Money talks: The impact of investors' networks on entrepreneurs' success

ABSTRACT

This paper analyzes the role of investors' network centrality on the company in which they are investing. Our longitudinal (1968-2020, across industries) study shows that an investor with a central network position is beneficial for entrepreneurs, both pre-IPO and post-IPO. We find that an investor with a central network position increases the likelihood that the investee will obtain subsequent funding, go public, and perform in the long term. We also show that to go public, the startup ideally first needs funding from a central investor – which could even come at the expense of receiving a higher amount from a less central investor – before broadening its investor base to include more investors as it moves toward exit via IPO. We further examine the effect of investor centrality on startup valuation at the time of the IPO and the firm's short and long term success.

Keywords: startup, network, investor, quantitative, centrality

INTRODUCTION

> ”The best assumption to make is that your VC’s primary value add is the cash they are investing. Then you’ll always be surprised on the upside.” [1]

In addition to the cash provided by business angels and venture capital (VC) firms, as investees, they add value to the startups they fund. This added value has been described as “smart money” (Morten, 2007), meaning the developmental advice in the form of counseling, talent recruitment, and structuring (Lerner, 1995; Croce et al., 2013; Hellmann & Puri, 2002). An essential asset provided by an investor is his or her connections (Lockett et al., 2006). The investor’s network represents a pool of resources and a group of the investor’s personal contacts. While network studies show that these contacts can be instrumental for providing informational advantages (Admati & Pfleiderer, 1994), allowing balance sheet diversification (Ewens et al., 2018), and maximizing returns for network members (Gompers et al., 1995), we know little about the effect of the investor’s network on the company in which he or she invests. In this paper, we investigate the impact of the investor’s network position on investees.

In particular, we examine if the investment from a central investor at an early stage increases the chances of its investee to secure later successful rounds of funding? Can a favorable network position of an investor increase the odds that a startup will go public?[2] Finally, can we infer from the network centrality of an investor the potential future success of a startup?

In the first section, we define the terms used in the paper and provide a brief overview of the relevant literature and aim of our study. The second and third sections describe the data and present our results. The fourth and fifth sections provide a discussion of our findings and conclude the paper.

[1] Quote from Marc Andreessen, http://blog.pmarca.com/, who, among other roles was cofounder of the venture capital firm Andreessen Horowitz which is headquartered in Silicon Valley and was an early investor in firms such as Airbnb, Facebook, Twitter, and Skype.

[2] Going public or launching an initial public offering (IPO) is considered most profitable, and therefore is preferred by investors.

LITERATURE

Syndication

The rise in the number of startups has attracted much academic research (Decker et al., 2014). According to the Bureau of Labor Statistics, the number of new companies in the United States rose from 608,769 (2009) to 679,072 (2016). Startup creation has a significant positive effect on productivity and GDP (Gourio et al., 2016). To create value, the startup must raise capital to develop its activities. The low rate of success related to startup development makes for a risky investment. People investing in startups at different stages are not the same. And their motives aren't the same either (Block et al., 2019).

One of the characteristics of VC financing is syndication [3] which involves cooperation among several investors to allow investment of joint capital in a startup at a moment in time or over a set period of time (Wang, 2020). This allows a larger investment than would be possible by a single investor. Our study sample includes a large proportion of syndicated deals (70%, see table 1).

There are three main reasons for syndication investments (Lerner, 1994): better decision making (Bayar et al., 2019), informational advantages (Admati & Pfleiderer, 1994), and "window dressing" (Lakonishok et al., 1991). All participants in the syndicate benefit from better decision making which reduces moral hazard (Bayar et al., 2019) and is in line also with the results in Sah & Stiglitz (1986). Informational advantages (Admati & Pfleiderer, 1994) derive from joining the syndicate which allows access to more accurate information on the startup than would be available to an outsider. This can enable more accurate assessment related to later rounds of funding and opportunities for future deals and their pricing. Syndication is beneficial also to the investor by providing organizational learning skills (Khurshed et al., 2020). Finally, syndication allows investors to join in a deal which would have been impossible were they an individual investor. It also provides a more attractive balance sheet and can be seen as a form of window dressing (Lakonishok et al., 1991) Rather than being purely profit driven, the investor's motive in this case

[3](Wilson, 1968) defines a syndicate as: "a group of individuals who must make a common decision under uncertainty that will result in a payoff to be shared jointly among them."

is to market him or herself by appearing a “better” investor. By joining a syndicate, an individual investor can “market” him or herself as an investor in a “hot” startup in which prominent investors have already invested, while being willing to receive a lower return on the investment. [4]

Ewens et al. (2018) and Gompers et al. (1995) point to risk management as one of the motives for syndication since a joint investment allows the investors to balance their portfolios better (diversification, ”spray and pray”), and if necessary to cut the funding.

While research shows that most investments in startups are made by syndicates, little is known about the investors’ respective network positions and their impact on the development and success of the investee companies. In the present paper, we focus on the network of connections enabled by syndication to analyze investment history in order to determine the most central actors in the investment scene and the impact of their status on investees.

Insert TABLE 1 about here.

Smart money

An investor’s attributes include more than just cash. The competences of the investor are very important for the development of the startup . These other attributes can include access to other investors and entrepreneur, counseling, and technical/legal help. All of these can be important for building relations and a successful company (Mosey & Wright, 2007; Davidsson & Honig, 2003). It is crucial that the startup forges links going beyond the entrepreneur’s immediate network (Zhang et al., 2008). Venture capitalists can intervene in nonmonetary ways to foster innovation, reduce the time to market for new products (Hellmann & Puri, 2000), and add to the startup’s professionalization (Hellmann & Puri, 2002). They can contribute experience and the resources likely to lead to firm success (Morten, 2007), and can increase the startup’s innovation/likelihood of successful exit by being more involved and dedicating more time to monitoring and helping the company (Bernstein et al., 2015)).

[4] The investor may be overpaying for syndicate entry if his or her rationale is to get noticed rather than receiving a large return on the investment.

Hsu (2005) shows that more prestigious venture capitalists are more likely to have their offers accepted and to pay a discounted rate (around 12%). This indicates that entrepreneurs value extrafinancial services and see them as contributing more to venture success than a pure cash offer. VC investors can play a direct role in firm growth through board membership which allows better opportunities for monitoring (Lerner, 1995; Kaplan & Strömberg, 2005). Alexy et al. (2012) show that the amount of funding is influenced by the VC investor's social capital, and current investments affect the willingness to invest. Tsai & Ghoshal (1998) suggest that social interactions lead to interunit exchanges of resources which have a significant effect on product innovation. A famous investor's backing can even help recruitment of new talents on its sole presence as an investor (Bernstein et al., 2020). Wal et al. (2016) work on the American information technology sector looks at the relation between investors' social capital and portfolio venture success. They find that startup success is boosted by investors that are part or open specialized networks or closed diverse networks.

Certification

In the case of private investors [5], research shows that information asymmetry and lack of information lead to certification bias. Megginson & Weiss (1991) highlight the impact of certification in the case of startups with prestigious VC investors. They show that the privileged situation of the investors allows extraction of surplus by VC investors.

