IPOs and syndication, a networking effort?

How different network structures change the importance of previous investment experience of Venture Capital firms

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Abstract

In less than nine years, the amount of Venture Capital nearly tripled from €10 billion to €28 billion. The purpose of this research is to shed light on contradicting points of view and to contribute to a further understanding of the internationalization of the Venture Capital industry and literature. In this research, the following research question is answered: '*Do the network structure and experience of Venture Capital firms (VCs) affect the probability of an IPO?*'. Two samples of firms that were backed by Venture Capital firms were taken from a larger dataset that was retrieved from Crunchbase. Information about the top five VCs is gathered and their network structure was determined. One sample contained syndicates that consisted of only domestic VCs and one sample contained syndicates that consisted of both domestic and cross-border VCs. A logistic regression was done for both samples and the results were compared. All findings were found to be non-significant. The results indicated that VCs' experience does not affect the probability of an IPO. In addition, network structure does not moderate the effect of experience on the probability of an IPO. Due to multicollinearity and issues with validity, these findings had to be interpreted with caution. It is for future research to unravel further understanding of the relationship between network structure, previous investment experience of VCs and IPOs. Interestingly, evidence for a positive relationship between innovativeness and IPO exits is found to be significant.

Key words: Venture Capital, Syndication network, IPO, Experience, Network structure

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1. Introduction

1.1 Venture Capital

More capital is invested in new ventures and start-ups than ever before. In less than nine years, the amount of Venture Capital (VC) nearly tripled from €10 billion to €28 billion (Schram & Wagemans, 2020). Venture Capital firms (VCs) do not only supply their portfolio firms with finance but also with much more valuable services (Fraser, Bhaumik & Wright, 2015).

Research done in multiple countries has shown a positive relation between portfolio firm performance and the fact that firms are backed by VCs (Manigart & Wright, 2013). The VCs' ultimate goal is to exit from their portfolio firms as successful as possible, which will deliver the most profit (Manigart & Wright, 2013). On average, VCs write off 75% of their investments (Ljungqvist, Marston & Wilhelm, 2009). 20.7% of the 25% originates from IPOs (Ljungqvist et al., 2009). This indicates that VCs gain from their investments by those portfolio firms that exit via an IPO (Hochberg et al., 2007). Therefore, in the VC literature, an IPO of a portfolio firm also referred to as 'going public', is considered the most successful exit route for the VCs next to trade sales (Manigart & Wright, 2013).

1.2 Current research

The current literature mainly focuses on VCs characteristics that determine the likelihood of a successful exit (Manigart & Wright, 2013). Among these characteristics are whether or not the VC firm is government-related or independent (Manigart, Baeyens & Van Hufte, 2002; Manigart et al., 2002), the type of VC firm and the knowledge embedded in its organisation in terms of human capital (Manigart & Wright, 2013), industry or task-specific knowledge (Zarutskie, 2010), the investment experience of the VC firm (Sørensen, 2007) and reputation of the VC firm (Nahata, 2008). More experienced VCs seem to be better at selecting the most promising opportunities, and they also seem better able to add more value to their portfolio firms (Nahata, 2008; Sørensen, 2007). Therefore, the VC firm's investment experience and reputation seem to be important determinants for a successful exit of their portfolio firms.

Within the VC literature, two ways of thinking about a VC firm's experience and reputation can be identified. The first stream of literature argues that young, inexperienced VCs want to signal quality by exiting their portfolio firms via an IPO (Gompers, 1996; Wang & Sim, 2001). The younger VCs do not possess a track record yet and would have an incentive to exit from their portfolio firms via an IPO (Wang & Sim, 2001). Contrary to Gompers (1996), who found empirical evidence favouring this way of thinking in the literature, Wang and Sim (2001) did not find a significant effect on the VC's reputation or experience. However, they explained this finding because the VC industry in Singapore was relatively young compared to the American VC industry.

The second stream of literature argues that more experienced and established VCs are better able to add value to their portfolio firms, which would enhance their performance (Manigart & Wright, 2013). Next to that, the more experienced VCs are argued to be better able to select the most promising opportunities (Sørensen, 2007; Nahata, 2008). The meta-analysis of Manigart and Wright (2013) found more evidence for this way of thinking, indicating that the more experienced VCs would have higher proportions of IPO exits among their portfolio firms compared to inexperienced VCs. In line with this second stream of literature, Giot and Schwienbacher (2007) argued that an exit via an IPO is more likely if the VC firm is an established one. However, they did not find a significant effect on the VC firm experience. Interestingly, they did find a significant effect of syndicate size on performance.

To make most portfolio firms exit via an IPO, VCs tend to invest together in a venture (Manigart & Wright, 2013). VCs investing together is also referred to as syndication. There are many reasons why a VC firm would invest together with other VCs. Most motives deal with risk reduction, risk-sharing or improving the quality of deal flow (Manigart & Wright, 2013; De Maeseneire & Van Halder, 2010). With syndication, a network of VCs emerges, which is referred to as a syndicate. It is widely acknowledged that VCs' network affects portfolio firms' performance because VCs are better able to source high-quality deal flow and the ability to support investments (Hochberg et al., 2007). The latter means that VCs are better able to add value to their portfolio firms. The ability to source high-quality deal flow means that the VCs are better able to select the more promising firms.

Hochberg et al. (2007) were the first to include network measures, such as degree and betweenness centrality, to see how these proxies affected the portfolio firms' performance. The authors showed that VCs that have a lot of other VCs connected to it and are acting as a mediator between other networks deliver more value to their portfolio firms. In other words, better networked VCs enhance portfolio firm's performance because they enjoy more access to better deal flow. Hochberg et al. (2007) argued that the experience of the VC firm could be an alternative explanation for enhancing the performance of portfolio firms. To rule out the possibility that the better networked VCs were the more experienced ones, the effect of previous investment experience was controlled for the network structure of the VCs (Hochberg et al., 2007). The authors found that the importance of VC experience reduced or even disappeared once the network structure of VCs was included. This finding could indicate that the network structure for VCs is more important than the previous investment experience of the VC firm.

1.3 Focus of this research

The focus of this research will be built upon the findings of Hochberg et al. (2007). In their study, Hochberg et al. (2007) use a sample of U.S.-based VC funds. As already said, they were the first to examine the effect of the network structure of VCs on their portfolio firm's performance. Their research showed that experience has a significant effect on portfolio firms' performance. However, once this relationship is controlled for the network structure of the VCs, the effect decreased or disappeared. In contrast, earlier research on the factors that increased the likelihood of an IPO did not find the expected effect of VC experience or showed contradicting findings, as described above. These studies did not include network measures, so perhaps the VCs from those studies were better networked, and therefore the researchers did not find a significant effect of VCs experience.

Recently there has been a shift in research towards more international flows of VC (Meuleman & Wright, 2011). Most VC-related research before 2010 mainly focussed on the local VC industry (Cumming & Dai, 2010). Hochberg et al. (2007) only focussed on the local VC industry in the U.S., so it is in line with research that was done before 2010. Therefore, it could be that the findings of Hochberg et al. (2007) are outdated or biased. Another possible explanation for the findings of Hochberg et al. (2007) could be the geographical location of the VC firms. The United States (U.S.) enjoy a very well-developed accelerator climate for young and/or promising start-ups (Giot & Schwienbacher, 2007). It is, for example, very likely that Silicon Valley enhances and accelerates the development of the start-ups situated there (Hellmann, 2001). As a result, it could be likely that there are more IPO exits in the U.S. compared to other geographical locations.

In their study, Hochberg et al. (2007) use a sample of U.S.-based VC funds. In a later study, Dai, Jo and Kassicieh (2011) show that partnerships between both domestic and cross-border VCs have a positive effect on portfolio firms' performance. The authors found that cross-border VCs are at a disadvantage regarding information asymmetry because they do not have access to the same sources of information as domestic VCs. However, this negative implication for exit performance is alleviated when a cross-border VC firm invests together with a domestic VC firm. Devigne, Vanacker, Manigart and Paeleman (2013) also show that a combination of both domestic and cross-border VCs enhances portfolio firms' performance. Because this is not taken into account by Hochberg et al. (2007), it is relevant to re-do a similar analysis with a dataset that includes syndicates that comprises both domestic and cross-border VCs. In addition, the dataset that will be used in this research also allows comparing the results with a sample of syndicates that comprises only domestic VCs.

This research will shed light on the contradicting points of view regarding VC experience and exit performance of their portfolio firms in terms of an IPO. It will also incorporate the findings of Dai et al. (2011) with those of Hochberg et al. (2007). The findings of Dai et al. (2011) apply to investments done in Asia. Therefore, this research is interested in the question of whether this effect is also present worldwide. To answer that question, one sample with only domestic VCs and one sample with both cross-border and domestic VCs will be compared.

The research question that will be answered in this research is: **Do the network structure and experience of VCs affect the probability of an IPO?** The research question will be divided into multiple sub-questions that will form the basis on which the hypotheses will be formulated:

1. *Does VC experience affect the probability of an IPO?*

2. *Does the effect of VC experience on portfolio firm performance differ for syndicates that comprise both domestic and cross-border VCs and syndicates that comprise only domestic VCs?*
3. *Does network structure of VCs affect the probability of an IPO?*
4. *Does the effect of network structure on portfolio firm performance differ for syndicates that comprise both domestic and cross-border VCs and syndicates that comprise only domestic VCs?*
5. *Does network structure moderate the effect of experience on the likelihood that portfolio firms exit via an IPO?*
6. *Does the moderating effect of network structure differ for syndicates that comprise both domestic and cross-border VCs and syndicates that comprise only domestic VCs?*

To answer the sub-questions and ultimately the research question, two samples of companies that went through a successful exit via an IPO in 2019 and 2020 will be taken from a larger dataset that is retrieved from Crunchbase. Crunchbase is a commercial database (Dalle, Den Besten & Menon, 2017) and includes companies from multiple countries that all received VC funding. For all companies, information about the VCs that invested in the firm is gathered. With this information, the network measures that form the network structure of the VC firm will be calculated. Over 100 companies exited via an IPO in the aforementioned timeframe. To complete the sample, companies that were founded in the same timeframe as those who did an IPO were included. From the dataset, two samples were generated: one sample with syndicates that comprises both domestic and cross-border VCs (sample 1) and one sample with syndicates that comprises only domestic VCs (sample 2). With these samples, a logistic regression analysis will be conducted to test the hypotheses and to compare the differences between the samples.

1.4 Research purpose

The purpose of this research consists of the theoretical and managerial implications. First, this research contributes to the contradicting points of view regarding the importance of the VC experience. Previous research showed that there are different outcomes regarding the importance of VC experience in relation to performance (e.g., Wang & Sim, 2001; Giot & Schwienbacher, 2007; Kaplan et al., 2007; Sørensen, 2007;

Nahata, 2008). These studies did not include network structures of VCs. Therefore, this research does include the network measures in line with Hochberg et al. (2007).

Second, Hochberg et al. (2007) tested whether VC experience was an alternative explanation for their finding that better networked VCs enhanced performance. The research conducted by Hochberg et al. (2007) showed that the effect of experience decreased once the relationship between experience and performance was controlled for the network structure of the VCs. However, this was done solely for U.S.-based VCs. This research builds upon the analysis done by Hochberg et al. (2007) and will add syndicates that comprise both domestic and cross-border VCs, which is found to have a positive effect on exit performance (Dai et al., 2011). However, the research of Dai et al. (2011) only focussed on investments in Asia. Therefore, the third contribution of this research is to answer the question of whether the effect found by Dai et al. (2011) is also present worldwide. In order to answer that question, the results of the two samples will be compared.

This research will contribute to the VC network literature because it shows the importance of network structure in relation to VC experience and IPO exits. Particularly, it can be important information for the younger VCs who do not possess a track record yet. The findings can help them to focus either on finding the right syndication partner or to choose their network strategy in order to enhance their portfolio firm's performance. In addition, the outcomes can also be important for more experienced VCs who can also change the focus of their networking strategy once they know what the effect of their network structure or their previous investment experience might be.

1.5 Research outline

The rest of this research is structured as follows. In the next section, an overview of the relevant literature and the conceptual framework will be provided. The third section will discuss the methodology and describe the dataset and data analysis methods that were used in this research. In the fourth section, the results will be given. This research will end with a discussion of the results and the conclusion, including the limitations and of this research.

2. Theoretical framework

The theoretical framework consists of two parts. The first part is the literature review. In this section, the relevant literature will be discussed. The second part of the theoretical framework is the conceptual framework which will show the relationships between the constructs. The conceptual framework also shows the corresponding hypotheses and its expected effect in parentheses.

2.1 Literature review

2.1.1 Venture Capital and portfolio firms' performance

Research done in multiple countries has shown a positive relation between portfolio firm performance and the fact that firms are backed by VCs (Manigart & Wright, 2013). Companies that are backed by VCs possess more assets, experience more growth in their employment (Chemmanur, Krishnan & Nandy, 2011) and grow their revenues faster compared to non-VC-backed companies (Puri & Zarutskie, 2012). These benefits are likely to contribute to more efficiency and productivity, which, in the end, is more likely to result in an exit via an IPO (Fraser et al., 2015). Noteworthy is the study of Bottazzi and Da Rin (2002), which did not find a difference between non-VC backed and VC-backed firms that did an IPO.

As already mentioned, the VCs' ultimate goal is to exit from their portfolio firms as successfully as possible, which will deliver the most profit (Manigart & Wright, 2013). VCs, on average, write off 75% of their investments (Ljungqvist, Marston & Wilhelm, 2009). 20.7% of the 25% originates from IPOs (Ljungqvist et al., 2009). This indicates that VCs gain from their investments by those portfolio firms that exit via an IPO (Hochberg et al., 2007). In the VC literature, an IPO of a portfolio firm is considered the most successful exit route for the VCs together with trade sales (Manigart & Wright, 2013). To narrow the scope of this research, trade sales will be excluded in this research. Therefore, an IPO will be used as the portfolio firm's performance indicator in this research.

2.1.2 Venture Capital firms' characteristics and performance

Several characteristics that enhance the likelihood of a portfolio firm to exit via an IPO were identified in previous research (e.g., Giot & Schwienbacher, 2007; Manigart & Wright, 2013). Among these characteristics is the type of VC firm and the knowledge embedded in its organisation in terms of human capital (Manigart & Wright, 2013), whether or not the VC firm is government-related or independent (Manigart, Baeyens & Van Hufte, 2002; Manigart et al., 2002), the presence of industry or task-specific knowledge (Zarutskie, 2010), the investment experience of the VC firm (Sørensen, 2007) and reputation of the VC firm (Nahata, 2008). Giot and Schwienbacher (2007) added the venture's geographical location, regional proximity, technological improvement and syndicate size to this list. The more experienced VCs are better at selecting the most promising opportunities and are also better able to add more value they are argued to enjoy higher IPO rates (Nahata, 2008; Sørensen, 2007). Therefore, VCs investment experience and reputation seem to be important determinants for a successful exit via an IPO of their portfolio firms.

Within the VC literature, there is a debate about the contribution of VC experience and enhancing the performance of the portfolio firm. The first stream of literature argues that young, inexperienced VCs want to signal quality by going public with their portfolio firms (Gompers, 1996; Wang & Sim, 2001). The younger VCs do not possess a track record yet and are said to have an incentive to exit from their portfolio firms via an IPO (Wang & Sim, 2001). Wang and Sim (2001) did not find a significant effect of the VCs' reputation nor experience. Contrary, Gompers (1996) did find empirical evidence favouring the way of thinking in line with this stream of literature.

The second stream of literature argues that older, more experienced, and established VCs are better able to add (more) value to their portfolio firms, which enhances portfolio firms' performance. Next to that, the more experienced VCs are argued to be better able to select the most promising opportunities (Sørensen, 2007; Nahata, 2008). Therefore, it is argued that the more experienced VCs would have higher proportions of IPO exits among their portfolio firms than inexperienced VCs (Manigart & Wright, 2013). This will be further discussed in paragraph 2.1.4.

