Venture capital firms and their syndicated network position: the importance of national culture

A comparative study between a collectivistic and an individualistic setting

Radboud Universiteit Nijmegen

Name	Rik steenmeijer
Student number	s1047271
Master	Business Administration: Innovation & Entrepreneurship
Supervisor 1	Dr M.H. de Rochemont
Supervisor 2	Dr N.G. Migchels

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Abstract

The aim of this research was to explore whether a favorable venture capital network position is determined by national culture. The literature used in this research consists of social network theory, venture capital network syndication and Hofstede's cultural dimension collectivism versus individualism. It was expected that especially strong network relationships increase the performance of venture capital firms in a collectivistic country, while structural holes and weak ties were expected to do essentially well in an individualistic country. The methodology strategy consisted of a comparative study, which helped to create two samples that represent a collectivistic, as well as an individualistic culture. Next, a regression analysis was conducted for both samples to measure the impact of strong- and weak ties, while also maintaining several control variables in the model. The results showed that indeed in a collectivistic society, strong ties are more beneficial for venture capital firms and the startups they invest in. However, in an individualistic society, no significant result was found, therefore indicating that neither strong- or weak ties prove to be more beneficial for venture capital firms. With these results, it can be stated that national culture does influence the favorable network position for venture capital firms. However, a concrete favorable network position can only be proposed in a highly collectivistic culture.

1: Introduction

The core business of venture capital firms is not only beneficial for themselves and the startups they invest in, it also significantly contributes to the general wealth (Dagogo & Ollor, 2009) and innovation (Kortum & Lerner, 2000) of a society. Making it important to investigate towards the most optimal way for venture capital firms to operate. Venture capital firms provide more than just an investment for startups, their expertise and broad network can help young companies grow into established successful firms (Hellmann & Puri, 2000). Typically, venture capital firms can also operate in a syndicating network, syndication occurs when two or more venture capital firms invest together in order to decrease (financial) risk (Wilson, 1968) and to share knowledge (Brander et al., 2002; Hopp & Rieder, 2011).

The business network of venture capital firms can be identified with ties, which represents the relationship between actors (Peverelli et al., 2011). Social network theory is greatly elaborated in business literature, where usually a distinction is made between strong and weak ties. However, it is contradicting which ties provide more value for an organization. The strength of a tie is determined by the amount of time, emotional intensity and intimacy, and the reciprocal service of the relationship (Granovetter, 1973). A network with mostly strong ties, also referred to as social closure or relational embeddedness, is beneficial for gaining complex and tacit information. It also increases the level of trust between actors (Adler & Kwon, 2002). A downside however, is that the information in the network becomes redundant due to a limited amount of diverse information (Granovetter, 1973). A network with mostly weak ties, referred to as structural holes, carries the advantage of having an open network with lots of different actors, making it possible to gain a diverse stream of information and bridges to new groups. Generally, this goes paired with a limited amount of trust between actors (Burt, 1992).

The degree of strong and weak ties determines the network position of a firm. Benefits and drawbacks of strong and weak ties have been determined numerous times in business literature regarding social network theory. However, it is not quite clear which type of network position is most beneficial specifically for the performance of venture capital firms. This is remarkable since the amount of information sharing (Xue et al., 2019) and the general network of a venture capital firm seems to significantly influence its performance (Hochberg et al., 2007). Only a few researchers tried to investigate the relationship between network position of venture capital firms on its performance. Ter Wal et al. (2016) developed a model where both types of ties are necessary for venture capital firms of high-tech startups in the United States. Yang et al. (2018) investigated the same relationship in China, where strong ties seems to be most important due to a high uncertainty in the weak legal framework, but also because of feeble professional norms; therefore a greater deal of trust is needed. Overall, these studies have their limitations by being scoped down to specific regions and industries, consequently the relationship between venture capital network position and performance remains largely unexplored.

While the study of Yang et al. (2018) provided great insights how strong relationships are preferred for venture capital firms in China, the argumentation for the statistical outcome is rather speculative. The failure rate of western firms investing in East Asia is very high, Dai & Nahata (2016) explain this phenomenon due to cultural disparities while creating a syndicated network in a foreign country. So not only do western venture capital firms underperform in East Asia, they also have trouble syndicating with other firms (Dai et al., 2012). Bruton et al. (1999) also emphasizes on this matter by stating that the Chinese business culture for example has a higher tolerance for information asymmetry. Bruton et al. (2004) further noted that doing business in East Asia heavily relies on strong relationships, they wondered to what extent foreign venture capital firms should adjust to this importance when investing in in this region. It is likely that for example strong ties are more preferred in China due to their collectivistic culture (Xiao & Tsui, 2007). While in an individualistic culture such as the United States, venture capital firms are reticent in sharing information in a syndicated network because actors tend to only look out for themselves (Sapienza et al., 1996).