The investor's willingness to invest his or her own money in the startup is a signal of trust in the quality of the entrepreneur (Lewis & Sappington, 2000), and especially since the entrepreneur's abilities or lack of them may penalize firm success whose cost will be borne by the investor. In general, the more renowned the investor, the stronger should be the signal that the company's prospects are good. Signaling effects apply also to other firm characteristics such as affiliation to a prestigious university for a sciencebased startup (Colombo et al., 2019). This intuition is confirmed by Bertoni et al. (2011) who analyze selection compared to real effects.

[5] This does not hold for public investors, e.g. grant funding from government agencies shows no observable signs of certification effects (Howell, 2017).

They show that startups benefit from higher gains from investments than typically would be due to simple selection bias (which would identify only high performing firms).

Reputation

More powerful and more well-known investors with central network positions are likely to have beneficial effects on investee firms. Nahata (2008) finds that more reputable VC investors (controlling for characteristics such as connectedness and syndication) are likely to induce better shortterm performance in the investee company. However, Gompers (1996) shows that younger venture capitalists, keen to increase their reputation, are more likely to promote faster development and a shorter time to IPO. Thus, even younger, less well known VCs have a noticeable impact on startup development. It has been shown (Inkpen & Tsang, 2005) that the social capital dimensions of the network have a significant effect on knowledge transfer (i.e. intracorporate networks, strategic alliances, and industrial districts.)

Based on a network study of selected industry participants, (Walske et al., 2007) find that startup success increases with the strength of venture syndicate ties. Reputation matters also in the case of the bank supervising the IPO process (the underwriter). There is a direct positive relationship between underwriter prestige and price of the IPO (Liu & Ritter, 2011), and in the short term underperformance is reduced by a more prestigious underwriter managing the transaction (Carter et al., 1998). The underwriter certifies risky issue prices reflecting potentially adverse insider information (Booth & Smith, 1986).

VC fund performance increases with the position of the VC investor in the network, as documented by Hochberg et al. (2007); Checkley et al. (2010), also suggesting that companies with better-networked investors have a higher chance of survival. To that first point, we will differ as in this paper we focus on the effects benefiting the startup rather than investors.

FRAMEWORK AND HYPOTHESES

The present paper contributes to the literature in several ways. Rather than taking the investor's perspective, we look at the entrepreneur's interests as a funder. We examine a diverse range of industries/periods and analyze funding/performance longitudinally. We address the problems encountered by startups during their life cycle, from first funding round to performance in the market.

Progressing to the next round

The ability to continue to raise cash is critical for young companies. It allows startups to continue growing, recruit new staff, develop their product, and take over new markets. The criticality of this ability suggests that the centrality of the startup's investors might increase the probability of subsequent funding.

Hypothesis 1. The participation of a more central investor in the first round of fundraising increases the likelihood of obtaining further funding.

Increasing funding amount

Although there may be exceptions, it tends to augur well for the startup if the amounts of cash raised increase to match the company's needs as it grows. Table 4 shows that after each round of founding the amount obtained by the startup is increasing.

Hypothesis 2. The participation of a more central investor in the first funding round increases the likelihood of obtaining a higher amount of funding in a subsequent round.

Going public

We test the emergence of a pre-IPO phase by looking at investor centrality and its influence on going public.

Hypothesis 3a. The participation of a more central investor in the first funding round *increases the likelihood of going public.*

Hypothesis 3b. The participation of a more central investor in the last funding round pre-IPO increases the likelihood of going public.

We focus on this outcome because (along with being acquired) it is the main measure of startup success and it is the objective of investors looking to maximize their return on investment.

IPO Valuation

For a sub-sample of companies, we can observe financial performance in terms of valuation at IPO.

Hypothesis 4. The participation of a more central investor increases the likelihood of a higher valuation for the startup at IPO.

Growth

In the second phase, we analyze firm growth rates in the first year and subsequent years of activity after an IPO.

Hypothesis 5a. The participation of a more central investor increases the short term likelihood of a higher share price after the IPO.

Hypothesis 5b. The participation of a more central investor increases the long term likelihood of a higher share price after IPO.

DATA & MEASURES

Our analysis relies on external data on startup investments and stock markets. Our primary source of data is Crunchbase (crunchbase.com) which provides access to data on the world's most innovative companies for use by investors and analysts. We use these data to build a network from past investment deals[6], and to derive the network centrality values used in our subsequent estimations. The data span from 1968 (with an investment in a promising chip company, Intel) to

[6] This means that both syndicates and single investments are included in the data.

2020. Until the end of the 1990s, syndicated deals were rare. The data provide information on around 240,000 funding rounds, from small seed funding to multibillion deals. They cover all open economies over five decades. This allows good representation of market activities and reduce risk of bias. [7]

Network

Using data from Crunchbase, we obtained information on the investments made by investors in each project which allowed us to map the investors who worked together (in a syndicate). This mapping is conducted for the period 1968-2010 and found that the pattern was very similar to the pattern for 1968-2019 in terms of computation of centrality measure (most of the leading investors were already present in the market in 2010). For the next part of the analysis, this period was used as training data to allow us to derive degree and other centrality metrics. The remaining data (accounting for the largest share of entries from 2010 to 2019) are used as our test set to estimate the coefficients.

Insert TABLE 2 about here.

The data cover investors from all continents although some areas are more represented than others, namely the Americas (53%), Europe (30%) with Asia at 14%. Most startups in our dataset achieved less than five rounds of funding (based on all available sources of funding, see table 2). The most represented group of participants are business angels (37%), investment partners (21%), and VC firms (19%) (table 3).

Insert TABLE 3 about here.

[7] Bias may arise if undisclosed deals are not included in the data i.e. if those undisclosed deals are correlated this could induce bias.

The result is an undirected network[8] in which the nodes are investors (either individuals or investment institutions) and the edges are the connections between them created by joint (syndicated) deals. The network presents a clear distinction between a large core of highly connected actors and an extended set of relatively isolated investors, with a large connected component and 91,313 weakly connected components.

Insert TABLE 4 about here.

We employ Blondel et al. (2008) algorithm which identifies a few large communities of investor and a multitude of isolated investors. [9] There are some communities within the range of 1200 to 2000 nodes, a few more 10-500 nodes communities, and a substantial number of isolated players which is to be expected given the basic segmentation of investors around locations and industries. We obtain a high average clustering coefficient of 0.695, spread unequally among investors. A lot of investors are close to 0 while a small part have higher indices.

Centrality measures

The next step after building a usable network is to extract the centrality measures which will be used later in the paper. We use the measures used widely in the network literature: degree and eigencentrality.

Degree measures the number of the agent's connections in the network. We find that their distribution is uneven. While the average degree is 1.71, most agents have a small number of connections while a few powerful ones account have as many as 2000. By relying only on pure links, without related information, we lose a layer of available information but we crowd out the risk of introducing a bias.

[8] We examine an undirected network rather than a directed network due primarily to the existence of inconsistencies in our dataset and to avoid introducing bias. The lead investor (the investor that initiated the syndication and around which other investors aggregated) is not reported for every deal.

[9] Communities should be understood according to Newman (2010), page 371, definition as: "groups of vertices that have few connections between them."

Eigencentrality (or eigenvector centrality) is a measure taken from graph theory which gives a score to the influence of a node in a network. As Newman (2010), page 169, puts it, ”think of degree centrality as awarding one ’centrality point’ for every network neighbor a vertex has. But not all neighbors are equivalent. Instead of awarding vertices just one point for each neighbor, eigenvector centrality gives each vertex a score proportional to the sum of the scores of its neighbors.”