2.1.3 Syndication and performance

As mentioned before, in order to make portfolio firms exit via an IPO, VCs tend to invest together, which is called syndication. Giot and Schwienbacher (2007) hypothesised that more extensive syndicate networks would be more helpful in adding value to the portfolio firm. This hypothesised effect was found to be significant. In the literature, there are multiple reasons given why syndication would improve the performance of the portfolio firms. According to Hochberg et al. (2007), syndication affects the two drivers of performance for a VC. These two reasons are the ability to select the more promising opportunities and the ability to add more value to their portfolio firms (Hochberg et al., 2007). Hochberg et al. (2007) provide three reasons why syndication would improve the ability to select the more promising opportunities. The first reason is that VCs expect future reciprocity from their fellow VCs because they invite each other to invest together in promising opportunities (Lerner, 1994). Secondly, in circumstances of uncertainty, the willingness of other VCs to invest in promising opportunities signals viability and potential of return (Sah & Stiglitz, 1986; Wilson, 1968). The VCs will be better able to select the best opportunity based on signals given by their peers in these uncertain circumstances. The third and last reason is that syndication helps VCs with diversifying their portfolios (Sorenson & Stuart, 2001). Most VCs possess expertise in both a location and a specific sector resulting in specific investment expertise (Hochberg et al., 2007). Additionally, syndication networks can also improve the ability to add value to the portfolio firms because such a network can facilitate the sharing of resources, contacts and information (Bygrave, 1988).

More recent research by Bellavitis (2018) showed even more positive effects of syndication networks. The performance of portfolio firms would be positively impacted because of access to more network resources (Gargiulo & Benassi, 2000; Stuart, Hoang & Hybels, 1999; Hite & Hesterly, 2001), networking benefits (Hochberg et al., 2007; Sorenson & Stuart, 2001), more risk diversification (Manigart et al., 2006), increased deal flow, improved monitoring, more activities that added value and better selection of investments (e.g., Brander et al., 2002; Lerner, 1994; Bygrave, 1987). Because of the positive effects of syndication networks, it is assumed that syndication provides a solid foundation for a successful exit via an IPO (Cumming & Walz, 2010). However, syndication would not be beneficial for the performance in all cases due to coordination costs and agency risks (Meuleman, Wright, Manigart & Lockett, 2009; Filatotchev, Wright & Arberk, 2006). Later research suggests that these negative implications can be alleviated, which will be discussed in section 2.1.5 (Dai et al., 2011; Devigne et al., 2013).

2.1.4 Network structure and experience

So far, we have seen that the likelihood of a portfolio firm to exit via an IPO is enhanced by VCs investing together in companies. Other factors that influence the likelihood of a portfolio firm to exit via an IPO include the network position or structure of the VC firm. The first example hereof was Hochberg et al. (2007). The authors found that better networked VCs performed better than the ones that were in a weaker position within their network. An alternative explanation for this finding could be that the better networked VCs are the ones with more experience due to previous investment experience. Therefore, the relation between VC experience and performance was controlled for the network structure of the VC (Hochberg et al., 2007). The authors found that the effect of VC experience reduced or even disappeared once the network measures of the VC were included. This indicates that the network position of a VC firm is more important than its experience from previous investments. However, Hochberg et al. (2007) used a sample of U.S.-based VC funds. As will be discussed in paragraph 2.1.5., this could be problematic and could possibly lead to a bias in their results.

The relationships of VCs with other VCs are a very important component of the social capital that is brought into the portfolio firms together with the investment itself (Ter Wal, Alexy, Block & Sandner, 2016). Due to prior investments with other VCs, a VC firm builds a network that can offer informational advantages and can help with making its investment decisions (Dimov & Milanov, 2010; Milanov & Shepherd, 2013; Liu & Maula, 2015). When embedded in syndication networks, this will offer VCs new information about investment opportunities (Sorenson & Stuart, 2001). This information is most of the time not available for actors outside the network. VCs build this network because of their past syndication experience (Hallen, 2008). The social capital that is built by VCs is, therefore, an important asset for the portfolio firm as well as for the VCs themselves (Hochberg et al., 2007). Because the VCs typically adopt some sort of advisory role after the first investment round, the social capital from past investments of the VC becomes available and can positively affect the portfolio firm's performance and thus also the return of the VC firm (Stuart, Hoang & Hybels, 1999). The number of actors in the VCs' network positively influences the performance of the portfolio firm (Hochberg et al., 2007), which increases the likelihood of a successful exit via an IPO (Shane & Stuart, 2002; Hsu, 2006).

The network measures used by Hochberg et al. (2007) were derived from Social Network Analysis/Social Network Theory (Burt, 1992). The two measures that form a VCs network structure and will be used in this research are degree centrality and betweenness centrality (Hochberg et al., 2007). The same definitions for the network measures will be used (Hochberg et al., 2007). Degree centrality captures the number of actors to which the VC firm is directly related to. If a VC firm has a lot of ties to its counterparts, there is a lot of opportunity for the exchange of information. VCs with a lot of ties are also less dependent on another VC for the deal flow or information, as discussed earlier. Additionally, with more ties, a VC firm can ensure a wider range of specific knowledge or other forms of capital. The more ties, the more influential the VC firm is.

Betweenness centrality can be seen as a structural hole, a bridge or a mediator between two other networks (Burt, 2004). The information that is provided through structural holes is likely to be non-redundant (Burt, 1992, 2004: Ter Wal et al., 2016). Therefore, a high degree of betweenness constitutes a situation in which the VC firm acts as an intermediary passing on investment opportunities or by bringing two VCs together with complementary capital, assets or skills (Hochberg et al., 2007). Compared to degree centrality, betweenness centrality was found to have less effect (Hochberg et al., 2007). Nonetheless, betweenness centrality still has a positive effect and does enhance portfolio firm's performance (Hochberg et al., 2007).

As Hochberg et al. (2007) showed, it is not the case that the more experienced VCs take better positions in the network and can therefore enhance portfolio firm's performance (Kaplan et al., 2007). Additionally, VCs that possess better track records are not without any doubt the ones that are better networked (Hochberg et al., 2007). Therefore, VCs with less experience might have to focus more on network strategy in order to enhance the portfolio firm's performance instead of working on their experience or building a track record.

2.1.5 Domestic and cross-border Venture Capital firms

Research in the VC industry has focussed mainly on the domestic VC industry for a long time (Cumming & Dai, 2010). However, more recently, there has been a strong growth of internationalization of the VC industry resulting in more international flows of VC across the world (Meuleman & Wright, 2011). These developments caused researchers to address the impact of both domestic and cross-border VCs on the performance of their portfolio firms (Dai et al., 2011; Devigne et al., 2013). Interestingly, both studies by Dai et al. (2011) and Devigne et al. (2013) found that a combination of both domestic and cross-border VCs enhanced the performance of the portfolio firm better than a syndicate with only domestic VCs. It is widely acknowledged that the experienced VCs are more likely to add more value to their portfolio firms and that they are better able in choosing the more promising opportunities (Gompers, Kovner, Lerner & Scharfstein, 2010; Hellmann & Puri, 2002). Dai et al. (2011) show that a combination of domestic and cross-border VCs results in a higher likelihood for the portfolio firm to exit via an IPO. In addition, the authors also show that cross-border VCs enjoy a relative advantage regarding previous investment experience when they invest together with a domestic VC firm.

Dai et al. (2011) proposed that the syndication networks with both domestic and cross-border VCs will experience the benefits of syndication as mentioned in 2.1.3. but they also profit from the structure of the syndication network because of three reasons (Dai et al., 2011). First, the value that both domestic and cross-border VCs add is enlarged because of the experience, skills, combined knowledge and additional resources from both VCs. Second, better monitoring and selection is possible because the friction that emerges due to geographical and cultural distances is reduced with help from the domestic VC firm. Third, investing in uncertain investment environments, the involvement of more investors is a means of risk-sharing. Earlier research showed that there is a positive impact of larger syndicate size on the exit performance of a portfolio firm (Brander et al., 2002). However, Dai et al. (2011) only focussed on investments in Asia. Therefore, this research is interested in the question of whether this effect is also present worldwide.

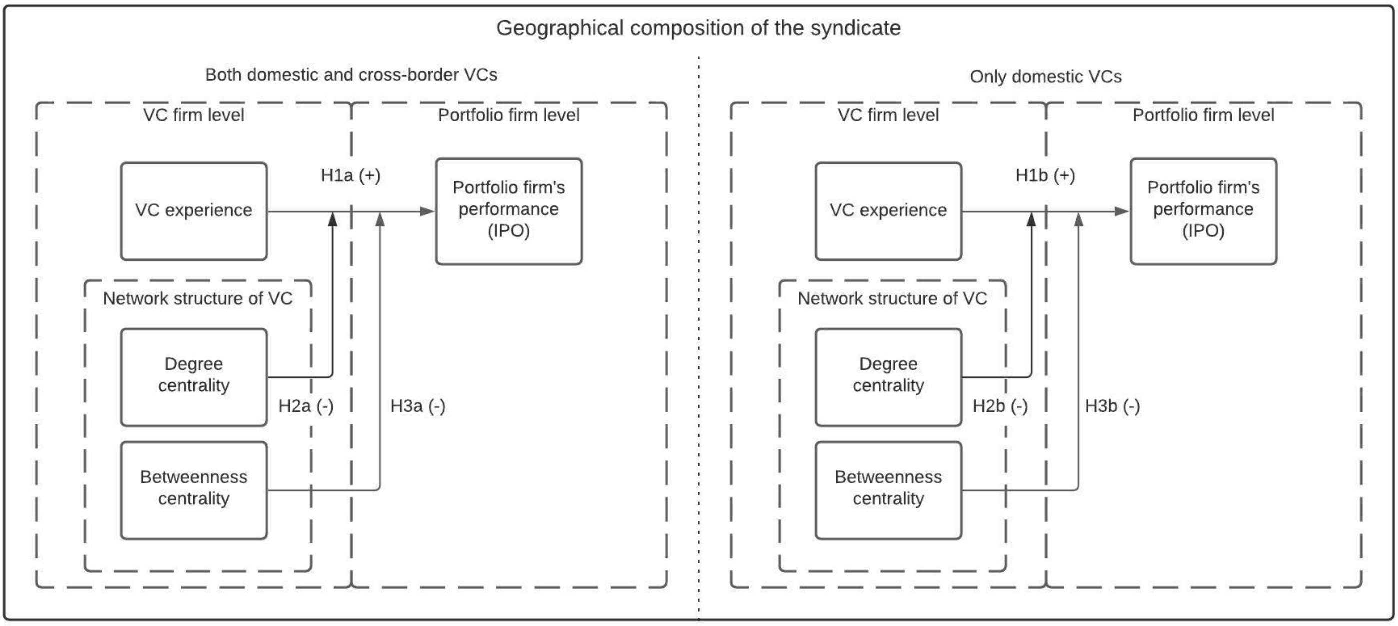
Devigne et al. (2013) found a similar effect of a syndicate that comprised both cross-border and domestic VCs. The authors found that portfolio firms backed by both domestic and cross-border VCs enjoy more growth in the long and short term (Devigne et al., 2013). The combination of both kinds of VCs enhances the performance of portfolio firms because of the support and knowledge of the domestic VC firm in combination with the legitimization provided by the cross-border VC firm. Additionally, the cross-border VC firm adds its international knowledge into the syndicate (Devigne et al., 2013). In other words, Devigne et al. (2013) found evidence for the findings of Dai et al. (2011), meaning that VCs bring complementary resources into the syndicate.

Where Hochberg et al. (2007) only focus on U.S.-based VC funds, the research done by Dai et al. (2011) and Devigne et al. (2011) takes into account the internationalization of the VC industry (Meuleman & Wright, 2011). As VC experience is an important determinant for the portfolio firms' performance, the findings of Dai et al. (2011) and Devigne et al. (2013) are very relevant today. Dai et al. (2011) found that cross-border VCs enjoy a relative advantage with regard to their previous investment experience compared to domestic VCs. This indicates that the cross-border VCs have more experience in terms of larger networks that they possess and the amount of capital that is possibly available, compared to domestic VCs (Dai et al., 2011).

2.2 Conceptual framework and hypotheses

The current state of the literature is presented above. In this section, the argumentation and hypotheses for this research will be presented. They will come together in the conceptual framework, which is presented in figure 1. The expected effect of the variables is given in parentheses.

Figure 1. Visualisation of conceptual framework and hypotheses



VC firm's experience

Recent research regarding VC takes into account the internationalization of the VC industry (Meuleman & Wright, 2011). These researches looked at the different compositions of syndicate networks and their impact on the performance of the portfolio firms. Dai et al. (2011) showed that cross-border VCs have a relative advantage regarding their experience, but they do suffer from some disadvantages such as cultural and geographical distance. These disadvantages are alleviated when the cross-border VC firm invests together with a domestic VC firm (Dai et al., 2011). Dai et al. (2011) provide three reasons why syndication with both domestic and cross-border VCs would enhance portfolio firm performance. Among those reasons is the enlarged added value of both domestic and cross-border VCs because of the experience, skills, combined knowledge and additional resources from both VCs. However, the research of Dai et al. (2011) only focussed on investments in Asia. Therefore, this research is interested in the question of whether this effect is also present worldwide. With the notion of domestic and cross-border VCs investing together in a syndicate and the enlarged added value because of the experience that both VCs bring into the syndicate, the following hypothesis is derived:

> **H1a**: VC experience has a more positive effect on the likelihood of an exit via an IPO in case the syndicate consists of both domestic and cross-border VCs, compared to syndicates that consist of only domestic VCs.

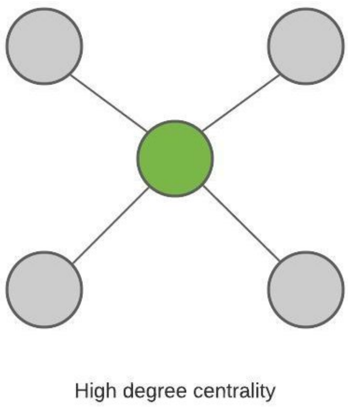
Before the internationalization of the VC industry, research mainly focused on the domestic VC industry. In the domestic VC literature, it is widely acknowledged that the more experienced VCs add more value to their portfolio firms and are better able to select the most promising investment opportunities (Gompers et al., 2010; Nahata, 2008; Sørensen, 2007; Hellmann & Puri, 2002). Therefore, more experienced VCs would enjoy higher proportions of IPO exits compared to less experienced VCs (Manigart & Wright, 2013). Given the more recent findings in literature on VC funding and its relation to performance (e.g., Nahata, 2008; Sørensen, 2007) plus the development and internationalization of the VC industry (Meuleman & Wright, 2011), this research proposes the following hypothesis:

> **H1b:** VC experience has a positive effect on the likelihood of an exit via an IPO in case the syndicate consists of only domestic VCs.

Degree centrality

Degree centrality captures the number of actors to which the VC firm is directly related (Hochberg et al., 2007; Zhang & Luo, 2017). An example can be found in figure 2, where the green dot represents a VC firm with a lot of actors connected to it. If a VC firm has a lot of ties connected to it, there is a lot of opportunity for the exchange of information. VCs with a lot of ties are also less dependent on another VC firm for the deal flow or receiving information (Hochberg et al., 2007). Additionally, with more ties, a VC firm can also ensure a wider range of specific knowledge or other forms of capital. The more ties, the more influential the VC firm is (Hochberg et al., 2007).

Figure 2. Example of degree centrality



As Hochberg showed, a VC firm will benefit from having more ties than its counterparts (Hochberg et al., 2007). Hochberg et al. (2007) also showed that the positive effect of previous investment experience would disappear once the network measures were included. Because cross-border VCs enjoy a relative advantage regarding experience (Dai et al., 2010), it is likely that the effect of experience will decrease once the focal VC firm is connected to a lot of actors. However, the effect of previous investment experience will not disappear for syndicates with both domestic and cross-border VCs. The following hypothesis is proposed:

> **H2a**: for syndicates with both domestic and cross-border VCs, degree centrality will decrease the effect of VC experience on portfolio firm performance.

Dai et al. (2010) conclude that domestic VCs do not enjoy a relative advantage regarding experience. Because more experienced VCs are better able to select the most promising opportunities (Sørensen, 2007; Nahata, 2008), they are said to have higher proportions of IPOs compared to less experienced VCs (Manigart & Wright, 2013). As Hochberg showed, a VC firm will benefit from having more ties than its counterparts (Hochberg et al., 2007). Therefore, one could expect that degree centrality is more detrimental for enhancing performance because of the reasons that are mentioned above. Experience will be less important for syndicates with only domestic VCs (Dai et al., 2010) in case the focal VC firm is connected to a lot of actors.

