweeness			0.22*	0.20*
			(1.81)	(1.66)
Year -1=1 # Max Betweeness			0.15	0.14
			(1.22)	(1.23)
Year 1=1 # Max Betweeness			0.26**	0.24**
			(2.41)	(2.39)
Year 2=1 # Max Betweeness			0.27**	0.25**
			(2.53)	(2.48)
Year 3=1 # Max Betweeness			0.20*	0.18*
			(1.80)	(1.65)

Year 4=1 # Max Betweeness			0.19	0.17
			(1.62)	(1.56)
Year 5=1 # Max Betweeness			0.23*	0.22*
			(1.90)	(1.88)
Constant	0.70***	0.74***	0.71***	0.76***
	(2.90)	(2.89)	(2.96)	(2.97)
Observations	2563	2563	2563	2563
Model	OLS	RE	OLS	RE
Country Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes

*Pooled OLS and panel regressions with portfolio-company random effects; not reported: country fixed effects and year effects; standard errors clustered at portfolio-company level; t-statistics in parentheses; significance: * 0.1, ** 0.05, *** 0.01.*

Table 9: Growth of sales dependent on maximum centrality (marginal effects)

	Year\Percentile	25	50	75	90	95
b	−2	−0.16	−0.14	−0.06	0.05	0.25
se	−2	(0.03)	(0.03)	(0.02)	(0.02)	(0.04)
b	−1	−0.1	−0.09	−0.04	0.02	0.13
se	−1	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
b	1	−0.43	−0.41	−0.33	−0.23	−0.04
se	1	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
b	2	−0.51	−0.49	−0.4	−0.29	−0.09
se	2	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
b	3	−0.59	−0.57	−0.5	−0.41	−0.25
se	3	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
b	4	−0.62	−0.6	−0.53	−0.43	−0.26
se	4	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
b	5	−0.73	−0.71	−0.63	−0.54	−0.38
se	5	(0.05)	(0.04)	(0.03)	(0.03)	(0.03)

Table 10: Growth of sales dependent on maximum betweenness (marginal effects)

	Year\Percentile	25	50	75	90	95
b	−2	−0.21	−0.14	0.01	0.34	0.49
se	−2	(0.04)	(0.03)	(0.02)	(0.06)	(0.11)
b	−1	−0.13	−0.08	0.02	0.25	0.36
se	−1	(0.04)	(0.03)	(0.02)	(0.05)	(0.09)
b	1	−0.51	−0.42	−0.25	0.15	0.34
se	1	(0.04)	(0.03)	(0.02)	(0.04)	(0.07)
b	2	−0.59	−0.5	−0.32	0.11	0.3
se	2	(0.04)	(0.03)	(0.02)	(0.04)	(0.07)
b	3	−0.63	−0.57	−0.44	−0.14	−0.01
se	3	(0.04)	(0.03)	(0.02)	(0.04)	(0.08)
b	4	−0.65	−0.59	−0.47	−0.18	−0.05
se	4	(0.04)	(0.03)	(0.02)	(0.06)	(0.09)
b	5	−0.8	−0.72	−0.57	−0.2	−0.04
se	5	(0.06)	(0.05)	(0.03)	(0.05)	(0.08)

Table 15: Instrumental variables Poisson model

	(5)	(6)	(7)	(8)
Expertise	0.00	−0.00	−0.00**	−0.01***
	(0.11)	(−1.52)	(−2.32)	(−3.57)
Syndicate Size	0.01	0.01	−0.00	−0.01***
	(1.36)	(1.39)	(−0.31)	(−3.31)
Total Known Funding (EUR) Bio	5.24***	5.28***	4.98***	5.17***
	(6.11)	(6.22)	(5.36)	(5.97)
Centrality	0.01			
	(0.21)			
Betweeness		0.08*		
		(1.73)		
Centrality Central Investor			0.22***	
			(2.91)	
Betweenness Central Investor				0.26***
				(2.89)
Constant	0.44***	0.45***	0.50***	0.54***
	(11.27)	(11.20)	(9.61)	(7.64)
Country	YES	YES	YES	YES
Industry	YES	YES	YES	YES
CF Residuals	−0.01	−0.08*	−0.19***	−0.25***
	(−0.18)	(−1.75)	(−2.76)	(−2.93)
Kleibergen-Paap Wald	120.874	625.863	281.743	552.771