We find that eigencentrality and degree show similar patterns of a large share of loosely connected agents with a few critical, highly connected agents. We find a large count of agents stuck at 0, and a few spread across $]0, 1]$. Given the extra value derived from syndication we find that a significant portion of investments are made by pools of investors. Here, the term investor can refer to both individuals cooperating to achieve a higher amount of capital, VC firms which find it beneficial to pool their resources on a deal, and banks which may follow the lead of other investors in a deal in a later stage of funding since the risk lower and the capital needed is higher (often second or third stage funding). For completeness, we collect the same information for a dataset with an unrestricted time frame (1968-2019); we find that the results (the distinction between many less connected and a few highly connected actors) are persistent; hence highlighting a recurrent pattern in links formation between investors.

The last step consists of constructing a measure for investee investment success. We focus on three factors: first, could the firm obtain subsequent funding? Could the startup go to IPO? Has the firm’s financial performance been improved? In the case of the first two, the data area available from Crunchbase.

As a measure of short term success, we measure growth in the company’s stock price after IPO. [10] Historical stock prices are available from Quandl and Google Finance. For a longer term view, we compute the annual growth rate from the data of the actual IPO to 2018 for each referenced stock[11]. We use the list of current prices provided by Google Finance

[10] Although Koller et al. (2010) would argue that this would be valid only in an ideal world, given data availability and in the interests of simplicity we adopt this measure.

[11] We focus on stock prices in the case of IPOs before 2017

Other measures

We look at the historical and current stock prices. For financial metrics, we rely on Quandl for historical values, and Google Finance which allows us to measure the sample companies' performance after going public.

Variables

In what follows, we define the variables used for our estimations.

Dependent Variables *Next round* is a dummy that is equal to 1 if the startup obtained more than one round of funding and 0 otherwise. *First raised amount* and *last raised amount* are logs of the amounts raised in USD in the first and last funding rounds. *IPO* is a dummy that is equal to 1 if the startup went public and 0 otherwise. *Value* is the firm valuation on entry to the market at IPO. $Growthfirst_{firstyear}$ and $Growth_{n-year}$ are the growth in stock prices in the first year and over several years over the annual rate of growth of the startup since the IPO.

Independent Variables *Log(highest degree)* is is the log of the degree of the most central investor in the funding round. *Higher centrality* is the higher eigencentrality among the round investors. *Max centrality* is the global maximum eigencentrality among all the investors that invested in the startup. *Size syndicate* is the number of investor taking part in the funding round. *Growth raised amount* is the growth in the amount raised in USD between the first and last funding rounds. *Total funding* is the log of the sum of all the funding from all funding rounds in USD.

Controls *Geographical area* is a group categorisation of the startup localisation.

We define *Sector Fit* as a binary variable that is equal to 1 if the investors in a funding round are specialized predominantly in the same sector of activity as the investee company (for example, that a mainly tech-focused investors back a tech startup). By ”specialized,” we mean that most of their investments are in companies operating in that particular sector. The sectors considered are defined according to the Global Industry Classification Standard (GICS) as *Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financials, Information Technology, Telecommunication Services, Utilities*, and *Real Estate*. We included the sector *Diversified* for investors with investments in several sectors.

METHODS

We observe two dimensions in our analysis. The first we call pre-IPO which refers to the success factors required for the startup to go public. In this period, we focus on two measures of success: how investor centrality affects the probability of obtaining another round of funding and ultimately increasing the probability of further funding? Does investor centrality influence the likelihood of going public? The second dimension is post-IPO which refers to firm financial success after going public. We examine whether investor centrality has an impact on the firm's short term (one year) or long-term (more than one year) stock price.

Progressing to the next round

To answer the interrogation raised by *Hypothesis 1*, we turn to a simple logit model, following equation 1, to estimate which factors affect the probability of reaching a new round of funding.

$$\begin{aligned}\text{Next round} =&\beta_0 + \beta_1 \times \text{Log(raised amount)} + \beta_2 \times \text{Log(highest degree)} \\ &+\beta_3 \times \text{Size syndicate} + \beta_4 \times \text{Sector fit} + \beta_5 \times \text{Geographical area} + \epsilon\end{aligned} \tag{1}$$

Note first that in our data, slightly less than 70% of the companies achieved one round of funding with the other 30% obtaining two or more rounds. Hence, a significant proportion of the deals are not syndicated. Table 1 shows that there is a large share of single investor deals, and that only 30% of investments involve five or more investors.

Increasing funding amount

We next investigate whether investor centrality increases the amount raised by the startup in the future (*Hypothesis 2*). We test whether higher centrality of investors contributes to higher funding in the future. Hence, we look for elements which might affect the amount of capital the startup could raise in the last round of funding before going public; for companies which didn't go public, we use the last available round of funding. We restrict the sample to the population of startups which accounted for two or more rounds across all sector.

$$\begin{aligned}\text{Raised amount}_{\text{last}} = & \beta_0 + \beta_1 \times \text{Raised amount}_{\text{first}} + \beta_2 \times \text{Syndicate Size} \\ & + \beta_3 \times \text{Sector fit} + \beta_4 \times \text{Higher centrality} + \epsilon\end{aligned} \tag{2}$$

Going public

Since our interest is in IPOs, we next study the startup performance induced by investor centrality. This excludes acquired companies since we cannot monitor the firm's development after it has merged with another company. [12]

To test *Hypothesis 3a* and *Hypothesis 3b*, we use the following regression:

$$\begin{aligned}\text{IPO} = & \beta_0 + \beta_1 \times \text{Log(Raised amount)} + \beta_2 \times \text{Higher centrality} \\ & + \beta_3 \times \text{Sector fit} + \beta_4 \times \text{Syndicate size} + \epsilon\end{aligned} \tag{3}$$

IPO Valuation

To test *Hypothesis 4*, we examine startup valuation after IPO.

$$\begin{aligned}\text{Value} = & \beta_0 + \beta_1 \times \text{Log(Raised amount)} + \beta_2 \times \text{Higher centrality} \\ & + \beta_3 \times \text{Global Sector fit} + \beta_4 \times \text{Growth Raised amount} + \epsilon\end{aligned} \tag{4}$$

[12] Following a merger, although the original startup's brand and logos may persist, its financial performance will be linked to that of the acquirer which makes it impossible to track the former firm's individual performance.

Post-IPO

Short-term growth To test *Hypothesis 5a*, we are interested in the rate of change in the price of the stock.[13]

$$\begin{aligned}\text{Growth}_{\text{first year}} = \beta_0 + \beta_1 \times \text{Higher Centrality} + \beta_2 \times \text{Raised amount} \\ + \beta_3 \times \text{Total Funding} + \beta_4 \times \text{Growth raised amount} + \epsilon\end{aligned} \tag{5}$$

Long-term growth In the case of *Hypothesis 5b*, we are interested in whether investor centrality plays a role in financial performance but over an extended period (more than 1 year). Here, we use the updated data on stock prices for summer 2018 and compute the startup's annual growth rate since the IPO.

$$\begin{aligned}\text{Growth}_{\text{n-year}} = &\beta_0 + \beta_1 \times \text{Growth}_{\text{Growth}} + \beta_2 \times \text{Growth raised amount} \\ &+\beta_3 \times \text{Max centrality} + \epsilon\end{aligned} \tag{6}$$

RESULTS

Progressing to the next round

We find a significant effect of investor centrality on investee's likelihood of obtaining more funding (*Hypothesis 1*). Table 5 shows that we found strong significance (at the 0.001 level) and a positive effect of 0.44 per 1 log of degree. Using the log of the degree of the investor with the highest degree among syndicate members, we find its impact is consistently positive (a 44% to 21% increase in the probability of obtaining another round for each increment of 1 log of degree); thus, a more central investor increases the likelihood that the investee receives more funding compared to a less connected investor.