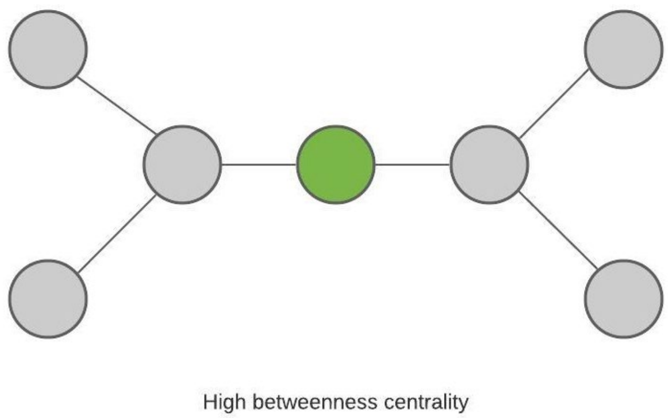
Therefore, the effect of experience is likely to decrease (and possibly disappear), in line with the findings of Hochberg et al. (2007). The following hypothesis is proposed:

> **H2b**: for syndicates with only domestic VCs, degree centrality will decrease the effect of VC experience on portfolio firm performance.

Betweenness centrality

In addition to degree centrality, betweenness centrality can be seen as a structural hole, a bridge or mediator between two other networks (Zhang & Luo, 2017; Hochberg et al., 2007; Burt, 2004). An example can be found in figure 3, where the green dot represents a VC firm that acts as a mediator between two other networks. The information that is provided through structural holes is likely to be non-redundant (Burt, 1992, 2004: Ter Wal, Alexy, Block & Sandner 2016). Therefore, a high degree of betweenness constitutes a situation in which the VC firm acts as an intermediary passing on investment opportunities or by bringing two VCs together with complementary capital, assets or skills (Hochberg et al., 2007).

Figure 3. Example of betweenness centrality



As Hochberg showed, a VC firm will benefit from acting as an intermediary between two other actors or VCs, albeit at a lower level than degree centrality (Hochberg et al., 2007). Because cross-border VCs enjoy a relative advantage regarding experience (Dai et al., 2010), it is likely that the effect of experience will decrease in case the focal VC firm acts as an intermediary. However, because of the relative advantage of cross-border VCs, it is not likely that the effect of experience will disappear in that case. Therefore, the following hypothesis is proposed:

H3a: for syndicates with both domestic and cross-border VCs, betweenness centrality will decrease the effect of VC experience on portfolio firm performance.

As Hochberg showed, a VC firm will benefit from acting as an intermediary between two other actors or VCs (Hochberg et al., 2007). Therefore, one could expect that betweenness centrality is more detrimental for enhancing performance because of the arguments that are presented above. Experience will be less important for syndicates with only domestic VCs (Dai et al., 2010) in case the focal VC firm acts as an intermediary. Therefore, the effect of experience is likely to decrease (and possibly disappear), in line with the findings of Hochberg et al. (2007). The following hypothesis is proposed:

H3b: for syndicates with only domestic VCs, betweenness centrality will decrease the effect of VC experience on portfolio firm performance.

To conclude, this research proposes that the network structure of VC firms will make the effect of experience on portfolio firms' performance decrease because better networked VCs can add more value to their portfolio firm (Hochberg et al., 2007). This research will provide evidence on whether the findings of Hochberg et al. (2007) are still present due to the internationalization of the VC industry. Besides, this research will compare the main and moderating effect of network structure on experience for syndicates that comprise only domestic VCs and syndicates that comprise both cross-border VCs and domestic VCs. The aforementioned hypotheses and conceptual model are represented at the beginning of section 2.2 in figure 1.

3. Methodology

This section will elaborate on the measurement of the variables and the description of the dataset that will be used to answer the hypotheses. It will also provide an overview of the conducted analyses.

3.1 Research method

The aim of this research was to discover whether network structure and experience of VCs affect the probability of an IPO. Therefore, this research used an exploratory approach (Yin, 2018). In order to answer the research question, a quantitative dataset from Crunchbase was used. The dataset will be further described in the following section. A table with all variables that are included in the dataset can be found in appendix 1.

3.2 Research design

The research design will describe how the research was conducted. This includes a description of the population and the samples that were used. Additionally, the process of data collection will be described.

3.2.1 Sample and population

This research used a dataset that was retrieved from Crunchbase. Crunchbase is a commercial database (Dalle et al., 2017). The database is becoming a primary source of information about businesses and is used by over 55 million users worldwide (Crunchbase, 2017a). Crunchbase sources its data through two channels: community contributors and a large network of investors (Crunchbase, 2017b; Dalle et al., 2017). Besides, to ensure that the data is accurate, data is processed with Artificial Intelligence (AI) and machine learning. In addition, there are several algorithms that search the web for information that can enrich the profiles (Dalle et al., 2017). The database is also being used more in the academic literature, which signals that it is reliable to use and to come to credible results (Dalle et al., 2017).

The dataset that was retrieved from Crunchbase consists of approximately 943,000 companies from all over the world, including countries like the U.S., China, The Netherlands and South Africa. The companies also vary in age. The oldest firm was founded in 1900 and the youngest one in 2020. Most firms in the dataset received VC funding. From those firms, data of the top five VCs were gathered and inserted into the dataset. Eventually, this led to two samples with firms that received VC funding. Network measures of the VCs were calculated to determine the network structure of a VC firm within the larger network of syndicates. This will be described in section 3.3.1.

In this research, there are two samples that were compared to each other. Sample 1 included syndicates with both domestic and cross-border VCs. Sample 2 included syndicates with only domestic VCs. The distribution of both samples can be found in table 1.

Table 1. Distribution of the samples

	Both domestic and cross-border VCs		**Only domestic VCs**	
	N	**Percentage**	***N***	**Percentage**
IPO	56	19.58%	43	19.55%
Private	230	80.42%	177	80.45%
Total	**286**	**100%**	**220**	**100%**

Table 2 shows the total number of VCs that invested in a firm. Table 3 provides the total numbers of VCs per firm that exited via an IPO. In total, most firms that exited via an IPO had more than 5 VCs that invested in them. This will be discussed further in the discussion and conclusion because it could bias results since only the top five VCs are taken into account. An overview of the geographical location of the portfolio firms for both samples can be found in table 4. Table 5 provides an overview of the industry in which the portfolio firms are active for both samples.

Table 2. Total number of VCs per portfolio firm

	Both domestic and cross-border VCs		**Only domestic VCs**	
Number of VCs	***N***	**Percentage**	***N***	**Percentage**
1-5	152	53.2%	133	60.5%
6-10	24	31.3%	48	21.8%
11-20	42	14.7%	34	15.4%
21-30			3	1.4%
31-70	1	0.4%	2	0.9%
> 70	1	0.4%		
Total	**286**	**100%**	**220**	**100%**

Table 3. Total number of VCs for portfolio firms that exited via an IPO

	Both domestic and cross-border VCs		**Only domestic VCs**	
Total number of VCs	***N***	**Percentage**	***N***	**Percentage**
1-5	17	30.36%	15	34.88%
> 5	39	69.64%	28	65.12%
Total	**56**	**100%**	**43**	**100%**

Table 4. Geographical location of the portfolio firms for both samples including distribution

Both domestic and cross-border VCs			Only domestic VCs		
Country	*N*	Percentage	**Country**	*N*	Percentage
U.S.	117	40.7%	U.S.	126	57.3%
China	24	8.4%	China	22	10%
United Kingdom	20	7%	Japan	16	7.3%
Israel	19	6.6%	United Kingdom	13	5.9%
India	12	4.2%	Germany	7	3.2%
Canada	11	3.9%	India	5	2.3%
Germany	9	3.2%	France	5	2.3%
France	8	2.9%	Spain	4	1.8%
Singapore	6	2.1%	Austria	2	0.9%
Australia	5	1.75%	Australia	2	0.9%
Brazil	5	1.75%	Canada	2	0.9%
Finland	5	1.75%	Denmark	2	0.9%
Denmark	4	1.4%	Italy	2	0.9%
Japan	4	1.4%	Sweden	2	0.9%
Portugal	3	1.05%	Brazil	1	0.45%
Spain	3	1.05%	Finland	1	0.45%
Sweden	3	1.05%	Indonesia	1	0.45%
Austria	2	0.7%	Ireland	1	0.45%
Estonia	2	0.7%	Israel	1	0.45%
New Zealand	2	0.7%	Jordan	1	0.45%
Russian Federation	2	0.7%	Mexico	1	0.45%
South Korea	2	0.7%	Russian Federation	1	0.45%
Switzerland	2	0.7%	The Netherlands	1	0.45%
The Netherlands	2	0.7%	United Arab Emirates	1	0.45%
United Arab Emirates	2	0.7%			
Belgium	1	0.35%			
Chile	1	0.35%			
Hong Kong	1	0.35%			
Ireland	1	0.35%			
Kenya	1	0.35%			
Pakistan	1	0.35%			
Poland	1	0.35%			
Saudi Arabia	1	0.35%			
Taiwan	1	0.35%			
Thailand	1	0.35%			
Turkey	1	0.35%			
Vietnam	1	0.35%			
Total	**286**	**100%**		**220**	**100%**

Table 5. Industry in which the portfolio firm is active

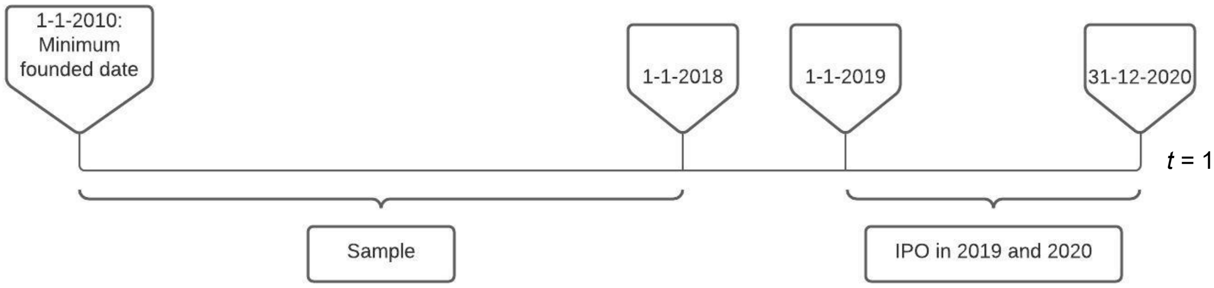
Both domestic and cross-border VCs			Only domestic VCs		
Industry	***N***	**Percentage**	**Industry**	***N***	**Percentage**
Biopharma, Biotechnology	40	14.1%	Consumer goods, E-Commerce	31	14.1%
Consumer goods, E-Commerce	28	9.8%	Biopharma, Biotechnology	26	11.8%
Apps, Gaming, Online	25	8.8%	Software	21	9.5%
Health care	25	8.8%	Health Care	17	7.7%
Software	21	7.4%	Financial services, FinTech	16	7.3%
Analytics, Big Data	17	5.9%	Artificial Intelligence	13	5.9%
Financial services, FinTech	17	5.9%	Internet, Internet of Things	12	5.5%
Internet, Internet of Things	17	5.9%	Analytics, Big Data	9	4.1%
Artificial Intelligence	12	4.2%	Accounting	8	3.7%
Cloud Services/Security	11	3.8%	Education	8	3.7%
Education	10	3.5%	Agriculture, Food and Beverage	7	3.2%
Agriculture, Food and Beverage	8	2.8%	Apps, Gaming, Online	7	3.2%

Table 5 – *Continued*

Both domestic and cross-border VCs			Only domestic VCs		
Industry	***N***	**Percentage**	**Industry**	***N***	**Percentage**
Advertising, CRM, Marketing	7	2.5%	Cloud Services/Security	7	3.2%
Transportation, Logistics	7	2.5%	News, (Social) Media	6	2.8%
3D Printing	6	2.2%	Music, Video, Streaming	5	2.4%
News, (Social) Media	6	2.2%	3D Printing	4	1.9%
Automotive	5	1.7%	Manufacturing	4	1.9%
Energy, Oil and Gas	5	1.7%	Real Estate	4	1.9%
Aerospace	4	1.4%	Transportation, Logistics	4	1.9%
Manufacturing	4	1.4%	Advertising, CRM, Marketing	2	0.9%
Music, Video, Streaming	4	1.4%	Aerospace	2	0.9%
Real Estate	3	1.1%	Energy, Oil and Gas	2	0.9%
Accounting	2	0.7%	Sports	2	0.9%
Sports	2	0.7%	Automotive	1	0.5%
Total	**286**	**100%**	**Total**	**220**	**100%**

Because the network measures for every VC firm were calculated at one certain point, t = 1, the data needed to be as close as possible to that moment. Therefore, the companies that were included in the samples were subject to the restricted timeframe, as shown in figure 4. In the literature, it is acknowledged that companies need a timeframe of approximately 5 to 7 years to go public (Sørensen, 2007; Dai et al., 2013). This research used a timeframe of 9 years to ensure an acceptable sample size. Because the start date of the investment is not known, this research included two samples of companies that were founded between 2010 and 2018. The aforementioned timeframe was chosen because the companies that did an IPO in 2019 and 2020 were founded within this timeframe, and it is important to keep all other factors equal as much as possible when selecting the samples. The youngest portfolio firm that did an IPO in 2019 and 2020 that was included in both samples was founded in 2018. Therefore, all companies that were founded after 1-1-2018 were excluded from the samples. This was done to avoid the bias that these companies did not have the chance to exit via an IPO because of the limited amount of time. This is shown in the timeframe in figure 4. The decision to exclude the companies founded after 1-1-2018 was made in accordance with, for example, Sørensen (2007).

Figure 4. Timeframe of the sample used in this research



In total, 37.673 companies met these requirements. A total of 381 companies did an IPO. However, only 105 did so in 2019 and 2020. Both samples were selected from the dataset using the endogenous stratified sampling method (King & Zeng, 2001), also known as case-control in other disciplines (Breslow, 1996). This method was used because it is important that the samples represent the broader population (Field, 2018). The proportion of IPOs in the dataset is substantially lower compared to other findings in the extent literature on VC investments. In the dataset of this research, the IPO rate is approximately 1.01% compared to 20.7% (Hochberg et al., 2007) and 19.6% (Sørensen, 2007) or even higher rates as found by Giot and Schwienbacher (2007). Ljungqvist et al. (2009) conclude that VCs write off about 75% of their investments, which would mean that they gain from the investments that exit via an IPO or trade sale, i.e., the other 25%. 20.7% of the 25% is established by IPOs (Ljungqvist et al., 2009).

This research used the IPO rate of Sørensen (2007) as 'valid' for the whole population because it is widely used in the literature and the IPO rates found in most research on VC funding varies between 19% and 25% (Ljungqvist et al., 2009). With only 1.01% of IPO rate, this value of the dependent variable was very rare in the population and thus underrepresented. Using a random sampling method would result in an outcome that does not reflect the population properly. Additionally, the required sample size of 10 observations for every value of the dependent variable will not be met because there will not be enough firms that exited via an IPO in the sample (Hair, Black, Babin & Anderson, 2019). In order to come to valid results, the endogenous stratified sampling method was used in this research (Hair et al., 2019; King & Zeng, 2001).

With the endogenous stratified sampling method, all or randomly selected observations for which $Y = 1$ (exit via IPO) are collected. To complete the sample, observations for which $Y = 0$ (private firm) will be randomly selected from the dataset that matches the requirements of the sample as described above. The distribution of the sample is based on a proportion of the 'ones' in the population. For this proportion, this research used the 19.6% as found by Sørensen (2007), which has shown to be a reliable benchmark across multiple studies, as discussed above. These other observations were randomly selected. Ultimately, this led to the distribution of the two samples that are shown in table 1 until 5.

After the samples were selected, four VC firms had to be deleted. For these VCs, something went wrong while importing the data into Excel. Therefore, these four VCs were removed from the dataset. However, this did not have an impact on the rest of the data.