There does seem to be a link between the degree of collectivism in a country and venture capital network structures. Hofstede (1980) describes collectivism as the relationship between the individual and the collectivity that is embedded in a society. Li & Zahra (2012) stated that this cultural dimension is especially relevant for venture capital activity in a country. Reasoning that venture capital firms rely on groups and relationships to acquire and exchange information. Furthermore, Wright et al. (2005) further argues how cultural factors influence the importance of information sharing between venture capital firms, but also to which extent actors reach for alternative information sources.

In conclusion, there is very little known about how venture capital firms should position themselves in a syndicated network. Previous scholars did find that venture capital network syndication positively impacts performance (Hochberg et al., 2007). Moreover, exchanging knowledge is an important driver for venture capital syndication (Brander et al., 2002; Hopp & Rieder, 2011). National culture seems to be a determinative factor that influences the optimal network structure of venture capital firms. More specific, the degree of collectivism in a society determines how relationships should be build and how information can be acquired (Xiao &

Tsui, 2007), therefore national culture might be an important factor for venture capital firms and the startups they invest in. It would be highly interesting to investigate the desired venture capital network structures in different cultural settings to create successful startup projects. Therefore, the following question will be the fundament of the current research:

To what extent does national culture affect the relationship between venture capital network position and startup performance?

By researching into national culture as a moderator, this research contributes to the rather unexplored relationship of venture capital network positions and the performance of the startups they invest in. To be more specific in terms of national culture, the degree of collectivism in a culture seems to cut close ties with a venture capitals network position. A high or low degree of collectivism determines how relationships are build and maintained (Hofstede, 1980), it also explains how information can be obtained and shared throughout a business network (Bruton et al., 2004; Xiao & Tsui, 2007).

Hofstede (1980) provided a revolutionary framework to describe collectivistic- and individualistic societies. He also managed to quantify countries on a scale of collectivism opposing to individualism. To bring focus and ensure a greater theoretical relevance to this research, Hofstede's (1980) cultural dimension will be taken into account while testing national culture on the discussed relationship. With this focus, the main research question can be answered by breaking it down in two sub questions.

1. *Which venture capital network position is most beneficial for startup performance in a collectivistic society?*
2. *Which venture capital network position is most beneficial for startup performance in an individualistic society?*

By providing further research in this topic, it can become more clear which aspects influence the relationship between a venture capital network position and the performance of the startups they invest in. Moreover, venture capital firms may take national culture into consideration while trying to build a syndicating network position. Either when operating in their home country or while syndicating with foreign venture capital firms and invest in startups abroad. This way, firms can optimize the performance of the startups they invest in, thereby also increasing the general innovation and wealth of a society (Dagogo & Ollor, 2009;Kortum & Lerner, 2000).

The effect of national culture will be tested by taking two samples from countries that radically differ in regard to societal collectivism. Previous research also speculated how the maturity of an economic market (Yang et al., 2018). Reasoning that a country needs to be economically and juridically developed to operate freely. Therefore, an extended comparative study will provide justification in the selection of two countries that seem most suitable for the analysis of this research. After settling for two countries that are suitable for this research, two regression analyses will examine the relationship between the network position of a venture capital network and the performance of startups. The provided database for this research was created by Crunchbase, who keeps the quality of the database intact. Partially by data scientist, but also by algorithms and machine learning (Crunchbase, 2021). This database consists of approximately 930.000 venture capital financed startups scattered over a wide variety of countries and industries.

2: Theoretical framework

This chapter dives into previous created literature regarding social network theory, venture capital markets and cultural discrepancy. Afterwards, adequate hypotheses and a concrete conceptual model can be created to form a base for the methodology chapter that will follow.

2.1 Introduction to social network theory

The origins of social network theory dates back a long time. A common direction in this topic is the description of nodes and ties, where nodes are actors and ties represent the relationship between those actors (Kadushin, 2004). The ties between actors can be either strong or weak, Granovetter (1973) describes the strength of a tie as *'a (probably linear) combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services'*. Granovetter (1973) was also one of the first researchers who emphasized the value of weak ties for organizational performance. Since then, there has been an ongoing discussion to which type of ties provide more value in the network structures of organizations.