[13] Although we obtained a large proportion of the stock prices for startups that went public, there may be a small induced bias. We were unable to obtain the information required for some less connected markets i.e. Mongolian Stock Exchange data.

Insert TABLE 5 about here.

Other metrics play a significant role in the chances of obtaining further funding. For example, the amount raised in the first round has a small impact. The number of investors participating in the first round is significant and strongly positive. Hence, a syndicated deal (involving two or more investors) makes it almost automatic, at least statistically, that the startup will receive another lot of funding. This result illustrates the benefits of a larger group of investors who are likely to demonstrate their trust in the company via a subsequent round of funding. We find also that sector fit has a significant positive impact on the odds of success in further funding. Finally, we find that geography plays a role. Certain startups in specific markets are more likely to receive further funding.

Increasing funding amount

We employ a linear regression model in line with equation 2which shows that the effect of investor centrality is strong and significant (above the 0.001 level) for all the dimensions tested (see table 6.) This verifiy (*Hypothesis 2*) Eigencentrality seems to have the strongest effect on the amount of capital raised in the last round of funding (coefficient of 1.90e + 07.) Thus, for every 1% increase in the mean centrality of investors there is an increase of more than USD 1.9 million in the amount raised in the last round.

Capital raised during the first round has a strong and significant effect, and a coefficient of 1.03 indicating a stable positive impact of the initial amount raised on the amount raised in the final round. On average, it suggests a slight increase of 3% on the first round (plus constant). Finally, we test for the impact of startup location but find no relationship to our dependent variable, while the effects of syndicate size and sector fit are small.

To check this result, we repeated the estimations using the degree as a metric (see annex 13.) The results were unchanged. There is a clear impact of investor network position on investee's chances of obtaining a higher amount of cash in the last round which is affected also by the amount raised in the first round of funding.

Insert TABLE 6 about here.

Going public

For our analysis, we wish to explain a dummy that is equal to 1 if the company had an IPO, and 0 otherwise. The upper panel in table 7 presents the results of our logit regression in equation 3. We find that the effect of investor centrality is significant and positive, and that higher centrality (corresponding to eigencentrality of the most central investor participating in the first funding round) has a coefficient of 1.9. On its own and assuming a constant of around -4, this variable indicates significant greater probability of going public. The amount of money raised in the first round of financing appears to have a significant and positive impact on the probability of an IPO with a coefficient of 0.65 per log of the amount raised.This effect combined with the high centrality effect, remains strong indication that investor centrality, and amount of cash raised, affect the chances of going public (which supports *Hypothesis 3a*). We observe also that there is a very strong and significant negative constant, indicating the barriers to going public.

Insert TABLE 7 about here.

For completeness, we estimate the same regression including eigencentrality for the last round of funding (lower panel of table 7). The effect is in the same direction as in the first round of financing which confirms the role of investor centrality in startup IPO activity. Support of a central investor in the initial funding is important but the effect is weaker on the last round of funding. However, the coefficient of centrality is weaker in this case (e.g., effect of centrality decreases from 1.9 to 1.7) but the influence of the amount of capital raised is almost the same. This is an interesting finding since the amount raised in the final round of funding tends to be higher than that raised in the initial round. We also observe decreased relevance of the effect of centrality in the last round (hence rejecting *Hypothesis 3b*.) This could be interpreted as the signaling effect of centrality shifting towards other variables such as the amount of cash raised and the size of the syndicate which might be more important immediately before the IPO.

Wu et al. (2008) suggest that the need for backing differs as the startup develops which might explain the previous result and would explain the significant role of investor centrality in the first round of funding compared to pre-IPO. If we repeat the estimates using degree rather eigencentrality the result do not change (see table 14). We can also suggest a more pragmatic but purely theoretical interpretation of those results. According to the analysis in column 3 in the upper panel of table 7 it could be assumed that ceteris paribus the entrepreneur might benefit equally from accepting a smaller investment from a central investor (with a high index of say above 0.5 eigencentrality) than accepting a greater offer from an "average" investor (mean eigencentrality of about 0.02 in our sample).

IPO Valuation

We find a robust positive effect of the amount of money raised in previous rounds (whether first or last, see table 8). The centrality of the most central investor in the last round appears to have a small but negative effect on company valuation (*Hypothesis 4*) Also, the investor-company fit has a low negative impact on the valuation of the IPO. This might be due to the signaling effect of a central investor in the last stage of funding.

Insert TABLE 8 about here.

Post-IPO

Short-term growth We find no clear relationship between our centrality metrics and stock price growth in the first year (*Hypothesis 5a* is rejected). Table 9 show that none of our estimators is important in the short-term analysis. Krigman et al. (1999) show that prediction of returns after one year is feasible. However, this seems not to apply to our sample and we can conclude that there is no observable impact of investor centrality in the network on investee's short term financial performance.

Insert TABLE 9 about here.

Long-term growth Table 10 shows the relevance of funding round for predicting longterm growth. Growth in the first year as a public company is significant in all our estimations (*Hypothesis 5b*). This is as expected since they are based on information revealed at IPO. The positive relationship between the two values is also logical given that the growth rate over nyears includes the primer value of the one year growth rate.

Insert TABLE 10 about here.

A more surprising and significant (at the 0.001 level) finding from this equation is the growth in the amounts raised in different rounds. The impact of this variable is positive although small. We compute it as the increase (in percentage points) of the funding that the startup raised in the first to the last rounds. We find that increased funding in subsequent rounds is a sign of a well structured company likely to show good performance over the long term. Finally, we test for the relevance of the eigencentrality of the most central investor. It is significant (although only at the 0.05 level) for predicting the startup's longterm growth. Its effect is nonnegligible since a 1% more central investor predicts a 0.28% increase in growth over the long term.

DISCUSSION

Theoretical implications

Accessing the market The pre-IPO phase shows that investor centrality affects obtaining additional funding, , the amount of funding received, and going public. This describes the logical path for the most promising startups and one which it can be assumed is driven by prominent investors. While previous research provides evidence of a certification effect, the pre-IPO phase highlights that startups can secure funding from a group of central investors who are likely to signal to the investing community that it is a good prospect. Hence, the company is likely to get noticed and obtain additional funding more easily from a larger group of investors. At worst, it will be able to extract value from this signal and obtain sufficient finance to remain viable.

Based on the influence deriving from investor centrality, the firm can develop faster than competitors. This investor centrality may derive in turn from previous good investments which result in a higher number of network links and more resources which the investee firm can access. This promotes startup growth while also increasing the need for more capital to enable expansion. It also improves the chances of obtaining larger amounts and more rounds of funding. These centrality effects are observed in most industries although *Communication Services, Health Care*, and *Information Technology* seem to benefit the most (see annex, table 11 and 12.) Our estimates appear robust to the inclusion of different centrality measures with both degree and eigencentrality producing very similar results . [14]

Finally, we observe that investor centrality increases the chances of further funding, and higher amounts of funding which in turn increase the chances of an IPO. This is in line with Banerjee et al. (2016)) who suggest that higher growth firms tend to go public earlier than low growth firms. This earlier entry to the market provides competitive edge after the IPO.