3.2.2 Additional data

In addition to the data that was available in the dataset, extra data was gathered. With this additional data, the experience of the VC firm could be determined. Additional data was also needed to determine whether the syndicate consisted of a combination of domestic and cross-border VCs or solely out of domestic VCs.

First, data to determine whether the VC is a domestic or a cross-border one was gathered. The country in which the portfolio firm is located is given in the dataset. This is retrieved from Crunchbase as described earlier. The location in which the VC firm is located was checked manually, also via Crunchbase. The samples were coded with the colour red if the syndicate comprises only domestic VCs. The syndicate was given the colour green if the syndicate comprised both domestic and cross-border VCs. An example of the coding process is shown in appendix 2.

Secondly, the VC firms' experience needs to be determined. Experience can either be measured in line with Hochberg et al. (2007) and Gompers (1996) or in the same way as Sørensen (2007). Hochberg et al. (2007) and Gompers (1996) used four proxies for VC experience: the age of the VC firm, the cumulative amount that the VC firm invested, the number of firms it has backed and the number of rounds the firm has participated in (Hochberg et al. 2007). This research used the measure of previous investment experience of the VC firm in line with Sørensen (2007), meaning that the experience was measured by the number of investments rounds the VC firm has participated in. Sørensen (2007) argues that the four proxies that were used by Hochberg et al. (2007) and Gompers (1996) are not an attractive alternative for three reasons. Firstly, age does not distinguish between active VC firms and inactive VC firms. Secondly, the number of companies can be subject to a bias because VC firms might be involved in different stages (early vs. final stages). The VC firms might invest in the same number of companies, but the first VC firm is better able to influence the later performance of the portfolio firm. Counting the number of investments rounds can help to overcome this bias. Third, and lastly, the amount that is invested can also be subject to a bias because later rounds involve larger amounts. Therefore, the number of investment rounds is a preferable measure and was used because of this in this research.

Both the additional data were gathered from Crunchbase and the LinkedIn pages of the VC firms. The network measures were not available at first in the dataset. For each VC firm, the network measures (degree centrality and betweenness centrality) were calculated and included in the dataset. How these measures were calculated will be addressed in the following section (3.3.1).

3.3 Variables

The independent, moderating, dependent and control variables will be discussed here consecutively. All variables will be presented in the table of operationalization. This table is given in table 6.

3.3.1 Independent and moderating variables

The independent variable is the previous investment experience of the VC firm. As explained in section 3.2.2., the experience will be measured in accordance with Sørensen (2007). For both samples, the number of funding rounds that each VC firm has participated in will be added to the dataset. These were added up for every portfolio firm so that it resulted in the cumulative amount of funding rounds for all VCs.

The moderating variables are the network measures. Together, the network measures are called the 'network structure' of the VC firm. The network measures that were calculated for each VC in this research are degree centrality and betweenness centrality (Hochberg et al., 2007). Hochberg et al. (2007) used a total of five network measures to reflect the network structure of a VC firm: degree centrality (1), indegree (2), outdegree (3), closeness (4) and betweenness (5). Indegree and outdegree both deal with the frequency by which the VC is invited or invites other VCs to co-invest

(Hochberg et al., 2007). Closeness deals with the quality of the actors to which the focal actor is linked to (Hochberg et al., 2007). This research is concerned with the actual network position of the VC, not the quality of the link between actors or the received and given invites to co-invest. Therefore, only degree and betweenness centrality were calculated and used in this research. After the network measures were calculated, the average of the values for each VC was calculated and inserted into the dataset. This average was used in the actual analysis. How these network measures were calculated is explained below.

Degree centrality captures the number of actors to which the VC firm is directly related to (Hochberg et al., 2007; Zhang & Luo, 2017). Degree centrality was calculated according to the equations shown in figure 5 (Bolland, 1988). Degree centrality (*Cd*) was calculated with equation (1) in figure 5, where $\sum_{j=1}^{n} Xij$ is the number of direct relations connected to node N, and *n* is the total number of nodes that are in the focal network (Zhang & Luo, 2017). Because the network may vary over time, Wasserman and Faust (1994) argue to make the first equation standardized. This was done in equation (2) of figure 5 with dividing equation (1) by *(n – 1)(n – 2)* (Nieminen, 1974). With standardizing the second equation in figure 5, degree centrality was calculated in line with Hochberg et al. (2007).

Figure 5. Equations to calculate Degree Centrality

$$Cd(Ni) = \sum_{j=1}^{n} Xij(i \neq j) \qquad (1)$$

$$C'd(Ni) = \frac{\sum_{j=1}^{n} Xij}{(n-1)(n-2)} \ (i \neq j) \qquad (2)$$

Note. Retrieved from "Degree Centrality, Betweenness Centrality, and Closeness Centrality in Social Network", by Zhang, J., & Luo, Y., 2017, *Advances in Intelligent Systems Research*, *132*, p. 301.

Betweenness centrality (*Cb)* can be seen as a structural hole, which is a bridge or mediator between two other networks (Zhang & Luo, 2017; Hochberg et al., 2007; Burt, 2004). Betweenness centrality was calculated according to the equations shown in figure 6. In both equations $\sum_{j<k}^{n} \frac{Gjk(Ni)}{Gjk}$ is "*the number of node N locate between any other two nodes in the network*" (Zhang & Luo, 2017, p. 301). Again, the network is likely to change over time, and according to Wasserman and Faust (1994), equation

(3) should be standardized. To standardize *Cb*, it was divided by $\frac{(n-1)(n-2)}{2}$ resulting in equation (4). With standardizing the third equation in figure 6, betweenness centrality was calculated in line with Hochberg et al. (2007).

Figure 6. Equations to calculate Betweenness Centrality

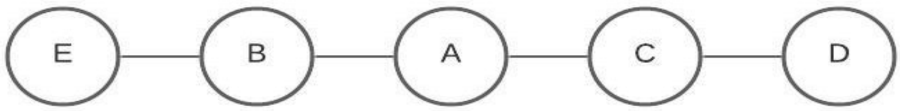
$$Cb(Ni) = \sum_{j<k}^{n} \frac{Gjk(Ni)}{Gjk} \qquad (3)$$

$$C'b(Ni) = \frac{2\sum_{j<k}\frac{Gjk(Ni)}{Gjk}}{(n-1)(n-2)} \qquad (4)$$

Note. Retrieved from "Degree Centrality, Betweenness Centrality, and Closeness Centrality in Social Network", by Zhang, J., & Luo, Y., 2017, *Advances in Intelligent Systems Research*, *132*, p. 301.

The aforementioned will be illustrated with an example which is also used by Zhang and Luo (2017). The example for degree centrality is given in figure 7 and for betweenness centrality in figure 8.

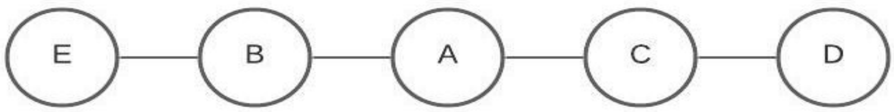
Figure 7. Example of values for degree centrality



Cd	1	2	2	2	1
C'd	0.083	0.167	0.167	0.167	0.083

Note. Adopted from "Degree Centrality, Betweenness Centrality, and Closeness Centrality in Social Network", by Zhang, J., & Luo, Y., 2017, *Advances in Intelligent Systems Research*, *132*, p. 301.

Figure 8. Example of values for betweenness centrality



Cb	0	3	4	3	0
C'b	0	0.4	0.53	0.4	0

Note. Adopted from "Degree Centrality, Betweenness Centrality, and Closeness Centrality in Social Network", by Zhang, J., & Luo, Y., 2017, *Advances in Intelligent Systems Research*, *132*, p. 301.

3.3.2 Dependent variable

The dependent variable is the performance of the portfolio firm. Portfolio firm performance is measured as whether or not the portfolio firm did an IPO because this is considered as the most successful exit in the literature (Manigart & Wright, 2013), together with trade sale. This research only focussed on IPO because the VCs' ultimate goal is to exit from their portfolio firms as successfully as possible, which will deliver them the most profit (Manigart & Wright, 2013). VCs, on average, write off 75% of their investments (Ljungqvist et al., 2009). 20.7% of the 25% originates from IPOs (Ljungqvist et al., 2009). This indicates that VCs gain from their investments by those portfolio firms that exit via an IPO (Hochberg et al., 2007). A dichotomous dummy variable was used to measure IPO. In case the portfolio firm did an IPO, it was labelled with a '1'. If a portfolio firm did not exit via an IPO, it was labelled with a '0'. The operationalization of all the variables and the source of the data is shown in table 6.

Table 6. Table of operationalization

Concept	Variable	Dimensions	Literature	Source
Geographical composition of the syndicate		Both domestic and cross-border Only domestic	Dai et al., 2011; Devigne et al., 2013.	Crunchbase and LinkedIn
Dependent variable	Portfolio firm performance	Public, 1 = IPO Private, 0 = no IPO	Manigart & Wright, 2013; Hochberg et al., 2007, p. 262.	Crunchbase
Independent variable	VC experience	Total number of funding rounds VC firm has participated in	Sørensen, 2007, p. 2739.	Crunchbase
Moderating variable	Network structure of VC firm	Degree centrality Betweenness centrality	Hochberg et al., 2007, 256-258.	Crunchbase
Control variables portfolio firm level	Total amount capital raised IP – Granted patents IP – Granted trademarks Number of funding rounds that a firm participated in	Total amount capital raised in USD Total number of patents Total number of trademarks Total number of funding rounds	Ter Wal et al., 2016; Hochberg et al., 2007; Baum & Silverman, 2004.	Crunchbase
Control variable syndicate level	Syndicate size	Total number of investors	Ter Wal et al., 2016.	Crunchbase

3.3.3 Control variables

This research includes a range of control variables that are considered to be other determinants for the performance of a portfolio firm (Manigart & Wright, 2013). The control variables are separated into two different levels: the portfolio firm level (1) and syndicate level (2).

The control variables on portfolio firm level that were included are the 'total amount of capital raised' by a firm and the 'number of funding rounds that a firm has participated in'. Additionally, 'granted patents' and 'granted trademarks' were included because both can signal quality of the portfolio firm towards a VC firm (Ter Wal et al., 2016; Hochberg et al., 2007; Baum and Silverman, 2004).

The control variable on syndicate level that was included in line with the extensive VC literature is 'syndicate size' (Ter Wal et al., 2016). All control variables were derived from the database at the same time as the dependent variable at t = 1.

3.4 Data analysis

The objective of this research is to explain differences among group members represented by the dependent variable (Hair et al., 2019), i.e., whether or not the portfolio firm did an IPO. The outcome was thus either yes or no. Because the dependent variable is a binary one, logistic regression was used to test the hypotheses. As described in section 3.2.1, this was done for two samples.

Throughout the analysis, tests were done to check the validity of the variables. In addition to the primary methods to assess the goodness-of-fit of the model, the Akaike information criterion (AIC) was calculated for every model for both samples. The AIC was used to compare the models for both samples to determine what model fits the data best (Hastie, Tibshirani & Friedman, 2016). The formula for the minimized Akaike information criterion is (Hastie et al., 2016):

$$AIC = -\frac{2}{N} * LL + 2 * \frac{k}{N}.$$

Where k is the number of parameters in the model and N is the sample size. The logistic regression models provided the *-2LL*, so to obtain the Log-Likelihood (*LL*), these values need to be divided by -2. This is presented in the formula:

$$LL = \frac{-2LL}{-2}.$$

All six hypotheses were tested by conducting multiple binary logistic regression analyses per sample. To test for the moderating effects, the main effects of network structure were first assessed separately. Thereafter, the interaction effect of VC experience and network structure was assessed. After the analyses, it was possible to identify whether or not VC experience and network structure of the VCs enhanced the probability of an IPO of the portfolio firm.

3.5 Reliability and validity

Validity is ensured by using measures for the variables that are widely used in the literature, as described in section 3.3 (Field, 2018). In addition, validity will be covered throughout section 4, in which the overall goodness-of-fit and the predictive accuracy of the regression model will be assessed. Another test to check validity is to compare the results with the theory (Snee, 1977), which will be done in section 5. Predictions with unexpected signs can indicate a poorly estimated model and thus invalid results (Snee, 1977). The reliability of the coefficients will be assessed while looking at the collinearity statistics in section 4 (Midi, Sarkar & Rana, 2010). In case multicollinearity is present, the reliability of the coefficients (or log-odds ratios) is affected (Midi et al., 2010).

3.6 Research ethics

This research was conducted with due regard for the research ethical principles, as described by the APA (Smith, 2003). These ethical issues included confidentiality and privacy but also considerations about deception. The data that was used in this research was retrieved from Crunchbase. In addition to this data, extra data was gathered from Crunchbase or public sources, such as the LinkedIn page of the VC firm or its own website. Therefore, this research did not make use of any data that is not meant to be used as such.

Normally, the process of data collection is the most important part with regard to ethical issues. However, since this research made use of an external dataset, issues like the right to withdraw did not play that big of a role in this research. Additionally, to ensure no deception in the data, it was treated with caution. No data was altered or deleted without good reason.

4. Results

In this section, the results are presented. First, the univariate analysis will be given. Thereafter, the assumptions for logistic regression will be addressed. After the assumption, the overall fit of the logistic regression model will be determined. Lastly, the results of the logistic regression will be presented.

4.1 Univariate analysis

As already described in section 3, two samples from a larger dataset were retrieved. At first, there were some missing values for the total funding amount that was invested in the portfolio firms (26 for sample 1 and 31 for sample 2). After gathering the additional data, there were no missing values left because the total funding amount was publicly available via Crunchbase for all companies. This led to the distribution of both samples, as shown in table 1 until 3, presented in section 3. Where sample 1 is the sample with both domestic and cross-border VCs, and sample 2 is the sample with only domestic VCs. Additionally, the descriptive statistics are presented in table 7 for sample 1 and table 8 for sample 2.

The mean for total funding amount is almost twice as high for sample 1 ($105,000,000) as for sample 2 ($57,000,000). For both samples, the average number of investors is approximately 6. The average experience of the syndicate is slightly higher for sample 1 (1,230 funding rounds) compared to sample 2 (1,155 funding rounds). Additionally, the companies in sample 1 (3,5 funding rounds) participated in slightly more funding rounds compared to sample 2 (2,9 funding rounds).

Table 7. Descriptive statistics for the sample with both domestic and cross-border VCs

	N					
Variable	Valid	Missing	Minimum	Maximum	Mean	Std. Dev.
Number of funding rounds	286	0	1	20	3.56	2,180
Total funding amount	286	0	16,898	4,912,500,000	105,710,137.69	378,550,793.251
Number of investors	286	0	2	74	6.59	5,756
IP – Trademarks	286	0	0	49	1.98	4,944
IP – Patents	286	0	0	312	4.75	26,372
VC Experience	286	0	3	8,133	1,230.00	1,316.691
Average degree cent.	286	0	0,000020	0,066533	0,008866	0,010878
Average between. cent.	286	0	0	0,029549	0,002530	0,004392

Table 8. Descriptive statistics for the sample with only domestic VCs

	N					
Variable	Valid	Missing	Minimum	Maximum	Mean	Std. Dev.
Number of funding rounds	220	0	1	10	2.96	1.909
Total funding amount	220	0	18,000	949,200,000	57,762,993,153	132,501,985.507
Number of investors	220	0	2	35	6.27	5.641
IP – Trademarks	220	0	0	60	2.19	6.930
IP – Patents	220	0	0	41	1.34	4.534
VC Experience	220	0	2	10,013	1,155.77	1,703.308
Average degree cent.	220	0	0,000020	0,067652	0,008857	0,013550
Average between. cent.	220	0	0	0,019160	0,001852	0,003551

The correlation matrix for both samples is shown in table 9. All correlations, except the dependent variable IPO, have an *r* value above .7, which is considered as a high correlation (Field, 2018). In addition, the *r* values of the network measures are above .8, indicating that there is a very high correlation among the network measures (Field, 2018). The high correlations between variables could indicate that multicollinearity is present. This will be discussed in section 4.2 in more detail.