It takes a fair amount of time to create strong ties, but they prove to carry many benefits. Strong relationships rely on a high level of trust between actors, they therefore become more dependent on each other (Larson, 1992). Having mostly strong ties in a network is also referred to as relational embeddedness or social closure. By having such strong relationships, the information exchange between one another becomes more complex and tacit (Adler & Kwon, 2002). Strong ties also encourage partnership behavior, by forming strong strategic alliances and joint ventures, aspects such as knowledge, (transaction) costs, risk and skills can be shared (Kogut, 1988). By dealing with mostly strong ties, one might end up with a limited number of social groups, since it takes a fair amount of effort to create and maintain strong relationships. The information from these social groups is generally easy to interpretate, but in the long run, the information will be rather homogeneous and redundant (Burt, 1992). Uzzi (1997) refers to this problem as the paradox of over embeddedness.

On the opposite side, weak ties prove to be beneficial for keeping a diverse stream in information sharing. The trust between actors may be lower, but one is connected to more social groups (Granovetter, 1973). The power of weak ties does not necessarily depend on single relationships, but rather on the large quantity (Friedkin, 1982). Having a lot of bridges towards different groups, is also referred to as structural holes. By having a lot of bridges, informational benefits arise. One can share and attract a lot of different (superficial) information by using these bridges (Burt, 1992). While the large quantity in weak ties carry benefits, it also results in a so called information overload, too much and diverse information can cause confusion and uncertainty (Ter Wal et al., 2016). The more (diverse) information is available, the harder it is to interpret and create a good overview of current market situations. Strong and weak ties prove to have both benefits as well as limitations. Rowley et al. (2000) suggests that environmental factors influence the decision of having mostly strong or weak ties. For example, in an uncertain environment, they suggest one should make use of weak ties to acquire more innovative and alternative strategies. While strong ties are useful when the environment is more stable.

2.2 The venture capital market and network syndication

2.2.1 Venture capital operations

Venture capital firms are professional investors who aim to finance promising startups, usually in the exchange of a share in the company. For a lot of entrepreneurs, external financing is needed to create successful startups. The urgency for venture capital financing generally arises when the entrepreneur wants to commercialize its product or service, which usually requires a great deal of financial resources (Zider, 1998). Accepting venture capital as an entrepreneurial firm is more expensive than other possible types of financing, but this translates back in the large amount of risk the investor carries, not many types of investors dare to step foot in the risky startup market. It is generally hard to determine when to invest in a startup, but also when to take a loss and abandon a project (Bergemann & Hege, 1998).

Before investing, venture capital firms follow current market developments and carefully analyze potential startups (Hellmann & Puri, 2000). Overall, venture capital firms tend to be in a hurry. When they invest, they mostly want to liquidize their profit as soon as possible. Usually, a venture capital firm has three ways of exiting the investment of its project; either by failure, an acquisition of the startup, or an initial public offering (IPO) (Freeman, 1999). An IPO is usually the most desired outcome due to the great return of investment and the immediate chance to liquidize the invested capital (Zider, 1998).

Besides offering financial resources, venture capital firms give managerial advice to the startups they invest in with their experience and broad network in the corresponding market (Hellmann & Puri, 2000). Venture capital firms need to make a tradeoff between the intensity of consultation and the portfolio size they carry. Overall, the less advice a venture capital firm offers, the more shared profit an entrepreneur requests (Kanniainen & Keuschnigg, 2003). The opportunity of managerial advice and financial injection seems to be a winning combination, Audretsch & Lehmann (2004) found empirical evidence that venture capital backed German high-tech startups significantly outperform (growth percentage) non venture capital backed firms. Besides growth, venture capital backed startups also seem to be more innovative (Kortum & Lerner, 2000).

2.2.2 What drives syndication?

Venture capital firms can choose to syndicate with one another while investing in a startup. Syndication occurs when two or more venture capital firms invest together. There are numerous reasons for this. A rather traditional view is that syndication is mostly driven to share financial risk, by investing with multiple firms, individual firms will lose less money when a project fails (Wilson, 1968). Likewise, by investing smaller amounts over a larger number of projects, a venture capital firm diversifies its portfolio and as a result it decreases its overall systematic risk (Lockett & Wright, 2001). Therefore, there is a significant relationship between the size of the startup (amount of funding needed), and the likelihood for venture capital firms to syndicate during an investment (Hopp & Rieder, 2011), which seems understandable since more money is at stake. Moreover, the current state of the startup in question influences the decision to syndicate. Gompers & Lerner (2002) for example stated that the further away an entrepreneurial firm is from commercialization, the more risk the venture capitalists perceive.