Achieving For the post-IPO phase the results are less intuitive. We find that investor centrality affects only long term but not shortterm success. This finding has been observed for the case of investors but we focus on investee performance. It might be due to the fact that after the IPO the effect of investor centrality as a means of certification vanishes while the smart money effect persists. The certification effect is critical for startups to signal quality and promote firm growth. In this first phase, startup expansion is fostered by the certification and smart money effects. After the IPO, more information becomes public and investors are more likely to cash-in

[14] See annex which conducts the same calculations including the degree and eigencentrality measures.

on their investment as suggested by Paeglis & Veeren (2013) , to focus on the development of new startups. As time goes by, the firm's intrinsic qualities are revealed. Hellmann & Puri (2002) suggest that the smart money effect persists over the long term. Professionalization is strengthened as are the links enabled by connections to central investors. This is evidence of a smart money effect which increases the firm's competitiveness.

This might explain the lack of a clear relation among the empirical results. While the certification effect fades quite quickly, it can take time for the smart money effect to emerge.

Practical implications

Our study has some implications for entrepreneurs and suggests that regardless of the amount of funding being offered, they should choose participation of the most central investors. A powerful backer is critical for improved survival chances and better performance. However, this statement should be nuanced; it might be equally beneficial for the entrepreneur to broaden his or her source of funding since size dominates investor centrality in relation to last round funding. This suggests that the size of the investor base would be more important than a famous VC's backing.

Limitations and future research

There could be some form of selection bias in operation whereby the best startups are chosen by the best investors (in our set, the most central investors). This would mean that these firms find it easier to access funding, go public, and increase their value. Yet, if it could indeed be the case that some startup presents a higher potential and face more favorable condition, we wouldn't agree with this view. Bertoni et al. (2011) show that investments have a significant impact on startup development (disentangling the treatment and selection effect of venture capital.) The startup's intrinsic higher profile wouldn't explain the absence of short-term growth in valuation that we observe. The startup should benefit even more from greater access to finance enabled by an IPO. This would suggest that a startup with more central investors should be more competitive but in our sample we observed the opposite. Finally, as our study covers all the available data points, this hypothesis wouldn't apply on such a scale. Given that our paper presents a significant conclusion on investments' impact for the whole group of startups on the studied period, such breakdown of high potential/low potential startups wouldn't be possible to explain the coefficients in our tables.

In contrast to previous studies, we do not consider investor size or resources. We only consider the position of the investor in the network. Future research could consider the different influence of different actors. We also had missing values for some items for some investors. Future work could focus on gathering this additional data.

CONCLUSION

This paper examined the effect of investor centrality in the global network of investors. We decomposed relevance on the pre-IPO development axis and found that investor centrality increased the chances of further and higher amounts of funding, and of going public. We attribute those positive factors to a certification effect which provides the startup with reputation and easier access to funding.

We also found that investor centrality was relevant to startup development and its future valuation. This is likely due to the persistence of a smart money effect which improves the startup's chances of survival and makes it more competitive based on access to the resources and ties of its backers.

This is the reason why cash may not be what matters the most.

References

Admati, A. R. and Pfleiderer, P. 1994. Robust financial contracting and the role of venture capitalists. ***The Journal of Finance***, 49(2): 371–402.

Alexy, O. T., Block, J. H., Sandner, P., and Wal, A. L. J. T. 2012. Social capital of venture capitalists and start-up funding. ***Small Business Economics***, 39(4): 835–851.

Banerjee, S., Güçbilmez, U., and Pawlina, G. 2016. Leaders and followers in hot ipo markets. ***Journal of Corporate Finance***, 37: 309–334.

Bayar, O., Chemmanur, T. J., and Tian, X. 2019. Peer monitoring, syndication, and the dynamics of venture capital interactions: Theory and evidence. ***Journal of Financial and Quantitative Analysis***, 1–40.

Bernstein, S., Giroud, X., and Townsend, R. R. 2015. The impact of venture capital monitoring. ***The Journal of Finance***, 71(4): 1591–1622.

Bernstein, S., Mehta, K., and Townsend, R. 2020. Does venture capital attract human capital? evidence from a randomized field experiment.

Bertoni, F., Colombo, M. G., and Grilli, L. 2011. Venture capital financing and the growth of high-tech start-ups: Disentangling treatment from selection effects. ***Research Policy***, 40(7): 1028–1043.

Block, J., Fisch, C., Vismara, S., and Andres, R. 2019. Private equity investment criteria: An experimental conjoint analysis of venture capital, business angels, and family offices. ***Journal of Corporate Finance***, 58: 329 – 352.

Blondel, V. D., Guillaume, J.-L., Lambiotte, R., and Lefebvre, E. 2008. Fast unfolding of communities in large networks. ***Journal of statistical mechanics: theory and experiment***, 2008(10): P10008.

Booth, J. R. and Smith, R. L. 1986. Capital raising, underwriting and the certification hypothesis. ***Journal of Financial Economics***, 15(1): 261 – 281.

Carter, R. B., Dark, F. H., and Singh, A. K. 1998. Underwriter reputation, initial returns, and the long-run performance of ipo stocks. ***The Journal of Finance***, 53(1): 285–311.

Checkley, M., Añón Higón, D., and Angwin, D. 2010. Venture capital syndication and its causal relationship with performance outcomes. ***Strategic Change***, 19(5-6): 195–212.

Colombo, M. G., Meoli, M., and Vismara, S. 2019. Signaling in science-based ipos: The combined effect of affiliation with prestigious universities, underwriters, and venture capitalists. ***Journal of Business Venturing***, 34(1): 141 – 177.

Croce, A., Martí, J., and Murtinu, S. 2013. The impact of venture capital on the productivity growth of european entrepreneurial firms: 'screening' or 'value added' effect? ***Journal of Business Venturing***, 28(4): 489 – 510.

Davidsson, P. and Honig, B. 2003. The role of social and human capital among nascent entrepreneurs. ***Journal of Business Venturing***, 18(3): 301 – 331.

Decker, R., Haltiwanger, J., Jarmin, R., and Miranda, J. 2014. The role of entrepreneurship in us job creation and economic dynamism. ***Journal of Economic Perspectives***, 28(3): 3–24.

Ewens, M., Nanda, R., and Rhodes-Kropf, M. 2018. Cost of experimentation and the evolution of venture capital. ***Journal of Financial Economics***, 128(3): 422 – 442.

Gompers, P. A. 1996. Grandstanding in the venture capital industry. ***Journal of Financial Economics***, 42(1): 133 – 156.

Gompers, P. A. et al. 1995. Optimal investment, monitoring, and the staging of venture capital. ***The Journal of Finance***, 50(5): 1461–1489.

Gourio, F., Messer, T., and Siemer, M. 2016. Firm entry and macroeconomic dynamics: A state-level analysis. ***American Economic Review***, 106(5): 214–18.

Hellmann, T. and Puri, M. 2000. The interaction between product market and financing strategy: The role of venture capital. ***The Review of Financial Studies***, 13(4): 959–984.

Hellmann, T. and Puri, M. 2002. Venture capital and the professionalization of start-up firms: Empirical evidence. ***The Journal of Finance***, 57(1): 169–197.