Observations	22534	22534	24852	24852

*Panel Poisson regressions with portfolio–company random effects; Centrality measures instrumented with dispersion from regular investment patterns; Wooldrgie and Lin (2019) control function approach used; Kleibergen-Paap rk Wald F statistics reported for an equivalent linear model; not reported: industry and country fixed effects; robust standard errors clustered at portfolio-company level; Z-statistics in parentheses; significance: * 0.1, ** 0.05, *** 0.01.*

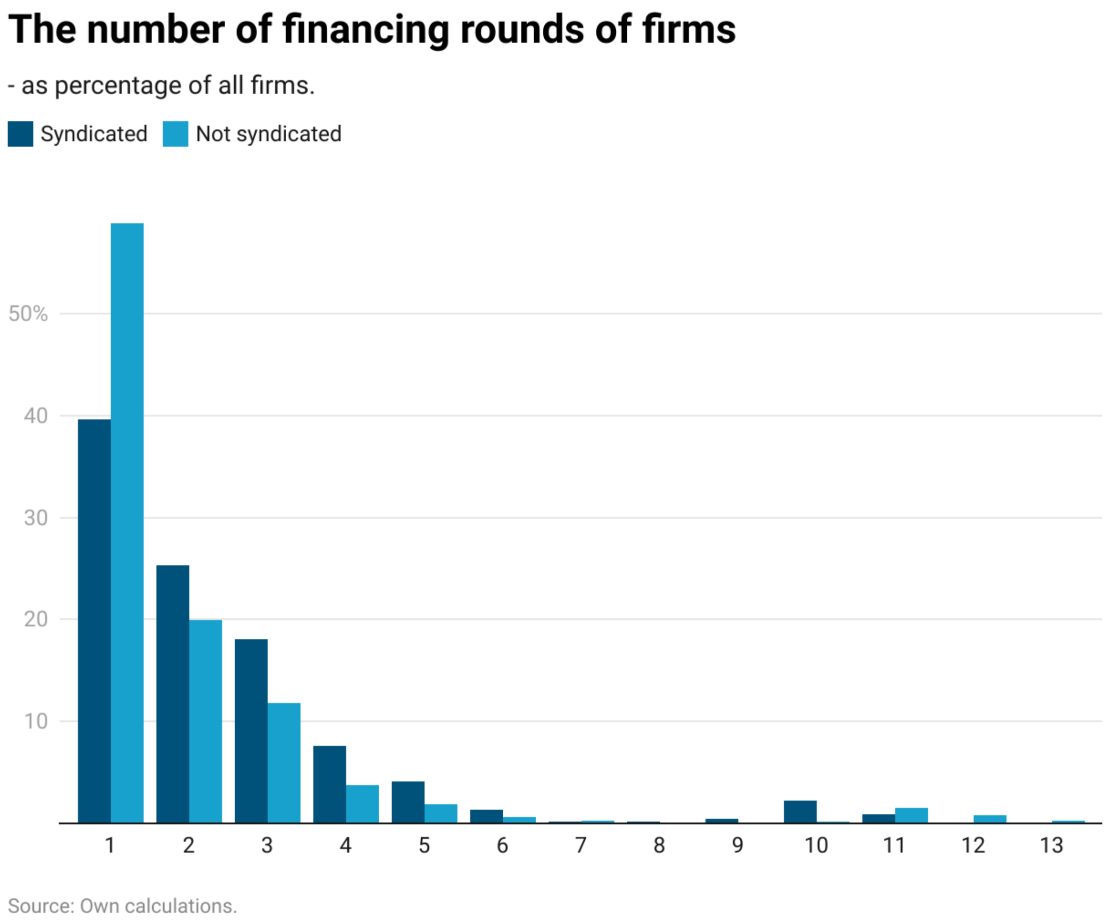
Table 16: Instrumental variables Poisson model: Interactions