Aiming towards syndication is definitely not an irrational move, Brander et al. (2002) found that syndication increases the overall return of startup projects. This has possibly little to do with the traditional based view as discussed earlier. Besides sharing financial risk, venture capital firms also syndicate to broaden their networks, resulting in the exchange of valuable knowledge (Hopp & Rieder, 2011). A syndicated investment can therefore also be a bridge for a venture capital firm to a new industry or location, which is usually difficult to enter due to knowledge barriers. By investing together with a firm who is already embedded in the corresponding market, a venture capital firm can diffuse new knowledge and diversify its portfolio (Sorenson & Stuart, 2001). Corresponding, being more open for syndication, venture capital firms seem to secure a greater overall network, which facilitates them with higher quality relationships (Hochberg et al., 2007). Like mentioned last paragraph, venture capital firms provide managerial advice to the startups they invest in. When investing with multiple firms, a greater deal of knowledge is available for the startups. Besides, the joined venture capital firms can decrease the individual workload of interfering in the startup operations (Zider, 1998).

Lastly, syndication enables a more proficient deal flow, which can be described as how agile and quick an investor can select and invest in projects. By working together with multiple venture capital firms, one can get ahold of more possible projects to invest in. This especially seems to be more important when the operating market of a firm is fierce and a lot of competitors are present (Bovaird, 1990). Moreover, when more venture capital firms invest in a startup, it gives an individual firm more conformation and confidence that the investment is a wise decision (Lockett & Wright, 2001).

2.2.3 Network position

As explained, syndication can positively influence the performance of a venture capital firm (Brander et al., 2002). It also affects the network a firm is embedded in (Hopp & Rieder, 2011;Hochberg et al., 2007;Sorenson & Stuart, 2001). Syndication enables venture capital firms to make more, as well as stronger network relationships (Hochberg et al., 2007). This can be translated back to social network theory as described in paragraph 2.1. Venture capital firms are able to position themselves in a syndication network that has numerous strong and weak ties, the amount of both can be described as a venture capitals network position.

Venture capital firms create a network position by syndicating with other firms. So far, it is rather unclear whether a network position of more strong or weak ties provides optimal value for venture capital firms. There is limited amount of research specified on this matter. Looking back at for example Rowley et al. (2000), who stated weak ties are essentially important in uncertain environments where multiple actors are looking for innovative and technological breakthrough. It seems likely that the same may apply for venture capital firms since the venture capital market is generally provided with such characteristics (Bergemann & Hege, 1998). However, Yang et al. (2018) provided empirical evidence how mostly strong ties are preferred for venture capital firms in China. They speculated that this was mainly the case due to China's underdeveloped market at that time, their uncertain governmental structure and the deeply embedded national culture that drives on relationships. Ter Wal et al. (2016) argued how a network actually needs both types of ties and it would be illogical to define a network by solely a dichotomy of either strong or weak ties.

2.3 Cultural impact on venture capital networks

2.3.1 Culture hurdles for the west in East Asia

Many venture capital firms are investing abroad and try to syndicate with foreign venture capital firms (Wright et al., 2005). East Asia seems to specifically be a target for western venture capital firms due to the incredibly rapid technological and economic development in this region the past decades (Pan et al., 2016). When venture capital firms try to invest abroad, the national culture of the host country influences the investment process (Wang & Wang, 2011). It can make the process rigid and challenging, which shows as for example western venture capital firms largely underperform when investing in East Asian startups (Pukthuanthong & Walker, 2007). Not only are successful exit performances affected, cultural disparity and information asymmetry also makes it challenging to select projects and syndicate with local venture capital firms (Dai et al., 2012). Overall, there seems to be a lack of understanding how the venture capital market in East Asia should be entered, cultural discrepancy ought to be one of the key elements (Bruton et al., 2004).

Digging deeper into which characteristics of culture affects the performance of venture capital firms, multiple aspects arise. First of all, culture can be defined as follows; *'Culture is refer as a collective programming of the mind which distinguishes one group from another'* (Hofstede, 1980). Culture is rather tacit and deeply embedded in collective groups. For this reason, it has always been difficult to measure culture in a quantitative way (Kluckhohn, 1962). Pukthuanthong & Walker (2007) describes a cultural shock as to what western investors experience while investing in East Asia. A lot of this has to do with the so called '*guanxi*' relational culture embedded in this region. Guanxi, originated from China, can be defined as: '*a group of people connected by particularistic interpersonal ties, which are cultivated and maintained through trust, obligation, and reciprocity*' (Chen et al., 2015). To accomplish success in Eastern Asia as a venture capital firm, it is essential to work with guanxi relationships, which heavily relies on trust and does not leave much space for structural holes in a business network (Miller & Guo, 2010). When investing in East Asia, western venture capital firms need to make an effort into building a solid business network that enables them to syndicate with local firms. When refusing to syndicate, other problems may arise. When investing alone, a firm needs a great deal of information transparency of the startup project before investing (Dai et al., 2012), this may be hard to acquire due to the high toleration of informational asymmetry in East Asia (Bruton et al., 1999). Another typical characteristic of the guanxi culture, is that it heavily relies on unwritten social rules. In contrast to western culture, where actors depend on written contracts and carefully set guidelines to protect their own interest. In East Asia, you rather depend on the social responsibilities of a guanxi relationship, which is generally hard to grasp for western investors (Pukthuanthong & Walker, 2007).