Table 9. Correlation matrix for both samples

	Both domestic and cross-border VCs				**Only domestic VCs**			
	1	2	3	4	1	2	3	4
1 IPO	1.000				1.000			
2 VC Experience	-.061	1.000			.000	1.000		
3 Average degree cent.	-.080	.869*	1.000		-.040	.925*	1.000	
4 Average between. cent.	-.159*	.769*	.884*	1.000	-.071	.857*	.933*	1.000
N	286	286	286	286	220	220	220	220

Note * $p < .01$; significance level $p < .01$ (2-tailed).

4.2 Assumptions logistic regression

For logistic regression, there are fewer assumptions that have to be met compared to discriminant analysis or multiple regression analysis (Hair et al., 2019). The assumptions and other issues that had to be addressed were: collinearity, sample size, independence of observations and the linearity of the logit (Hair et al., 2019; Field, 2018; Stoltzfus, 2011).

The first important check was for multicollinearity. Because the correlation matrix showed some high correlations, it is important to further explore the issue of multicollinearity. To check whether multicollinearity is present, the VIF and tolerance values were examined. Both are shown in table 10. Bowerman and O'Connell (1990), together with Myers (1990), suggested that in case the largest VIF is greater than 10, this can cause problems for the interpretation of the results. Additionally, they also argue that the same can be said in case the largest tolerance is below .1. Menard (2002) suggests that a tolerance below .2 can indicate potential problems with the interpretation. For sample 1, the largest VIF is below 10, and the largest tolerance is .131. However, this is still below the threshold of .2, as suggested by Menard (2002). Overall, sample 1 shows a moderate correlation, although not alarming.

Table 10. Collinearity statistics for both samples

	Both domestic and cross-border VCs		**Only domestic VCs**	
	Tolerance	VIF	Tolerance	VIF
VC Experience	.245	4.084	.144	6.938
Average degree cent.	.131	7.651	.071	14.167
Average between. cent.	.218	4.584	.130	7.697

For sample 2, the largest VIF value is greater than 10 (VIF = 14.167) (Bowerman & O'Connell, 1990; Myers, 1990). Additionally, all tolerance values are below the threshold of .2, as suggested by Menard (2002). This indicates that there is a moderate or high correlation, which is a major implication for the interpretation of the results of sample 2. As shown in table 9, there are some very high correlations (r > .8 or .9), especially in sample 2 (Field, 2018). This is also an indication of a high correlation among the independent variables for sample 2. Therefore, the results need to be interpreted with caution because coefficients of important antecedents can become non-significant, or coefficients can have unexpected signs. In addition, due to multicollinearity, the reliability of the estimates is affected.

The second consideration before running the actual analysis is the sample size. For logistic regression, a minimum of 400 samples is considered to be adequate (Hair et al., 2019). Both samples do not meet this threshold with a sample size of 286 and 220, respectively. There is another important issue regarding the sample size per category of the dependent variable (Hair et al., 2019). Both samples consist of a minimum of 200, which is given as a lower threshold in order to prevent the occurrence of potential biases in the estimated probabilities as well as the estimated coefficients and log-odds ratios for the independent variables (Hair et al., 2019). Additionally, following Hair et al. (2019), the threshold of 10 observations per estimated parameter is met because the *N* of both categories of the independent variable is at least 30 (Hair et al., 2019). This was already described in section 3.2.1.

The third assumption is the independence of observations (Stoltzfus, 2011). This is met because of the nature of the dataset and the research design (Hair et al., 2019). This research did not use repeated measures or something the like (Field, 2018).

The fourth and last assumption is the linearity of the logit. This was checked using the Box-Tidwell transformation. Firstly, an interaction term of the log value of each independent variable was created (Hair et al., 2019). Secondly, these interaction terms were inserted in the regression model. A non-significant interaction term means that the logit is linear (Hair et al., 2019). The interaction term for VC experience is labelled 'trvcexp', the interaction term for degree centrality is labelled 'trdegree', and the interaction term for betweenness centrality is labelled 'trbetween'. As shown in table 11, all interaction terms are non-significant, indicating that the logit is linear. Therefore, this assumption is met.

Table 11. Box-Tidwell transformation

	Both domestic and cross-border VCs	**Only domestic VCs**
	Sig.	Sig.
trvcexp	.055	.132
trdegree	.631	.785
trbetween	.081	.385

Note. Variables that were included in the analyses but are excluded here are: 'average degree centrality', 'average betweenness centrality' and 'VC experience'.

4.3 Logistic regression analysis

Two logistic regression analyses were conducted to test the hypotheses for both samples. The results of the logistic regression are presented in table 15 and 16. The full output from SPSS can be found in appendix 3 for sample 1 and appendix 4 for sample 2.

4.3.1 Goodness-of-fit

Firstly, the goodness-of-fit of the estimated model was assessed. This was done by looking at the overall measure of significance of the model fit, pseudo R^2 values and the predictive accuracy (Hair et al., 2019).

The first approach to assess goodness-of-fit is to check the pseudo R^2 and the overall measure of significance of the model fit (Hair et al., 2019). Table 15 and 16 provide the most important goodness-of-fit measures. The *–2LL* is lower for every model that includes an additional independent variable compared to model 1, meaning that the model fit improved by adding the independent and moderating variables. This is true for both sample 1 and sample 2. The statistical significance of the reduction in *–2LL* was assessed by looking at the Chi-square test, which is presented at the lower half of tables 15 and 16. The overall model is, in all cases for both samples, significant ($p < .01$). However, the contribution of the independent variables (except betweenness centrality in model 4 of sample 1) do not improve the reduction in *–2LL* value significantly. Important to note is that these Chi-square tests are sensitive for sample size, and since this is an issue here, one should be careful with drawing conclusions solely based on this value (Hair et al., 2019). Therefore, the goodness-of-fit will be considered in combination with the Pseudo R^2 values and the Akaike information criterion (AIC).

The pseudo R^2 values Cox & Snell R^2 and Nagelkerke R^2 were given and are presented in the lower half of table 15 and 16. For all models of sample 1, the Cox & Snell R^2 indicates an acceptable fit with a value between .2 and .3. The Nagelkerke R^2 indicates a good fit with a value above .4 from model 2 onwards. For all models of sample 2, the Cox & Snell R^2 indicates an acceptable fit with a value between .2 and .4. The Nagelkerke R^2 indicates a good fit for model 1 until 4 and a very good fit for model 5 and 6 with a value above .5. For both samples, the pseudo R^2 values improved each time once an additional independent variable was included in the model.

In addition to the more standard criteria for goodness-of-fit, the AIC was calculated for each model of both samples. The AIC provides information about how well the model fits the data (Hastie et al., 2016). Table 12 provides the AIC for all models for both samples. The full calculation of the AIC for all models is provided in appendix 5.

Because the minimized AIC was calculated, the model with the lowest AIC fits the data best (Hastie et al., 2016). All values for the AIC are shown in table 12. For sample 1, the AIC of model 4 suggests the best fit between the data and the model. The Chi-square test was also significant for this model. The AIC for model 1 of sample 2 suggests that it fits the data best, which is in line with the Chi-square tests presented above. This indicates that the other models do not fit the data best, which should be taken into account in the remainder of this research.

Table 12. Akaike's information criterion for both samples

	Both domestic and cross-border VCs	Only domestic VCs
Model 1	.719	.567
Model 2	.717	.572
Model 3	.722	.662
Model 4	.705	.671
Model 5	.711	.642
Model 6	.716	.651

The second approach to assess goodness-of-fit is by checking the predictive accuracy of the estimated model. The Hosmer and Lemeshow test is the only statistical test for predictive accuracy. The results from the Hosmer and Lemeshow test are presented in table 13 and 14. Some models are significant, which means that these models do not fit well in terms of predictive accuracy (Hair et al., 2019). The models that show non-significance (*p* < .05) fit well in terms of predictive accuracy (Hair et al., 2019).

Table 13. Hosmer and Lemeshow test for the sample with both domestic and cross-border VCs

	Both domestic and cross-border VCs					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Chi-square	15.308	17.620*	19.654*	9.876	6.247	6.839

Note. N = 286; * $p < 0.05$; ** $p < 0.01$.

Table 14. Hosmer and Lemeshow test for the sample with only domestic VCs

	Only domestic VCs					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Chi-square	17.987*	19.126*	12.236	15.791*	11.305	12.425

Note. N = 220; * $p < 0.05$; ** $p < 0.01$.

For sample 1, the Hosmer and Lemeshow test for the variable VC experience and degree centrality indicate that these models do not fit well. For sample 2, the same goes for VC experience and betweenness centrality. Therefore, it can be said that predictive accuracy, and thus also the goodness-of-fit, could be a serious problem in this research. In addition, the variables VC experience, degree and betweenness centrality do not significantly improve the explanatory power of the model. This will be discussed further in the discussion (section 5.2).

Validity and reliability

Overall, looking at the overall measure of significance (*–2LL*) and the pseudo R^2, the goodness-of-fit for all models of sample 1 and 2 seem to be acceptable to good. The *–2LL* value reduced for every model, although the Chi-square tests show that most reductions are not statistically significant. However, the conclusions based on the Chi-square tests had to be taken into account with caution because they were sensitive to sample size. The values for the AIC showed a similar sign as the Chi-square tests. Therefore, the models did not improve significantly in fit, except for model 4 of sample 1 and model 5 of sample 2. This indicates that the network measures do not improve the explanatory power of the models significantly, which could indicate that the validity of the regression models could be a problem.

The Hosmer and Lemeshow tests showed varying results. Where model 4 for the sample with both domestic and cross-border VCs reduces the *–2LL* significantly, the Hosmer Lemeshow test is not significant, indicating that the model fits well. The same goes for model 5 for the sample with only domestic VCs. For both models 2, who included VC experience in the analysis, the Hosmer and Lemeshow test is significant. This indicates that the models do not fit well. For the sample with both domestic and cross-border VCs, this is also applicable for degree centrality (model 3). For the sample with only domestic VCs, the same can be said for betweenness centrality (model 4). Therefore, the conclusion regarding the goodness-of-fit would be that the models do not fit good and that validity could be a serious issue for this research.

Midi et al. (2010) argued that multicollinearity does affect the reliability of the coefficients or log-odds ratios. Snee (1977) argued that VIF values higher than five could indicate that the coefficient is poorly estimated, affecting the validity of the model.

Because multicollinearity is present and some VIF values are above 5 (or close to that), one should be aware of the possible issue with validity and reliability.

To conclude, the statistical tests for the goodness-of-fit in combination with the presence of multicollinearity indicate that validity and reliability could be an issue in this research. Therefore, the results should be interpreted with caution.

Table 15. Log-odds ratios sample with both domestic and cross-border VCs

	Both domestic and cross-border VCs					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	.102** (.437)	.111** (.437)	.114** (.441)	.111** (.448)	.100** (.493)	.095** (.495)
Number of funding rounds	.918 (.109)	.948 (.111)	.942 (.112)	.980 (.114)	.978 (.114)	.987 (.114)
Total funding amount	1.000** (.000)	1.000** (.000)	1.000** (.000)	1.000** (.000)	1.000** (.000)	1.000** (.000)
Number of investors	1.036 (.047)	1.059 (.050)	1.059 (.050)	1.023 (.053)	1.020 (.053)	1.024 (.053)
IP – Trademarks	1.087* (.043)	1.092* (.043)	1.096* (.044)	1.086† (.045)	1.087† (.046)	1.083† (.046)
IP – Patents	1.080* (.028)	1.074* (.028)	1.073* (.028)	1.073* (.028)	1.072* (.028)	1.070* (.028)
VC experience		1.000 (.000)	1.000 (.000)	1.001 (.001)	1.001 (.001)	1.001 (.001)
Average degree cent.			.000 (72.339)	7760.058 (97.343)	7.498E+17 (112.978)	3,155E+66 (161.643)
Average between. cent.				.000* (372.170)	.000† (376.397)	.000† (633.529)
Average degree cent.*VC experience					.983 (.034)	.947 (.053)
Average between. cent.*VC experience						1.221 (.177)
-2 Log likelihood	195.618	192.959	192.562	185.774	185.480	184.783
Cox & Snell R^2	.251	.259	.260	.279	.280	.282
Nagelkerke R^2	.389	.400	.402	.431	.433	.436
Chi-square Step	75.304**	2.659	.397	6.788**	.294	.697
Chi-square Block	75.304**	2.659	.397	6.788**	.294	.697
Chi-square Model	75.304**	77.963**	78.360**	85.148**	85.442**	86.139**
N	286	286	286	286	286	286

Note. Log-odds ratios with robust standard errors in parentheses; † $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; dependent variable is IPO (1 = yes; 0 = no); SPSS 'binary logistic regression' procedure.

Table 16. Log-odds ratios sample with only domestic VCs

	Only domestic VCs					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	.083** (.463)	.087** (.465)	.085** (.479)	.082** (.490)	.040** (.597)	.040** (.598)
Number of funding rounds	1.199 (.143)	1.185 (.143)	1.175 (.143)	1.183 (.144)	1.214 (.151)	1.213 (.152)
Total funding amount	1.000** (.000)	1.000** (.000)	1.000** (.000)	1.000** (.000)	1.000** (.000)	1.000** (.000)
Number of investors	.942 (.052)	.965 (.061)	.980 (.064)	.980 (.064)	.970 (.065)	.968 (.067)
IP – Trademarks	1.010 (.058)	1.010 (.058)	1.018 (.058)	1.018 (.059)	1.051 (.065)	1.052 (.065)
IP – Patents	1.188** (.066)	1.189* (.066)	1.192* (.069)	1.183* (.070)	1.192* (.078)	1.193* (.079)
VC experience		1.000 (.000)	1.001 (.001)	1.001 (.001)	1.002† (.001)	1.002† (.001)
Average degree cent.			.000 (129.494)	.000 (130.553)	16.784 (134.726)	4.545E+10 (183.799)
Average between. cent.				.000 (216.813)	.000 (208.171)	.000 (880.354)
Average degree cent.*VC experience					.938* (.025)	.931 (.048)
Average between. cent.*VC experience						1.048 (.270)
-2 Log likelihood	134.266	133.687	131.743	131.577	123.193	123.163
Cox & Snell R^2	.285	.287	.295	.295	.326	.326
Nagelkerke R^2	.439	.443	.454	.455	.502	.502
Chi-square Step	63.427**	.579	1.944	.166	8.384**	.030
Chi-square Block	63.427**	.579	1.944	.166	8.384**	.030
Chi-square Model	63.427**	64.006**	65.950**	66.116**	74.500**	74.529**
N	220	220	220	220	220	220

Note. Log-odds ratios with robust standard errors in parentheses; † $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; dependent variable is IPO (1 = yes; 0 = no); SPSS 'binary logistic regression' procedure.

4.3.2 Interpretation of the results

Now the goodness-of-fit is determined, the results can be interpreted in terms of the hypotheses that were proposed in section 2.2. For interpretation purposes, the log-odds ratios of all models are presented in table 15 and 16. Model 1 represented the model with only the control variables and was used as the null model. The hypotheses will be discussed consecutively. Thereafter, table 17 will provide a summary of the results. The six hypotheses were tested to answer the following three sub-questions:

- Does VC experience affect the probability of an IPO?
- Does network structure affect the probability of an IPO?
- Does network structure moderate the effect of experience on the likelihood that portfolio firms exit via an IPO?

Hypothesis 1a predicted a positive effect of experience on portfolio performance for syndicates that consists of both domestic and cross-border VCs. Model 2 of sample 1 added experience and does not find support for the hypothesis (Exp(*B*) = 1.000, p = .132). Therefore, hypothesis 1a had to be rejected.

Hypothesis 1b predicted a positive effect of experience on portfolio performance for syndicates that consists of only domestic VCs. Model 2 of sample 2 added experience and does not find support for the hypothesis (Exp(*B*) = 1.000, p = .471). Therefore, hypothesis 1b had to be rejected.

Hypothesis 2a predicted a moderation effect of degree centrality for syndicates that consists of both domestic and cross-border VCs in such a way that it decreases the effect of experience on portfolio firm performance. Model 3 of sample 1 added the main effect of degree centrality, which was found to be non-significant (Exp(*B*) = .000, p = .530). Model 5 of sample 1 added the interaction term with experience to check for the moderation effect. The interaction term does support the hypothesis but is found to be non-significant (Exp(*B*) = .983, p = .601). Therefore, hypothesis 2a had to be rejected.