	(5)	(6)	(7)	(8)
Expertise	0.00	−0.00	−0.00**	−0.01***
	(0.02)	(−1.37)	(−2.21)	(−3.49)
Early=1	−0.11**	−0.11**	−0.10*	−0.09*
	(−2.27)	(−2.26)	(−1.80)	(−1.92)
Syndicate Size	0.01	0.01	−0.00	−0.01***
	(1.43)	(1.47)	(−0.35)	(−2.66)
Total Known Funding (EUR) Bio	4.94***	4.98***	4.74***	4.94***
	(5.53)	(5.63)	(4.87)	(5.48)
Centrality	0.02			
	(0.27)			
Early=1 # Centrality	0.02**			
	(2.06)			
Betweeness		0.07*		
		(1.74)		
Early=1 # Betweeness		0.01		
		(0.91)		
Centrality Central Investor			0.20***	
			(2.61)	
Early=1 # Centrality Central Investor			0.03**	
			(2.26)	
Betweenness Central Investor				0.23***
				(3.00)

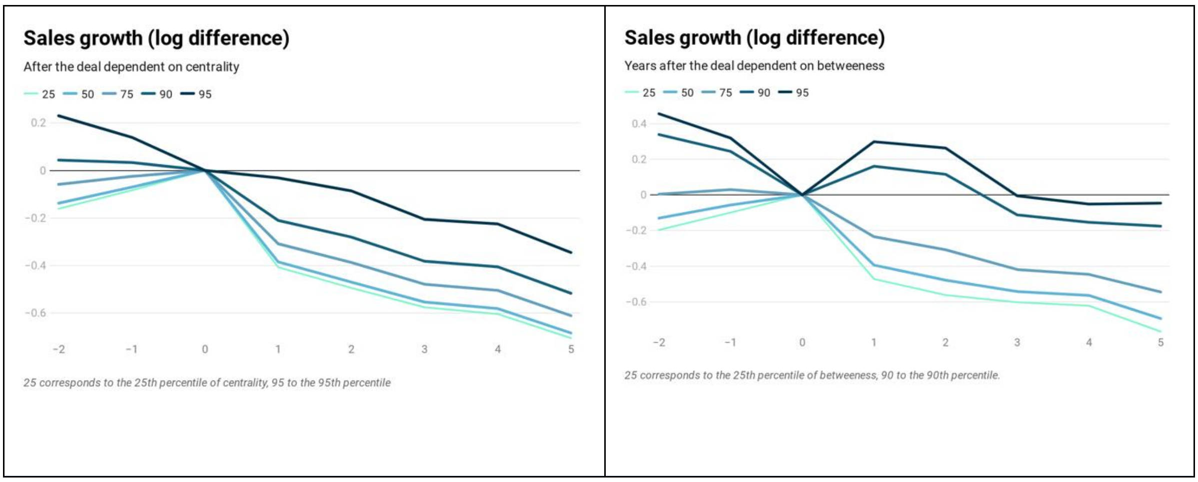
Early=1 # Betweenness Central Investor				0.00
				(0.39)
Constant	0.49***	0.49***	0.54***	0.56***
	(9.33)	(9.42)	(7.98)	(7.32)
Country	YES	YES	YES	YES
Industry	YES	YES	YES	YES
CF Residuals	−0.02	−0.07*	−0.19**	−0.22***
	(−0.27)	(−1.79)	(−2.54)	(−3.06)
Kleibergen-Paap Wald	45.143	232.291	76.620	239.217
Observations	22534	22534	24852	24852

*Panel Poisson regressions with portfolio-company random effects; Centrality measures instrumented with dispersion from regular investment patterns; Wooldrgie and Lin (2019) control function approach used; Kleibergen-Paap rk Wald F statistics reported for an equivalent linear model; not reported: industry and country fixed effects; robust standard errors clustered at portfolio-company level; Z-statistics in parentheses; significance: * 0.1, ** 0.05, *** 0.01.*

Figures



Source: Own calculations.



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