Hochberg, Y. V., Ljungqvist, A., and Lu, Y. 2007. Whom you know matters: Venture capital networks and investment performance. ***The Journal of Finance***, 62(1): 251–301.

Howell, S. T. 2017. Financing innovation: Evidence from r&d grants. ***American Economic Review***, 107(4): 1136–64.

Hsu, D. H. 2005. What do entrepreneurs pay for venture capital affiliation? ***The Journal of Finance***, 59(4): 1805–1844.

Inkpen, A. C. and Tsang, E. W. K. 2005. Social capital, networks, and knowledge transfer. ***Academy of Management Review***, 30(1): 146–165.

Kaplan, S. N. and Strömberg, P. 2005. Characteristics, contracts, and actions: Evidence from venture capitalist analyses. ***The Journal of Finance***, 59(5): 2177–2210.

Khurshed, A., Mohamed, A., Schwienbacher, A., and Wang, F. 2020. Do venture capital firms benefit from international syndicates? ***Journal of International Business Studies***, 51(6): 986–1007.

Koller, T., Goedhart, M., Wessels, D., et al. 2010. ***Valuation: measuring and managing the value of companies***, volume 499. John Wiley and Sons.

Krigman, L., Shaw, W. H., and Womack, K. L. 1999. The persistence of ipo mispricing and the predictive power of flipping. ***The Journal of Finance***, 54(3): 1015–1044.

Lakonishok, J., Shleifer, A., Thaler, R., and Vishny, R. 1991. Window dressing by pension fund managers. ***American Economic Review***, 81(2): 227–231.

Lerner, J. 1994. The syndication of venture capital investments. ***Financial management***, 16–27.

Lerner, J. 1995. Venture capitalists and the oversight of private firms. ***The Journal of Finance***, 50(1): 301–318.

Lewis, T. R. and Sappington, D. E. M. 2000. Motivating wealth-constrained actors. ***American Economic Review***, 90(4): 944–960.

Liu, X. and Ritter, J. R. 2011. Local underwriter oligopolies and ipo underpricing. ***Journal of Financial Economics***, 102(3): 579–601.

Lockett, A., Ucbasaran, D., and Butler, J. 2006. Opening up the investor–investee dyad: Syndicates, teams, and networks. ***Entrepreneurship Theory and Practice***, 30: 117 – 130.

Megginson, W. L. and Weiss, K. A. 1991. Venture capitalist certification in initial public offerings. ***The Journal of Finance***, 46(3): 879–903.

Morten, S. 2007. How smart is smart money? a two□sided matching model of venture capital. ***The Journal of Finance***, 62(6): 2725–2762.

Mosey, S. and Wright, M. 2007. From human capital to social capital: A longitudinal study of technology–based academic entrepreneurs. ***Entrepreneurship Theory and Practice***, 31(6): 909–935.

Nahata, R. 2008. Venture capital reputation and investment performance. ***Journal of Financial Economics***, 90(2): 127 – 151.

Newman, M. 2010. ***Networks: An Introduction***. OUP Oxford.

Paeglis, I. and Veeren, P. 2013. Speed and consequences of venture capitalist post-ipo exit. ***Journal of Corporate Finance***, 22: 104 – 123.

Sah, R. K. and Stiglitz, J. E. 1986. The architecture of economic systems: Hierarchies and polyarchies. ***American Economic Review***, 716–727.

Tsai, W. and Ghoshal, S. 1998. Social capital and value creation: The role of intrafirm networks. ***Academy of Management Journal***, 41(4): 464–476.

Wal, A. L. T., Alexy, O., Block, J., and Sandner, P. G. 2016. The best of both worlds: The benefits of open-specialized and closed-diverse syndication networks for new ventures' success. ***Administrative Science Quarterly***, 61(3): 393–432. PMID: 27499546.

Walske, J. M., Zacharakis, A., and Smith-Doerr, L. 2007. Effects of venture capital syndication networks on entrepreneurial success. ***Frontiers of Entrepreneurship Research***, 27(3): 2.

Wang, P. 2020. Broadening versus reinforcing investor portfolios: Social structure and the search for venture capital investors. ***Journal of Business Venturing***, 35(1): 105915.

Wilson, R. 1968. The theory of syndicates. ***Econometrica***, 119–132.

Wu, L., Wang, C., Chen, C., and Pan, L. 2008. Internal resources, external network, and competitiveness during the growth stage: A study of taiwanese high–tech ventures. ***Entrepreneurship Theory and Practice***, 32(3): 529–549.

Zhang, J., Souitaris, V., Soh, P.-H., and Wong, P. K. 2008. A contingent model of network utilization in early financing of technology ventures. ***Entrepreneurship Theory and Practice***, 32: 593 – 613.

CENTRALITY MEASURES FOR THE PERIOD 1968-2018

Insert TABLE 11 about here.

Insert TABLE 12 about here.

PRE-IPO

Insert TABLE 13 about here.

Insert TABLE 14 about here.

TABLE 1: Number of deals by size of syndicate

Size syndicate	No.	%	Cum.
1	73148	30,67	30,67
2	38073	15,96	46,64
3	31593	13,25	59,88
4	26618	11,16	71,05
5	21659	9,08	80,13
6	16615	6,97	87,09
7	12441	5,22	92,31
8	9619	4,03	96,34
9	6958	2,92	99,26
10-19	1652	0,69	99,95
20-29	91	0,04	99,99
30-39	11	0,00	100,00
40-91	6	0,00	100,00
Total	238484	100	100,00

TABLE 2: Description of the dataset: number of rounds, worldwide data.

# of rounds	# of startups	%
1	21,443.0	44.2
2	7,915.0	16.3
3	4,643.0	9.6
4	3,037.0	6.3
5	2,174.0	4.5
6	1,615.0	3.3
7	1,240.0	2.6
8	1,036.0	2.1
9	841.0	1.7
10-14	2426.0	5.0
15-19	1012.0	2.0
20-24	547.0	1.1
25-29	257.0	0.5
30+	279.0	0.7
Total	48,465.0	100.0

TABLE 3: Type of investors, worldwide data.

Type of investor	No.	%
Accelerator	1,948	3.6
Angel	20,116	37.1
Angel group	1,147	2.1
Co working space	186	0.3
Corporate venture capital	482	0.9
Entrepreneurship program	82	0.2
Family investment office	347	0.6
Fund of funds	164	0.3
Government office	371	0.7
Hedge fund	224	0.4
Incubator	934	1.7
Investment bank	709	1.3
Investment partner	11,347	20.9
Micro VC	1,772	3.3
Pension funds	11	0.0
Private equity firm	3,525	6.5
Secondary purchaser	13	0.0
Startup competition	23	0.0
University program	248	0.5
Venture capital	10,465	19.3
Venture debt	155	0.3
Total	54,270	100.0

TABLE 4: Mean and SD of raised amount (USD) by type of investment

Investment type	Raised amount (USD)	
	Mean	SD
Angel	966,468.6	2,726,533.4
Product crowdfunding	1,516,525.4	4,030,590.8
Equity crowdfunding	1,000,690.9	2,026,943.6
Convertible note	1,451,348.4	7,008,926.6
Seed	1,405,246.5	1,805,027.7
Grant	2,152,300.6	13,861,871.4
Non equity assistance	227,596.3	994,540.1
Series A	10,769,576.0	33,298,436.7
Series B	25,387,729.6	85,827,872.9
Series C	41,493,086.0	121,142,638.9
Series D	58,333,802.7	101,133,567.5
Series E	99,278,388.0	200,978,245.6
Series F	161,624,235.1	394,276,879.4
Series G	237,134,088.1	434,885,136.3
Series H	146,857,242.9	234,256,986.7
Series I	200,000,000.0	
Initial coin offering	66,139,437.4	249,619,041.3
Private equity	169,075,019.4	692,803,892.0
Corporate round	111,900,059.2	346,399,276.7
Debt financing	64,165,246.0	213,421,458.6
Post IPO debt	176,053,899.8	406,768,998.7
Post IPO equity	201,831,329.6	891,347,218.1
Post IPO secondary	605,162,898.8	1307456583.0
Secondary market	517,594,073.4	1558137393.0
Undisclosed	52,248,875.6	310,588,452.0
Total	20,768,499.6	150,531,540.7

TABLE 5: Logit estimation of the probability of getting more than one round of funding.