Hypothesis 2b predicted a moderation effect of degree centrality for syndicates that consists of only domestic VCs in such a way that it decreases the effect of experience on portfolio firm performance. Model 3 of sample 2 added the main effect degree centrality, which was found to be non-significant (Exp(*B*) = .000, p = .206). Model 5 of sample 2 added the interaction term with experience to check for the moderation effect.

The interaction term shows support for the hypothesis and was found to be significant (Exp(*B*) = .938, *p* = .012). However, because of the non-significance of the moderator, hypothesis 2b had to be rejected.

Hypothesis 3a predicted a moderation effect of betweenness centrality for syndicates that consists of both domestic and cross-border VCs in such a way that it decreases the effect of experience on portfolio firm performance. Model 4 of sample 1 added the main effect of betweenness centrality, which was found to be significant (Exp(*B*) = .000, *p* = .048). Model 6 of sample 1 added the interaction term with experience to check for the moderation effect. The interaction term shows no support for the hypothesis and is not significant (Exp(*B*) = 1.221, *p* = .260). Therefore, hypothesis 3a had to be rejected.

Hypothesis 3b predicted a moderation effect of betweenness centrality for syndicates that consists of only domestic VCs in such a way that it decreases the effect of experience on portfolio firm performance. Model 4 of sample 2 added the main effect betweenness centrality, which was found to be non-significant (Exp(*B*) = .000, *p* = .684). Model 6 of sample 2 added the interaction term with experience to check for the moderation effect. The interaction term shows no support for the hypothesis and is not significant (Exp(*B*) = 1.048, *p* = .863). Therefore, hypothesis 3b had to be rejected.

The aforementioned results are presented as a summary in table 17 below.

Table 17. Overview of hypotheses and results

Hypothesis	Supported or not	Significant or not
H1a	Not supported	Not significant
H1b	Not supported	Not significant
H2a	Supported	Not significant
H2b	Supported	Not significant
H3a	Not supported	Not significant
H3b	Not supported	Not significant

To conclude this section, the differences between the samples will be described to answer the following three sub-questions:

- Does the effect of VC experience on portfolio firm performance differ for syndicates that comprise both domestic and cross-border VCs and syndicates that comprise only domestic VCs?

- Does the effect of network structure on portfolio firm performance differ for syndicates that comprise both domestic and cross-border VCs and syndicates that comprise only domestic VCs?
- Does the moderating effect of network structure differ for syndicates that comprise both domestic and cross-border VCs and syndicates that comprise only domestic VCs?

To answer these sub-questions, the log-odds ratios will be used for interpretation purposes and can be found in table 15 and 16. Regarding VC experience, the log-odds ratio for both sample 1 and 2 is *1.000*. This indicates that experience does not enhance the odds of a portfolio firm to exit via an IPO. Additionally, there is no difference between the composition of the syndicate.

For both samples, the network structure negatively affects the probability of an IPO. The log-odds ratios of both network measures are *.000* for both samples. This indicates that there is no difference between the samples.

Both the moderating effects show the same direction, albeit that degree centrality decreases the effect of experience and betweenness centrality increases the effect of experience. For degree centrality, the interaction effect is slightly more negative for sample 2 with a log-odds ratio of *.938* compared to *.983* for sample 1. The interaction effect of betweenness centrality is greater for sample 1 with a log-odds ratio of *1.221* compared to *1.048* for sample 2. With those differences, there seems to be a difference in the odds that a portfolio firm will exit via an IPO for syndicates that comprises both domestic and cross-border VC and syndicates that comprises only domestic VCs. However, all these findings were found to be non-significant.

5. Discussion and conclusion

5.1 Discussion

The purpose of this research was to shed light on contradicting points of view and to contribute to a further understanding of the internationalization of the VC industry and literature. Two samples were used to test the hypotheses, compare the findings and answer the sub-questions and the research question. The results showed that there was no significant effect of previous investment experience. For network structure, contrarily to expectations, there were two different moderation effects for degree and betweenness centrality, but these effects were also found to be non-significant.

VC firm's experience

The extent literature on VCs and the effect of experience assumes a positive relationship between experience of VCs and portfolio firms' performance. For example, Sørensen (2007) and Nahata (2008) argue that more experienced VCs are better able in selecting the most promising opportunities. Therefore, they would enjoy higher proportions of IPO exits among their portfolio firms (Manigart & Wright, 2013). Contrarily, there are some authors who argue that young and inexperienced VCs are more likely to make portfolio firms exit via an IPO because they want to signal quality and build a track record (Gompers, 1996; Wang & Sim, 2001).

VC experience was added in the second regression Model for both samples. The log-odds ratio of *1.000* for VC experience suggests that experience does not enhance the odds of a portfolio firm to exit via an IPO. This is contrary to both streams of literature on the effect of experience as described above. Wang and Sim (2001) did not find any significant effect of a VC firm's experience. However, the authors indicated that their unexpected finding could be due to the relatively young VCs in Singapore.

An explanation for the unexpected finding could be that previous studies measured experience at individual VC firm level (Hochberg et al., 2007; Wang & Sim, 2001; Gompers 1996). In this research, experience is measured at syndicate level because of the nature of the dataset. Therefore, the findings of this research could indicate that the total investment experience of the syndicate does not enhance the portfolio firm's performance. However, that does not mean that experience is not important at the individual VC firm level, as shown many times in the VC literature (Manigart & Wright, 2013; Sørensen, 2007; Gompers 1996).

To conclude, the total experience of (the top five) syndicates does not enhance the odds of a portfolio firm to exit via an IPO. Nonetheless, the individual experience of VCs could still be important.

Main effects of network structure

Hochberg et al. (2007) showed that VCs benefit from a high level of both degree and betweenness centrality. A high level of degree centrality grants a lot of opportunities to exchange information and ensures that the VC firm is less dependent on other VCs. Additionally, VCs can ensure a wider range of specific knowledge with a lot of actors in their network. A high level of betweenness centrality means that the VC acts as a bridge or mediator between two other networks (Burt, 2004). Hochberg et al. (2007) showed that a VC firm passes on investments opportunities in such situations and that this can enhance portfolio firm's performance.

The main effects of degree and betweenness centrality were added in Model 3 and 4 for both samples. The negative log-odds ratios for both main effects suggest that both negatively affect the probability of an IPO. For the sample with both domestic and cross-border VCs, the main effect of betweenness centrality is significant. The others were not. Contrarily to previous findings in the literature, these findings suggest that portfolio firm performance is not enhanced if a VC firm has a lot of ties connected to it or if the VC firm acts as a mediator between two other networks. However, due to multicollinearity, these findings have to be interpreted with caution because the log-odds ratios could have become non-significant, or log-odds ratios could have unexpected signs.

Another explanation for the unexpected findings might be the validity and reliability of the regression models. These unexpected signs of the coefficients or log-odds ratios could indicate a poorly estimated model, resulting in an issue with validity (Snee, 1977). In addition, the presence of multicollinearity and VIF values that are close to or higher than 5 affect the reliability of the log-odds ratios (Midi et al., 2010; Snee, 1977).

To conclude, looking at the log-odds ratios, the main effects of degree and betweenness centrality do negatively affect the probability of an IPO, although not significant. Therefore, degree and betweenness centrality do not seem to affect the probability of an IPO. Nonetheless, the effects are questionable due to the presence of multicollinearity in combination with issues regarding the validity and reliability of the regression models.

Interaction effects of network structure and experience of VCs

In Model 5 for both samples, the interaction effect of degree centrality and experience was added to test the moderating effect. The negative log-odds ratio of the interaction effect suggests that degree centrality decreases the effect of experience on portfolio firm performance. If you have a lot of ties connected to you, experience becomes less important. These findings show similarities with the findings of Hochberg et al. (2007), who showed that experience becomes less important if a VC firm is better networked. The interaction term for the sample with only domestic VCs was significant, but the main effect was not. Therefore, the hypothesis had to be rejected. For the sample with both domestic and cross-border VCs, both the main effect and the interaction term were not significant. Because the findings of this research are found to be non-significant, this indicates that degree centrality does not moderate the effect of VC experience on portfolio firms' performance.

In Model 6 for both samples, the interaction effect of betweenness centrality and experience was added to test the moderating effect. The positive log-odds ratio of the interaction effect suggests that betweenness centrality increases the effect of experience on portfolio firm performance. That means that if a VC is in a structural hole or acts as a mediator between two other networks, experience is even more important. This was not expected because Hochberg et al. (2007) showed that experience became less important once a VC firm is better networked. One possible explanation could be that a VC has to manage their position as mediator between other networks and that previous investment experience is beneficial in such a situation. For the sample with both domestic and cross-border VCs, the main effect of betweenness centrality is significant. The other main and interaction effects were found to be non-significant. Therefore, the hypotheses had to be rejected, indicating that betweenness centrality does not moderate the effect of VC experience on portfolio firms' performance.

To conclude, the interaction effect of degree centrality and experience show support for the hypothesis, although not significant. This could indicate that the effect of experience becomes less important in case a VC firm has a high level of degree centrality. The interaction of betweenness centrality shows an unexpected, though explainable, effect. Again, one should be careful with drawing conclusions based upon the findings because of the presence of multicollinearity and issues with validity and reliability. The hypotheses had to be rejected, indicating that the network structure of VCs does not moderate the effect of VC experience on portfolio firms' performance. Nonetheless, the findings show some interesting insights that need further research.

Internationalization (differences between samples)

Dai et al. (2011) and Devigne et al. (2013) both found that a combination of both domestic and cross-border VCs is more beneficial for the portfolio firm's performance. Dai et al. (2011) only focussed on the Asian VC industry. This research was interested in the question of whether this effect is also present worldwide. Therefore, the findings for the six hypotheses were compared.

Regarding VC experience, no difference between both samples was found. This finding was not expected because it is widely acknowledged that experience does enhance the portfolio firm performance. However, as noted before, one possible explanation for this unexpected finding is the way that VC firms' experience was measured in this research.

Regarding the moderating effects, the interaction term with degree centrality and experience does decrease the effect of experience on portfolio firm performance, although not significant. The decrease for the sample with only domestic VCs is bigger than for the sample with both domestic and cross-border VCs. These findings indicate that experience is less important in case a VC firm has a high level of degree centrality. Thus, experience is relatively more important for syndicates that comprises both domestic and cross-border VCs. This finding shows similarities with the findings of Dai et al. (2011) and Devigne et al. (2013), although they were found to be non-significant in this research.

The interaction term with betweenness centrality and experience does increase the effect of experience on portfolio firm performance. This increase is bigger for the sample with both domestic and cross-border VCs compared to the sample with only domestic VCs. These findings could indicate that experience becomes more important in case a VC firm acts as a mediator between two other networks, although not significant. The increase is bigger for the sample with both domestic and cross-border VCs, which indicates that experience enhances performance more in case a syndicate comprises both domestic and cross-border VCs. This finding shows similarities with the findings of Dai et al. (2011) and Devigne et al. (2013), although they were found to be non-significant in this research.

However, because the experience was measured at syndicate level, it is not completely sure whether the decrease and increase in the effect of VC experience are because of the fact that the VC firm is a cross-border one or not. In order to find out whether the cross-border VCs enjoy a relative advantage regarding experience, further research could build upon the findings presented in this research.

Intellectual Property and IPO

One final remark about patents and trademarks will be made. For both samples, patents positively affected the probability of an IPO, and this effect was found to be significant. For the sample with both domestic and cross-border VCs, trademarks positively affected the probability of an IPO as well. Baum and Silverman (2004) argued that granted patents and trademarks signal quality of a firm in such a way that it attracts VC investments. In addition, granted patents would also enhance start-up performance (Baum & Silverman, 2004). These findings are in line with earlier research that found a positive relationship between patents and IPO exits (Stuart et al., 1999). Both studies of Baum and Silverman (2004) and Stuart et al. (1999) focussed on the biotechnology industry. Baum and Silverman (2004) focussed on Canada, and Stuart et al. (1999) focussed on the U.S. The findings of this research indicate that their findings could be present worldwide and in multiple industries since the biotechnology industry covers only around 11% and 14% of the samples that were used in this research. Both patents and trademarks are argued to be innovativeness indicators (Hasanov, Abada & Aktamov, 2015). Therefore, based on the findings of this research, one could argue that innovativeness positively affects the probability of an IPO.

5.2 Conclusion

The research question that is answered in this research was: **Do the network structure and experience of VCs affect the probability of an IPO?** To answer the research question, multiple sub-questions were proposed. These sub-questions were:

1. *Does VC experience affect the probability of an IPO?*
2. *Does the effect of VC experience on portfolio firm performance differ for syndicates that comprise both domestic and cross-border VCs and syndicates that comprise only domestic VCs?*
3. *Does network structure affect the probability of an IPO?*
4. *Does the effect of network structure on portfolio firm performance differ for syndicates that comprise both domestic and cross-border VCs and syndicates that comprise only domestic VCs?*
5. *Does network structure moderate the effect of experience on the likelihood that portfolio firms exit via an IPO?*
6. *Does the moderating effect of network structure differ for syndicates that comprise both domestic and cross-border VCs and syndicates that comprise only domestic VCs?*

The first two sub-questions were answered with testing hypotheses 1a and 1b. The results showed that VC experience does not significantly affect the probability of an IPO. There is also no difference between the two samples. However, these unexpected results could be explained due to the way VC experience was measured. Because VC experience was measured at syndicate level, the experience of VCs could still be important, as is shown in the VC literature (Manigart & Wright, 2013; Sørensen, 2007; Gompers 1996).

The third until the sixth sub-questions were answered with testing hypotheses 2a, 2b, 3a and 3b and comparing the results. The results showed an unexpected negative effect of degree and betweenness centrality on the probability of an IPO. However, these effects were found to be non-significant. In addition, due to multicollinearity and validity issues, the results had to be interpreted with caution. Degree centrality decreased the importance of the effect of VC experience on portfolio firms' performance, although not significant. Betweenness centrality increased the importance of the effect of VC experience on portfolio firms' performance, which was also found to be non-significant.

To conclude, both VC experience and the network structure of a VC firm do not affect the probability of an IPO. Network structure does also not moderate the effect of VC experience on portfolio firms' performance. However, the findings show some similar signs in line with the extent literature of the VC industry. Due to the presence of multicollinearity and issues with validity and reliability, one cannot state that VC experience and network structure do not affect the probability of an IPO at all based on this research.

5.3 Managerial implications

This research contributes to the VC network literature because it shows the importance of network structure in relation to VC experience. Particularly, it is important information for the younger VCs who do not possess a track record yet. The finding indicated that young and inexperienced VCs should focus on building a track record instead of trying to find the right syndication partner or choosing their network strategy. The network structure of a VC firm does not affect the probability of an IPO. For the individual VC firm, experience might still be important. In addition, the outcomes could also be important for more experienced VCs who should not change their networking strategy because this will not change their performance. Therefore, they should try to expand their experience because this will probably affect their portfolio firms' performance.

Further relevance lies in the difference in composition of the syndicate. For syndicates that comprises both domestic and cross-border VCs, the findings show similarities with previous research of Dai et al. (2010) and Devigne et al. (2013). This could indicate that experience is relatively more important for cross-border VCs.

5.4 Limitations

The first limitation is that only the top five VCs are taken into account in the dataset. At least 60% of the firms that exited via an IPO had more than five VCs that invested in them for both samples. These VCs were not taken into account in this research. Ultimately this also has an impact on the network measures because these were calculated based on the dataset. In reality, some VCs could have had a much higher level of degree or betweenness centrality than was captured by the dataset.

The second and probably most important limitation is the issue with both multicollinearity and validity. Due to multicollinearity, the log-odds ratios could have become non-significant or log-odds ratios could have shown unexpected signs. Validity might be an issue because the independent and moderating variables did not improve the explanatory power of the model significantly. The third and corresponding limitation is the way in which the network structure and experience of VCs was measured. Both are measured at syndicate level, and this could have led to biased results, as explained in section 5.

The fourth limitation is the fact that degree centrality and betweenness centrality do not capture the full network position of a VC firm. Hochberg et al. (2007) also included indegree, outdegree and closeness centrality. This had to be limited because of the feasibility of this research and dataset constraints.