	Access next round of funding (1= startup had 2+ rounds)				
	(1)	(2)	(3)	(4)	(5)
First raised amount	0.175***	0.0438***	-0.0852***	-0.0844***	-0.0898***
(log of USD)	(0.00430)	(0.00861)	(0.0118)	(0.0118)	(0.0121)
Log highest degree		0.444***	0.241***	0.238***	0.216***
		(0.0132)	(0.0185)	(0.0185)	(0.0191)
Size syndicate			9.058***	9.051***	9.007***
			(1.000)	(1.000)	(1.000)
Sector fit				0.187***	0.142**
				(0.0480)	(0.0487)
Geographical area					
Africa					-0.784**
					(0.299)
Americas (base)					0
					(.)
Asia					0.0257
					(0.0713)
Europe					-0.238***
					(0.0573)
Oceania					0.0511
					(0.258)
Constant	-2.141***	-0.597***	-9.049***	-9.133***	-8.840***
	(0.0588)	(0.120)	(1.012)	(1.013)	(1.013)
Observations	48454	20264	20263	20263	19697
Pseudo R^2	0.026	0.067	0.572	0.573	0.569

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Data: worldwide, 2010-2019.

TABLE 6: Regression of the determinants impacting the last amount of capital (USD) raised by startups.

	Raised amount (USD) at last round				
	(1)	(2)	(3)	(4)	(5)
Raised amount (USD)	1.03***	1.03***	1.03***	1.03***	1.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Syndicate size		1.12e+06***	1.12e+06***	791844.66***	792035.16***
		(113667.17)	(113737.12)	(118189.00)	(123027.49)
Sector fit			-8.01e+05	-7.29e+05	-9.59e+05
			(552941.42)	(552404.18)	(582816.83)
Higher centrality				1.90e+07***	1.78e+07***
				(1.87e+06)	(1.95e+06)
Geographical area					
Africa					368812.44
					(2.70e+06)
Americas (base)					0.00
					(.)
Asia					5.79e+06***
					(791990.05)
Europe					-9.06e+05
					(624366.53)
Oceania					-1.51e+06
					(2.07e+06)
Constant	3.79e+06***	1.47e+06***	1.88e+06***	1.67e+06***	1.42e+06*
	(256551.94)	(348670.84)	(448830.84)	(448827.66)	(574572.83)
Observations	48465	48452	48452	48452	45964
Adjusted R^2	0.854	0.854	0.854	0.855	0.852

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Data: worldwide, 2010-2019.

TABLE 7: Logit estimation of the probability of going public. Upper panel uses metrics responding to the first round of funding, lower panel take metrics from the last round of funding before IPO.

	IPO dummy (1 = startup went public)				
	(1)	(2)	(3)	(4)	(5)
First round					
Log raised amount	0.653***		0.643***	0.648***	0.652***
	(0.0255)		(0.0260)	(0.0262)	(0.0262)
Higher centrality		1.909***	0.598**	0.604**	0.770***
		(0.174)	(0.191)	(0.191)	(0.192)
Sector fit				0.288*	0.274*
				(0.117)	(0.115)
Syndicate size					-0.0983***
					(0.0245)
Constant	-13.95***	-4.238***	-13.87***	-14.11***	-13.89***
	(0.418)	(0.0541)	(0.423)	(0.437)	(0.438)
Observations	27020	27022	27020	27020	27015
Pseudo R^2	0.154	0.020	0.156	0.157	0.161
Last round					
Log raised amount	0.737***		0.729***	0.735***	0.732***
	(0.0276)		(0.0281)	(0.0282)	(0.0283)
Higher centrality		1.776***	0.375*	0.364*	0.181
		(0.159)	(0.176)	(0.176)	(0.188)
Sector fit				0.295*	0.296*
				(0.128)	(0.130)
Syndicate size					0.0537**
					(0.0169)
Constant	-15.80***	-4.266***	-15.74***	-15.99***	-16.12***
	(0.473)	(0.0555)	(0.478)	(0.494)	(0.497)
Observations	27020	27022	27020	27020	27010
Pseudo R^2	0.179	0.021	0.180	0.181	0.183

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Data: worldwide, 2010-2019.

TABLE 8: Regression of the determinants impacting the valuation of a startup at IPO.

	Valuation at IPO				
	(1)	(2)	(3)	(4)	(5)
First raised amount	0.228***				
	(0.0480)				
Last raised amount		0.665***	0.672***	0.673***	0.647***
		(0.0397)	(0.0496)	(0.0489)	(0.0498)
Higher centrality			-0.132**	-0.131**	-0.134***
			(0.0400)	(0.0395)	(0.0391)
Global sector fit				-0.480**	-0.440*
				(0.183)	(0.182)
Growth raised amount					0.000564*
					(0.000251)
Constant	16.45***	8.482***	8.834***	9.098***	9.520***
	(0.806)	(0.705)	(0.878)	(0.872)	(0.884)
Observations	275	275	215	215	215
Adjusted R^2	0.073	0.506	0.461	0.476	0.485

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Data: worldwide, 2010-2019.

TABLE 9: Regression of the determinants impacting the growth of startup price on markets over 1 year. Lower centrality, respectively higher centrality, is the eigencentrality of the investor with the lowest, respectively highest, eigencentrality among last round investors. Mean centrality is the mean of eigencentrality for last round investors.

	Growth over 1 year past IPO					
	(1)	(2)	(3)	(4)	(5)	(6)
Lower centrality	-0.266					
	(1.784)					
Mean centrality	1.061					
	(2.050)					
Higher centrality	-0.899	-0.537	-0.381	-0.395	-0.365	-0.379
	(0.714)	(0.323)	(0.331)	(0.332)	(0.331)	(0.332)
Raised amount			-0.133	-0.183	-0.148*	-0.196*
			(0.0684)	(0.0958)	(0.0703)	(0.0968)
Total funding				0.0800		0.0764
				(0.107)		(0.107)
Growth raised amount					0.000233	0.000226
					(0.000250)	(0.000250)
Constant	0.397**	0.403**	2.647*	2.019	2.895*	2.288
	(0.125)	(0.124)	(1.160)	(1.435)	(1.190)	(1.466)
Observations	273	273	273	273	273	273
R^2	0.012	0.010	0.024	0.026	0.027	0.029

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Data: worldwide, 2010-2018.

TABLE 10: Regression of the determinants impacting the growth of startup price on markets over several years.

	Growth (annual) past IPO		
	(1)	(2)	(3)
Growth 1 year	0.0922***	0.0894***	0.0931***
	(0.0218)	(0.0205)	(0.0203)
Growth raised amount		0.000446***	0.000450***
		(0.0000804)	(0.0000795)
Max centrality			0.279*
			(0.110)
Constant	-0.0192	-0.0371	-0.136**
	(0.0352)	(0.0333)	(0.0509)
Observations	234	234	234
Adjusted R^2	0.068	0.174	0.192

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Data: worldwide, 2010-2018.

TABLE 11: Top 10 most central investors for Communication Services, Consumer Discretionary sectors and Health Care.

Investor	Type	Rounds	Centrality
Communication Services			
Steamboat Ventures	Corporate VC	108	0,0766
Centre Partners	Private Equity Firm	6	0,0544
Constellation Technology Ventures	Corporate VC	54	0,0475
Attractor Investment Management	Private Equity Firm	23	0,0416
Peacock Equity	Venture Capital	17	0,0371
United Capital Investment Group	Angel Group	8	0,0305
Information Capital LLC	Venture Capital	3	0,0291
Farallon Capital Management	Venture Capital	17	0,0268
Comcast		16	0,0247
Liberty Digital		11	0,0245
Consumer Discretionary			
Brentwood Associates	Private Equity Firm	14	0,0448
SDL Ventures	Venture Capital	10	0,0312
AdInvest	Venture Capital	7	0,0150
Gordon Brothers Group		5	0,0145
Zero2IPO Ventures	Venture Capital	29	0,0143
Sentinel Capital Partners	Private Equity Firm	8	0,0131
New Millenium Partners	Venture Capital	8	0,0129
Times Mirror Company	Venture Capital	2	0,0101
Phillips Smith Specialty Group	Venture Capital	3	0,0101
Caterina Fake	Angel	16	0,0083
Health Care			
Alta Partners	Venture Capital	206	0,4020
Sofinnova Ventures	Venture Capital	203	0,3132
Flagship Pioneering	Venture Capital	195	0,3120
Versant Ventures	Venture Capital	270	0,3084
MPM Capital	Venture Capital	192	0,2977
Domain Associates	Venture Capital	233	0,2602
ARCH Venture Partners	Venture Capital	273	0,2548
Three Arch Partners	Venture Capital	114	0,2518
J. & J. Development Corporation	Corporate VC	146	0,2505
Frazier Healthcare Partners	Private Equity Firm	142	0,2186

TABLE 12: Top 10 most central investors for Diversified (across multiple other sectors), Financial sectors and Information Technology.

Investor	Type	Rounds	Centrality
Diversified			
Technology Partners	Venture Capital	71	0,0962
Hearst Ventures	Venture Capital	100	0,0888
Silver Creek Ventures	Venture Capital	29	0,0873
Hambrecht & Quist Capital Management	Venture Capital	40	0,0742
Mesirow Financial	Private Equity Firm	23	0,0732
Mitsubishi International Corporation	Corporate VC	24	0,0705
North Hill Ventures	Venture Capital	45	0,0674
ABN AMRO Fund	Corporate VC	47	0,0638
i-Hatch Ventures	Venture Capital	25	0,0620
Partnership Fund for New York City	Venture Capital	39	0,0511
Financials			
International Finance Corporation	Government Office	114	0,0202
QED Investors	Venture Capital	106	0,0146
Irwin Ventures	Venture Capital	5	0,0132
David Pottruck	Investment Partner	2	0,0125
efinanceworks		5	0,0125
TTV Capital	Venture Capital	50	0,0038
New Cycle Capital	Venture Capital	8	0,0029
Ottawa Angel alliance	Angel Group	2	0,0028
Winton Partners	Micro VC	4	0,0020
Martin Tobias	Investment Partner	3	0,0017
Information Technology			
Intel Capital	Corporate VC	1246	1,0000
New Enterprise Associates	Venture Capital	1446	0,8750
Goldman Sachs	Investment Bank	649	0,7563
Accel	Venture Capital	1171	0,6850
DFJ	Venture Capital	798	0,6708
Sequoia Capital	Venture Capital	1580	0,6544
Kleiner Perkins Caufield & Byers	Venture Capital	1032	0,6479
Bessemer Venture Partners	Venture Capital	790	0,6302
Venrock	Venture Capital	564	0,6273
U.S. Venture Partners (USVP)	Venture Capital	470	0,6252

TABLE 13: Regression of the determinants impacting the last amount of capital (USD) raised by startups.

	Raised amount (USD) at last round				
	(1)	(2)	(3)	(4)	(5)
Raised amount	1.03***	1.03***	1.03***	1.03***	1.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Syndicate size		1.12e+06***	1.12e+06***	804436.75***	800456.23***
		(113667.17)	(113737.12)	(118363.61)	(123217.50)
Sector fit			-8.01e+05	-7.29e+05	-9.63e+05
			(552941.42)	(552473.67)	(582874.30)
Higher degree				56,615.19***	53,158.55***
				(5,895.58)	(6,150.79)
Geographical area					
Africa					328775.80
					(2.70e+06)
Americas (base)					0.00
					(.)
Asia					5.83e+06***
					(792123.80)
Europe					-9.87e+05
					(623786.56)
Oceania					-1.55e+06
					(2.07e+06)
Constant	3.79e+06***	1.47e+06***	1.88e+06***	1.64e+06***	1.42e+06*
	(256551.94)	(348670.84)	(448830.84)	(449074.57)	(574944.75)
Observations	48465	48452	48452	48452	45964
Adjusted R^2	0.854	0.854	0.854	0.855	0.852

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Data: worldwide, 2010-2019.

TABLE 14: Logit estimation of the probability of going public. Upper panel uses metrics responding to the first round of funding, lower panel take metrics from the last round of funding.

	IPO dummy (1 = startup went public)				
	(1)	(2)	(3)	(4)	(5)
First round					
Log raised amount	0.653***		0.675***	0.682***	0.683***
	(0.0255)		(0.0326)	(0.0329)	(0.0332)
Log higher degree		0.271***	0.112**	0.108**	0.131***
		(0.0340)	(0.0347)	(0.0348)	(0.0351)
Sector fit				0.345*	0.334*
				(0.135)	(0.132)
Syndicate size					-0.0975***
					(0.0261)
Constant	-13.95***	-4.481***	-14.57***	-14.86***	-14.61***
	(0.418)	(0.123)	(0.546)	(0.562)	(0.567)
Observations	27020	14761	14760	14760	14759
Pseudo R^2	0.154	0.019	0.148	0.150	0.155
Last round					
Log raised amount	0.737***		0.775***	0.786***	0.781***
	(0.0276)		(0.0353)	(0.0356)	(0.0356)
Log higher degree		0.261***	0.0669	0.0602	0.0297
		(0.0335)	(0.0343)	(0.0343)	(0.0358)
Sector fit				0.407**	0.401**
				(0.138)	(0.140)
Syndicate size					0.0584**
					(0.0181)
Constant	-15.80***	-4.531***	-16.63***	-17.00***	-17.07***
	(0.473)	(0.126)	(0.614)	(0.632)	(0.632)
Observations	27020	15478	15477	15477	15474
Pseudo R^2	0.179	0.018	0.171	0.174	0.177

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Data: worldwide, 2010-2019.