The fifth limitation is the sampling method (including timeline) and overall sample size. The overall sample size does not meet the threshold of 400 (Hair et al., 2019). However, both samples meet the required ten observations for every estimated variable per category of the dependent variable because $N > 30$. The sampling method led to an arbitrary percentage of IPO exits. The percentage of 19.5 was treated as ‘true’ for the overall population, which may have led to biased results.

The sixth and last limitation is that the start date of the investment is unknown. Some firms got their investment later than others. Therefore, some firms did not have the full 5 to 7 years that are needed on average to exit via an IPO, which could have led to a bias in the results.

5.5 Further research suggestions

Future research could use other measures for VC experience. In this research, VC experience was measured using the total number of investments (Sørensen, 2007). However, they were added up per syndicate. Future research could measure VC experience at the individual VC firm level, in line with previous research on the effect of VC experience (e.g., Sørensen, 2007; Hochberg et al., 2007; Gompers, 1996).

Future research could also include more than just the top five VCs. At least 60% of the portfolio firms that exited via an IPO had more than five VCs that invested in them. Therefore, the results from this research could be biased. For example, the research of Sørensen (2007) used a sample where the maximum number of investments done by one VC is 443, with a mean of 69. The sample that was used by Hochberg et al. (2007) focussed on the individual VC firm, and the maximum number of portfolio firms per VC firm was 601 with a mean of 30. By including all the VCs that invested in a firm, this bias can be prevented, and a better understanding of the effect of VC experience can be established.

Where the research of Baum and Silverman (2004) focussed on Canadian biotechnology start-ups, the findings of this research indicated that innovativeness positively affects the probability of an IPO worldwide and in multiple industries. Future research could focus on possible differences in the effect of innovativeness per the composition of the syndicate, extending the findings of Dai et al. (2010) and Devigne et al. (2013).

To conclude, both VC experience and the network structure of a VC firm do not affect the probability of an IPO. Network structure does also not moderate the effect of VC experience on portfolio firms' performance. However, the findings show some similar signs in line with the extent literature on VC and portfolio firm's performance. Due to the presence of multicollinearity and issues with validity and reliability, one cannot state that VC experience and network structure do not affect the probability of an IPO at all. Interestingly, evidence for a positive relationship between innovativeness and IPO exits is found to be significant.

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7. Appendices

Appendix 1: Variables in dataset

Organization Name	*Name*
Organization Name URL	*https:// from Crunchbase*
Website	*https:// website organization*
Industries	*Summary of industry*
Headquarters Location	*Location*
Estimated Revenue Range	*Range in USD*
Operating Status	*Active or Closed*
Founded Date	*Date*
Exit Date	*Date*
Closed Date	*Date*
Company Type	*For profit or different type*
Number of Exits	*In numbers*
Number of Exits (IPO)	*In numbers*
Number of Employees	*In numbers*
Number of Funding Rounds	*In numbers*
Funding Status	*Status of funding (e.g., seed or IPO)*
Total Equity Funding Amount Currency (in USD)	*Equity funding amount in USD*
Total Funding Amount Currency (in USD)	*Funding amount in USD*
Top 5 Investors	*Names of top 5 investors*
Number of Lead Investors	*In numbers*
Number of Investors	*In numbers*
IPO Status	*Public or Private*
IPO Date	*Date*
Delisted Date	*Date*
Money Raised at IPO Currency (in USD)	*In USD*

Valuation at IPO Currency (in USD)	*In USD*
IPqwery - Trademarks Registered	*In numbers*
IPqwery - Patents Granted	*In numbers*
Location Country	*Location*
Age of Company	*Age in years*
Investor 1	*Name investor 1*
Investor 2	*Name investor 2*
Investor 3	*Name investor 3*
Investor 4	*Name investor 4*
Investor 5	*Name investor 5*
Degree centrality Investor 1	*Standardized value between 0 and 1*
Degree centrality Investor 2	*Standardized value between 0 and 1*
Degree centrality Investor 3	*Standardized value between 0 and 1*
Degree centrality Investor 4	*Standardized value between 0 and 1*
Degree centrality Investor 5	*Standardized value between 0 and 1*
Betweenness centrality Investor 1	*Standardized value between 0 and 1*
Betweenness centrality Investor 2	*Standardized value between 0 and 1*
Betweenness centrality Investor 3	*Standardized value between 0 and 1*
Betweenness centrality Investor 4	*Standardized value between 0 and 1*
Betweenness centrality Investor 5	*Standardized value between 0 and 1*

Appendix 2: Example additional data and coding

Organiz-ation name	*VC experience*	*VC experience syndicate*	*Degree centrality*	*Average degree centrality syndicate*	*Betweenness centrality*	*Average betweenness centrality syndicate*
XXX	3509	6042	0.102138761	0.05044209	0.02091178	0.016371404
XXY	38	246	0.002130794	0.00171260	0.00027619	0.000146746

Appendix 3: SPSS output sample 1

Block 0: Beginning Block

Classification Table[a,b]

Observed			Predicted IPO 0	Predicted IPO 1	Percentage Correct
Step 0	IPO	0	204	0	100,0
		1	56	0	,0
	Overall Percentage				78,5

a. Constant is included in the model.

b. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-1,293	,151	73,432	1	,000	,275

Variables not in the Equation[a]

			Score	df	Sig.
Step 0	Variables	Number of Funding Rounds	9,857	1	,002
		Total Funding Amount Currency (in USD)	31,458	1	,000
		Number of Investors	14,984	1	,000
		IPqwery - Trademarks Registered	30,976	1	,000
		IPqwery - Patents Granted	19,705	1	,000

a. Residual Chi-Squares are not computed because of redundancies.

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	75,304	5	,000
	Block	75,304	5	,000
	Model	75,304	5	,000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	195,618[a]	,251	,389

a. Estimation terminated at iteration number 7 because parameter estimates changed by less than ,001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	15,308	8	,053

Contingency Table for Hosmer and Lemeshow Test

		IPO = 0		IPO = 1		
		Observed	Expected	Observed	Expected	Total
Step 1	1	25	24,167	1	1,833	26
	2	26	23,888	0	2,112	26
	3	25	23,697	1	2,303	26
	4	24	23,549	2	2,451	26
	5	26	23,328	0	2,672	26
	6	24	22,967	2	3,033	26
	7	20	22,394	6	3,606	26
	8	17	20,374	9	5,626	26
	9	11	15,376	15	10,624	26
	10	6	4,261	20	21,739	26

Classification Table[a]

Observed			Predicted IPO 0	Predicted IPO 1	Percentage Correct
Step 1	IPO	0	196	8	96,1
		1	32	24	42,9
	Overall Percentage				84,6

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	95% C.I.for EXP(B) Upper
Step 1[a]	Number of Funding Rounds	-,085	,109	,610	1	,435	,918	,742	1,137
	Total Funding Amount Currency (in USD)	,000	,000	15,641	1	,000	1,000	1,000	1,000
	Number of Investors	,035	,047	,561	1	,454	1,036	,945	1,135
	IPqwery - Trademarks Registered	,084	,043	3,857	1	,050	1,087	1,000	1,182
	IPqwery - Patents Granted	,077	,028	7,465	1	,006	1,080	1,022	1,141
	Constant	-2,286	,437	27,319	1	,000	,102		

a. Variable(s) entered on step 1: Number of Funding Rounds, Total Funding Amount Currency (in USD), Number of Investors, IPqwery - Trademarks Registered, IPqwery - Patents Granted.

Block 2: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	2,659	1	,103
	Block	2,659	1	,103
	Model	77,963	6	,000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	192,959[a]	,259	,400

a. Estimation terminated at iteration number 7 because parameter estimates changed by less than ,001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	17,620	8	,024

Contingency Table for Hosmer and Lemeshow Test

		IPO = 0		IPO = 1		
		Observed	Expected	Observed	Expected	Total
Step 1	1	26	25,040	0	,960	26
	2	25	24,179	1	1,821	26
	3	26	23,633	0	2,367	26
	4	25	23,362	1	2,638	26
	5	25	23,134	1	2,866	26
	6	23	22,749	3	3,251	26
	7	20	22,077	6	3,923	26
	8	16	20,460	10	5,540	26
	9	11	15,243	15	10,757	26
	10	7	4,122	19	21,878	26

Classification Table[a]

			Predicted		
			IPO		Percentage
Observed			0	1	Correct
Step 1	IPO	0	195	9	95,6
		1	32	24	42,9
	Overall Percentage				84,2

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[a]	Number of Funding Rounds	-,054	,111	,238	1	,626	,948	,763	1,177
	Total Funding Amount Currency (in USD)	,000	,000	14,282	1	,000	1,000	1,000	1,000
	Number of Investors	,057	,050	1,313	1	,252	1,059	,960	1,167
	IPqwery - Trademarks Registered	,088	,043	4,156	1	,041	1,092	1,003	1,188
	IPqwery - Patents Granted	,072	,028	6,725	1	,010	1,074	1,018	1,134
	VC Experience syn.	,000	,000	2,268	1	,132	1,000	,999	1,000
	Constant	-2,195	,437	25,215	1	,000	,111		

a. Variable(s) entered on step 1: VC Experience syn..

Block 3: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	,397	1	,529
	Block	,397	1	,529
	Model	78,360	7	,000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	192,562[a]	,260	,402

a. Estimation terminated at iteration number 7 because parameter estimates changed by less than ,001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	19,645	8	,012

Contingency Table for Hosmer and Lemeshow Test

		IPO = 0		IPO = 1		
		Observed	Expected	Observed	Expected	Total
Step 1	1	26	25,127	0	,873	26
	2	26	24,201	0	1,799	26
	3	25	23,654	1	2,346	26
	4	25	23,353	1	2,647	26
	5	25	23,130	1	2,870	26
	6	24	22,693	2	3,307	26
	7	18	22,041	8	3,959	26
	8	17	20,326	9	5,674	26
	9	11	15,380	15	10,620	26
	10	7	4,096	19	21,904	26

Classification Table[a]

Observed			Predicted IPO 0	Predicted IPO 1	Percentage Correct
Step 1	IPO	0	195	9	95,6
		1	32	24	42,9
	Overall Percentage				84,2

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	95% C.I.for EXP(B) Upper
Step 1[a]	Number of Funding Rounds	-,060	,112	,286	1	,593	,942	,757	1,173
	Total Funding Amount Currency (in USD)	,000	,000	14,464	1	,000	1,000	1,000	1,000
	Number of Investors	,057	,050	1,306	1	,253	1,059	,960	1,168
	IPqwery - Trademarks Registered	,092	,044	4,350	1	,037	1,096	1,006	1,195
	IPqwery - Patents Granted	,070	,028	6,473	1	,011	1,073	1,016	1,133
	VC Experience syn.	,000	,000	,001	1	,970	1,000	,999	1,001
	Gem DC syn.	-45,468	72,339	,395	1	,530	,000	,000	6,735E+41
	Constant	-2,169	,441	24,171	1	,000	,114		

a. Variable(s) entered on step 1: Gem DC syn..

Block 4: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	6,788	1	,009
	Block	6,788	1	,009
	Model	85,148	8	,000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	185,774[a]	,279	,431

a. Estimation terminated at iteration number 9 because parameter estimates changed by less than ,001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	9,876	8	,274

Contingency Table for Hosmer and Lemeshow Test

		IPO = 0		IPO = 1		
		Observed	Expected	Observed	Expected	Total
Step 1	1	26	25,964	0	,036	26
	2	25	24,952	1	1,048	26
	3	25	23,638	1	2,362	26
	4	25	23,279	1	2,721	26
	5	25	23,030	1	2,970	26
	6	23	22,532	3	3,468	26
	7	19	21,753	7	4,247	26
	8	20	19,864	6	6,136	26
	9	10	14,622	16	11,378	26
	10	6	4,365	20	21,635	26

Classification Table[a]

Observed			Predicted IPO 0	Predicted IPO 1	Percentage Correct
Step 1	IPO	0	193	11	94,6
		1	32	24	42,9
	Overall Percentage				83,5

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	95% C.I.for EXP(B) Upper
Step 1[a]	Number of Funding Rounds	-,020	,114	,030	1	,862	,980	,784	1,225
	Total Funding Amount Currency (in USD)	,000	,000	12,976	1	,000	1,000	1,000	1,000
	Number of Investors	,023	,053	,183	1	,669	1,023	,922	1,135
	IPqwery - Trademarks Registered	,083	,045	3,309	1	,069	1,086	,994	1,187
	IPqwery - Patents Granted	,071	,028	6,377	1	,012	1,073	1,016	1,134
	VC Experience syn.	,001	,001	,961	1	,327	1,001	,999	1,002
	Gem DC syn.	8,957	97,343	,008	1	,927	7760,058	,000	5,607E+86
	Gem BC syn.	-736,798	372,170	3,919	1	,048	,000	,000	,001
	Constant	-2,199	,448	24,035	1	,000	,111		

a. Variable(s) entered on step 1: Gem BC syn..

Block 5: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	,294	1	,588
	Block	,294	1	,588
	Model	85,442	9	,000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	185,480[a]	,280	,433

a. Estimation terminated at iteration number 9 because parameter estimates changed by less than ,001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	6,247	8	,620

Contingency Table for Hosmer and Lemeshow Test

		IPO = 0		IPO = 1		
		Observed	Expected	Observed	Expected	Total
Step 1	1	26	25,982	0	,018	26
	2	25	24,908	1	1,092	26
	3	25	23,692	1	2,308	26
	4	25	23,414	1	2,586	26
	5	25	23,087	1	2,913	26
	6	22	22,524	4	3,476	26
	7	20	21,655	6	4,345	26
	8	20	19,780	6	6,220	26
	9	11	14,544	15	11,456	26
	10	5	4,414	21	21,586	26

Classification Table[a]

Observed			Predicted IPO 0	Predicted IPO 1	Percentage Correct
Step 1	IPO	0	194	10	95,1
		1	31	25	44,6
	Overall Percentage				84,2

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[a]	Number of Funding Rounds	-,022	,114	,039	1	,844	,978	,782	1,223
	Total Funding Amount Currency (in USD)	,000	,000	11,923	1	,001	1,000	1,000	1,000
	Number of Investors	,020	,053	,144	1	,705	1,020	,920	1,132
	IPqwery - Trademarks Registered	,084	,046	3,322	1	,068	1,087	,994	1,190
	IPqwery - Patents Granted	,069	,028	6,058	1	,014	1,072	1,014	1,132
	VC Experience syn.	,001	,001	1,194	1	,275	1,001	,999	1,002
	Gem DC syn.	41,159	112,978	,133	1	,716	749823482122540160,000	,000	1,102E+114
	Gem BC syn.	-712,242	376,397	3,581	1	,058	,000	,000	116701465599,495
	Gem DC syn. by VC Experience syn.	-,018	,034	,274	1	,601	,983	,920	1,050
	Constant	-2,302	,493	21,824	1	,000	,100		

a. Variable(s) entered on step 1: Gem DC syn. * VC Experience syn. .

Block 6: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	,697	1	,404
	Block	,697	1	,404
	Model	86,139	10	,000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	184,783[a]	,282	,436

a. Estimation terminated at iteration number 9 because parameter estimates changed by less than ,001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	6,839	8	,554

Contingency Table for Hosmer and Lemeshow Test

		IPO = 0		IPO = 1		
		Observed	Expected	Observed	Expected	Total
Step 1	1	26	25,951	0	,049	26
	2	25	24,984	1	1,016	26
	3	25	23,811	1	2,189	26
	4	25	23,445	1	2,555	26
	5	25	23,120	1	2,880	26
	6	22	22,560	4	3,440	26
	7	20	21,634	6	4,366	26
	8	19	19,714	7	6,286	26
	9	11	14,487	15	11,513	26
	10	6	4,295	20	21,705	26

Classification Table[a]

Observed			Predicted IPO 0	Predicted IPO 1	Predicted Percentage Correct
Step 1	IPO	0	194	10	95,1
		1	31	25	44,6
	Overall Percentage				84,2

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	95% C.I.for EXP(B) Upper
Step 1[a]	Number of Funding Rounds	-,013	,114	,013	1	,911	,987	,789	1,235
	Total Funding Amount Currency (in USD)	,000	,000	11,473	1	,001	1,000	1,000	1,000
	Number of Investors	,023	,053	,191	1	,662	1,024	,922	1,136
	IPqwery - Trademarks Registered	,080	,046	3,079	1	,079	1,083	,991	1,185
	IPqwery - Patents Granted	,068	,028	5,950	1	,015	1,070	1,013	1,130
	VC Experience syn.	,001	,001	1,006	1	,316	1,001	,999	1,002
	Gem DC syn.	153,119	161,643	,897	1	,344	3,155E+66	,000	1,229E+204
	Gem BC syn.	-1225,740	633,529	3,743	1	,053	,000	,000	8479134,657
	Gem DC syn. by VC Experience syn.	-,055	,053	1,094	1	,296	,947	,854	1,049
	Gem BC syn. by VC Experience syn.	,200	,177	1,269	1	,260	1,221	,863	1,728
	Constant	-2,358	,495	22,726	1	,000	,095		

a. Variable(s) entered on step 1: Gem BC syn. * VC Experience syn. .

Appendix 4: SPSS output sample 2

Block 0: Beginning Block

Classification Table[a,b]

			Predicted		
			IPO		Percentage
Observed			0	1	Correct
Step 0	IPO	0	148	0	100,0
		1	41	0	,0
	Overall Percentage				78,3

a. Constant is included in the model.

b. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-1,284	,176	52,902	1	,000	,277

Variables not in the Equation[a]

			Score	df	Sig.
Step 0	Variables	Number of Funding Rounds	19,812	1	,000
		Total Funding Amount Currency (in USD)	51,205	1	,000
		Number of Investors	8,019	1	,005
		IPqwery - Trademarks Registered	19,751	1	,000
		IPqwery - Patents Granted	31,178	1	,000

a. Residual Chi-Squares are not computed because of redundancies.

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	63,427	5	,000
	Block	63,427	5	,000
	Model	63,427	5	,000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	134,266[a]	,285	,439

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than ,001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	17,987	8	,021

Contingency Table for Hosmer and Lemeshow Test

		IPO = 0		IPO = 1		
		Observed	Expected	Observed	Expected	Total
Step 1	1	19	17,758	0	1,242	19
	2	19	17,461	0	1,539	19
	3	18	17,364	1	1,636	19
	4	19	17,197	0	1,803	19
	5	18	17,097	1	1,903	19
	6	15	16,793	4	2,207	19
	7	16	16,398	3	2,602	19
	8	14	15,607	5	3,393	19
	9	6	10,830	13	8,170	19
	10	4	1,493	14	16,507	18

Classification Table[a]

Observed			Predicted: IPO 0	Predicted: IPO 1	Percentage Correct
Step 1	IPO	0	144	4	97,3
		1	21	20	48,8
	Overall Percentage				86,8

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[a]	Number of Funding Rounds	,181	,143	1,614	1	,204	1,199	,906	1,585
	Total Funding Amount Currency (in USD)	,000	,000	10,596	1	,001	1,000	1,000	1,000
	Number of Investors	-,060	,052	1,357	1	,244	,942	,851	1,042
	IPqwery - Trademarks Registered	,010	,058	,029	1	,866	1,010	,901	1,132
	IPqwery - Patents Granted	,172	,066	6,831	1	,009	1,188	1,044	1,351
	Constant	-2,486	,463	28,783	1	,000	,083		

a. Variable(s) entered on step 1: Number of Funding Rounds, Total Funding Amount Currency (in USD), Number of Investors, IPqwery - Trademarks Registered, IPqwery - Patents Granted.

Block 2: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	,579	1	,447
	Block	,579	1	,447
	Model	64,006	6	,000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	133,687[a]	,287	,443

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than ,001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	19,126	8	,014

Contingency Table for Hosmer and Lemeshow Test

		IPO = 0		IPO = 1		
		Observed	Expected	Observed	Expected	Total
Step 1	1	19	18,071	0	,929	19
	2	19	17,463	0	1,537	19
	3	19	17,312	0	1,688	19
	4	19	17,119	0	1,881	19
	5	17	17,014	2	1,986	19
	6	15	16,719	4	2,281	19
	7	16	16,334	3	2,666	19
	8	14	15,595	5	3,405	19
	9	6	10,925	13	8,075	19
	10	4	1,449	14	16,551	18

Classification Table[a]

			Predicted		
			IPO		Percentage
Observed			0	1	Correct
Step 1	IPO	0	144	4	97,3
		1	22	19	46,3
	Overall Percentage				86,2

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[a]	Number of Funding Rounds	,170	,143	1,403	1	,236	1,185	,895	1,570
	Total Funding Amount Currency (in USD)	,000	,000	10,079	1	,001	1,000	1,000	1,000
	Number of Investors	-,035	,061	,328	1	,567	,965	,856	1,089
	IPqwery - Trademarks Registered	,010	,058	,031	1	,860	1,010	,901	1,133
	IPqwery - Patents Granted	,173	,066	6,818	1	,009	1,189	1,044	1,353
	VC Experience syn.	,000	,000	,520	1	,471	1,000	,999	1,000
	Constant	-2,444	,465	27,609	1	,000	,087		

a. Variable(s) entered on step 1: VC Experience syn..

Block 3: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	1,944	1	,163
	Block	1,944	1	,163
	Model	65,950	7	,000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	131,743[a]	,295	,454

a. Estimation terminated at iteration number 7 because parameter estimates changed by less than ,001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	12,236	8	,141

Contingency Table for Hosmer and Lemeshow Test

		IPO = 0		IPO = 1		
		Observed	Expected	Observed	Expected	Total
Step 1	1	19	18,449	0	,551	19
	2	19	17,628	0	1,372	19
	3	19	17,329	0	1,671	19
	4	19	17,158	0	1,842	19
	5	16	16,937	3	2,063	19
	6	16	16,625	3	2,375	19
	7	16	16,255	3	2,745	19
	8	14	15,402	5	3,598	19
	9	7	10,786	12	8,214	19
	10	3	1,429	15	16,571	18

Classification Table[a]

Observed			Predicted IPO 0	Predicted IPO 1	Percentage Correct
Step 1	IPO	0	144	4	97,3
		1	21	20	48,8
	Overall Percentage				86,8

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[a]	Number of Funding Rounds	,161	,143	1,261	1	,261	1,175	,887	1,556
	Total Funding Amount Currency (in USD)	,000	,000	9,396	1	,002	1,000	1,000	1,000
	Number of Investors	-,020	,064	,100	1	,751	,980	,865	1,110
	IPqwery - Trademarks Registered	,017	,058	,090	1	,764	1,018	,908	1,140
	IPqwery - Patents Granted	,176	,069	6,408	1	,011	1,192	1,040	1,366
	VC Experience syn.	,001	,001	1,221	1	,269	1,001	,999	1,003
	Gem DC syn.	-163,612	129,494	1,596	1	,206	,000	,000	1,477E+39
	Constant	-2,467	,479	26,481	1	,000	,085		

a. Variable(s) entered on step 1: Gem DC syn..

Block 4: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	,166	1	,684
	Block	,166	1	,684
	Model	66,116	8	,000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	131,577[a]	,295	,455

a. Estimation terminated at iteration number 7 because parameter estimates changed by less than ,001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	15,791	8	,045

Contingency Table for Hosmer and Lemeshow Test

		IPO = 0		IPO = 1		
		Observed	Expected	Observed	Expected	Total
Step 1	1	19	18,488	0	,512	19
	2	19	17,658	0	1,342	19
	3	19	17,355	0	1,645	19
	4	19	17,171	0	1,829	19
	5	16	16,940	3	2,060	19
	6	15	16,612	4	2,388	19
	7	16	16,258	3	2,742	19
	8	14	15,359	5	3,641	19
	9	7	10,684	12	8,316	19
	10	4	1,474	14	16,526	18

Classification Table[a]

Observed			Predicted: IPO 0	Predicted: IPO 1	Predicted: Percentage Correct
Step 1	IPO	0	144	4	97,3
		1	21	20	48,8
	Overall Percentage				86,8

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	95% C.I.for EXP(B) Upper
Step 1[a]	Number of Funding Rounds	,168	,144	1,362	1	,243	1,183	,892	1,570
	Total Funding Amount Currency (in USD)	,000	,000	9,426	1	,002	1,000	1,000	1,000
	Number of Investors	-,021	,064	,105	1	,746	,980	,864	1,110
	IPqwery - Trademarks Registered	,018	,059	,088	1	,767	1,018	,906	1,143
	IPqwery - Patents Granted	,168	,070	5,709	1	,017	1,183	1,031	1,358
	VC Experience syn.	,001	,001	1,367	1	,242	1,001	,999	1,003
	Gem DC syn.	-153,890	130,553	1,389	1	,238	,000	,000	1,965E+44
	Gem BC syn.	-88,251	216,813	,166	1	,684	,000	,000	1,677E+146
	Constant	-2,505	,490	26,176	1	,000	,082		

a. Variable(s) entered on step 1: Gem BC syn..

Block 5: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	8,384	1	,004
	Block	8,384	1	,004
	Model	74,500	9	,000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	123,193[a]	,326	,502

a. Estimation terminated at iteration number 8 because parameter estimates changed by less than ,001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	11,305	8	,185

Contingency Table for Hosmer and Lemeshow Test

		IPO = 0		IPO = 1		
		Observed	Expected	Observed	Expected	Total
Step 1	1	19	18,834	0	,166	19
	2	19	18,041	0	,959	19
	3	17	17,856	2	1,144	19
	4	18	17,593	1	1,407	19
	5	18	17,244	1	1,756	19
	6	15	16,727	4	2,273	19
	7	18	15,993	1	3,007	19
	8	16	14,817	3	4,183	19
	9	5	9,343	14	9,657	19
	10	3	1,552	15	16,448	18

Classification Table[a]

			Predicted		
			IPO		Percentage
Observed			0	1	Correct
Step 1	IPO	0	144	4	97,3
		1	18	23	56,1
	Overall Percentage				88,4

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	Number of Funding Rounds	,194	,151	1,640	1	,200	1,214	,902	1,633
	Total Funding Amount Currency (in USD)	,000	,000	7,825	1	,005	1,000	1,000	1,000
	Number of Investors	-,030	,065	,211	1	,646	,970	,854	1,103
	IPqwery - Trademarks Registered	,049	,065	,582	1	,445	1,051	,926	1,192
	IPqwery - Patents Granted	,175	,078	5,001	1	,025	1,192	1,022	1,390
	VC Experience syn.	,002	,001	3,252	1	,071	1,002	1,000	1,003
	Gem DC syn.	2,820	134,726	,000	1	,983	16,784	,000	8,021E+115
	Gem BC syn.	-42,522	208,171	,042	1	,838	,000	,000	5,352E+158
	Gem DC syn. by VC Experience syn.	-,064	,025	6,335	1	,012	,938	,892	,986
	Constant	-3,218	,597	29,090	1	,000	,040		

a. Variable(s) entered on step 1: Gem DC syn. * VC Experience syn. .

Block 6: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	,030	1	,863
	Block	,030	1	,863
	Model	74,529	10	,000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	123,163[a]	,326	,502

a. Estimation terminated at iteration number 9 because parameter estimates changed by less than ,001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	12,425	8	,133

Contingency Table for Hosmer and Lemeshow Test

		IPO = 0		IPO = 1		
		Observed	Expected	Observed	Expected	Total
Step 1	1	19	18,825	0	,175	19
	2	19	18,039	0	,961	19
	3	17	17,855	2	1,145	19
	4	19	17,604	0	1,396	19
	5	17	17,246	2	1,754	19
	6	15	16,724	4	2,276	19
	7	18	15,982	1	3,018	19
	8	16	14,829	3	4,171	19
	9	5	9,354	14	9,646	19
	10	3	1,541	15	16,459	18

Classification Table[a]

Observed			Predicted IPO 0	Predicted IPO 1	Percentage Correct
Step 1	IPO	0	144	4	97,3
		1	18	23	56,1
	Overall Percentage				88,4

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	95% C.I.for EXP(B) Upper
Step 1[a]	Number of Funding Rounds	,193	,152	1,615	1	,204	1,213	,901	1,632
	Total Funding Amount Currency (in USD)	,000	,000	7,846	1	,005	1,000	1,000	1,000
	Number of Investors	-,033	,067	,236	1	,627	,968	,849	1,104
	IPqwery - Trademarks Registered	,051	,065	,607	1	,436	1,052	,926	1,195
	IPqwery - Patents Granted	,176	,079	4,989	1	,026	1,193	1,022	1,392
	VC Experience syn.	,002	,001	3,282	1	,070	1,002	1,000	1,003
	Gem DC syn.	24,540	183,799	,018	1	,894	4,545+10	,000	1,281E+167
	Gem BC syn.	-189,452	880,354	,046	1	,830	,000	,000	.
	Gem DC syn. by VC Experience syn.	-,071	,048	2,155	1	,142	,931	,847	1,024
	Gem BC syn. by VC Experience syn.	,046	,270	,030	1	,863	1,048	,617	1,778
	Constant	-3,208	,598	28,830	1	,000	,040		

a. Variable(s) entered on step 1: Gem BC syn. * VC Experience syn. .

Appendix 5: Calculation of the Akaike information criterion

Formula for the minimized Akaike information criterion (Hastie et al., 2016):

$AIC = -\frac{2}{N} * LL + 2 * \frac{k}{N}$. Where *k* is the amount of parameters in the model and *N* is the sample size. The logistic regression models only provided the -2LL, so to obtain the LL these values need to be divided by -2. This is presented in the formula: $LL = \frac{-2LL}{-2}$.

Calculations sample 1

Model 1:

$LL = \frac{195.618}{-2} = -97.809$

k = 5 and *N = 286*

$$AIC = -\frac{2}{286} * -97.809 + 2 * \frac{5}{286} = .719$$

Model 2:

$LL = \frac{192.959}{-2} = -96.4795$

k = 6 and *N = 286*

$$AIC = -\frac{2}{286} * -96.4795 + 2 * \frac{5}{286} = .717$$

Model 3:

$LL = \frac{192.562}{-2} = -96.281$

k = 7 and *N = 286*

$$AIC = -\frac{2}{286} * -96.281 + 2 * \frac{7}{286} = .722$$

Model 4:

$LL = \frac{185.747}{-2} = -92.8735$

k = 8 and *N = 286*

$$AIC = -\frac{2}{286} * -92.8735 + 2 * \frac{8}{286} = .705$$

Model 5:

$LL = \frac{185.480}{-2} = -92.74$

k = 9 and *N = 286*

$$AIC = -\frac{2}{286} * -92.74 + 2 * \frac{9}{286} = .711$$

Model 6:

$LL = \frac{184.783}{-2} = -92.3915$

k = 10 and *N = 286*

$$AIC = -\frac{2}{286} * -92.3915 + 2 * \frac{10}{286} = .716$$

Calculations sample 2

Model 1:

$LL = \frac{134.266}{-2} = -67.133$

k = 5 and *N = 220*

$$AIC = -\frac{2}{220} * -67.133 + 2 * \frac{5}{220} = .567$$

Model 2:

$LL = \frac{133.687}{-2} = -66.8435$

k = 6 and *N = 220*

$$AIC = -\frac{2}{220} * -66.8435 + 2 * \frac{6}{220} = .572$$

Model 3:

$LL = \frac{131.743}{-2} = -65.8715$

k = 7 and *N = 220*

$$AIC = -\frac{2}{220} * -65.8715 + 2 * \frac{7}{220} = .662$$

Model 4:

$LL = \frac{131.577}{-2} = -65.7885$

k = 8 and *N = 220*

$$AIC = -\frac{2}{220} * -65.7885 + 2 * \frac{8}{220} = .671$$

Model 5:

$LL = \frac{123.193}{-2} = -61.5965$

k = 9 and *N = 220*

$$AIC = -\frac{2}{220} * -61.5965 + 2 * \frac{9}{220} = .642$$

Model 6:

$LL = \frac{123.163}{-2} = -61.5815$

k = 10 and *N = 220*

$$AIC = -\frac{2}{220} * -61.5815 + 2 * \frac{10}{220} = .651$$