2.3.2 Hofstede's cultural dimensions

Hofstede (1980) created a model to operationalize culture. It consists of six dimensions with two opposing ends, these dimensions can be applied to different collective groups to identify their culture. It is widely used to compare countries on its cultural values. Two of these dimensions are especially important for venture capital development, which are the degree of uncertainty avoidance and collectivism that opposes individualism (Li & Zahra, 2012). Uncertainty avoidance refers to how a collective group deals with the fact that the future is unpredictable. Within organizations it can translate into the technology, rules and rituals we are certain of and we can fall back on (Hofstede, 1980). The importance regarding venture capital development lies in the fact that the venture capital market is generally fierce and full of risks (Bergemann & Hege, 1998). Even though venture capital firms try to diversify their portfolio to reduce systematic risk (Lockett & Wright, 2001), a lot of times a venture capital portfolio relies on the trust that just one startup exits via an IPO. The success of a single project can make a portfolio 'successful' (Kanniainen & Keuschnigg, 2003), but there is generally an uncertainty whether this will happen or not.

The second discussed cultural dimension is closely aligned with the network formation of venture capital firms. Hofstede (1980) describes collectivism as the relationship between the individual and the collectivity that is embedded in a society. It is important to what extent interdependence exist between individuals, do people mostly look out for themselves, or do they rely on groups that gives them unconditional loyalty? A high degree of societal collectivism brings a greater importance to informal relationships and can decrease potential transaction costs. On the other hand, it limits the deal flow of venture capital firms and it makes it harder for them to syndicate with one another since a greater amount of trust is needed (Li & Zahra, 2012). Gong & Suzuki (2013) also found a significant influence of Hofstede's collectivism on guanxi actions, as described in section 2.3.1. Cultural collectivism cuts close ties on how business relationships are formed and maintained (Hofstede, 1980). A typical collectivistic culture diminishes the presence of structural holes, which makes it challenging to gain valuable knowledge as an outsider (Xiao & Tsui, 2007).

An individualistic culture puts a great emphasis on equal rights and opportunities (Gelfand & Christakopoulou, 1999). Companies tend to reward and punish employees solely on their own actions and relationships have a tendency to be more independent (Han & Shavitt, 1994). This is also visible in the venture capital markets of individualistic societies, where there is a very low tolerance for information asymmetry. Venture capital firms and startups tend to be careful which information is shared with one another, since individuals and organizations mostly only look out for themselves. This can make the investment process challenging (Shane & Cable, 2002). Overall, when settling in an individualistic culture, structural holes tend to be more present and there will be less focus on social groups (Kalish & Robins, 2006).

In conclusion, it is continuously argued how both strong and weak ties are beneficial for a firm's performance. During the early days of social network theory, the focus generally lied on creating strong relationships. However, Granovetter (1973) justified the importance and benefits that weak ties have. While a conclusion could simply mean that both type of ties provide equal value, it is likely that the preferred network position of venture capital firms might change in a collective society compared to a individualistic society. Even though the network position of venture capital firms is largely unexplored, weak ties and structural holes seem to be important since the venture capital market is rather uncertain and heavily relies on (technological) innovations (Bergemann & Hege, 1998). Moreover, Rowley et al. (2000) emphasized how structural holes are preferred in unstable environments where technological breakthroughs are desired, which is in line with a venture capital market. However, Yang et al. (2018) provided empirical evidence that strong ties are more preferable in China, despite previous indications that weak ties ought to be better for venture capital firms. In the following chapter, a more detailed description will be described regarding the relationships of strong- and weak ties in different cultural settings.

3: Hypotheses development and conceptual model

The network position of venture capital firms affects the performance of their investment projects (Hochberg et al., 2007). This research will test whether this relationship is moderated by the cultural dimension collectivism versus individualism. The network position of a venture capital firm can be broken down into the amount of strong- and weak ties. Chapter two gave an extended elaboration how the favorable network position of venture capital firms might change in different cultural settings. In this chapter, the specific relationships will be highlighted, accompanied with suitable hypotheses. These hypotheses ought to answer the sub questions as formed in the introduction of this research. The end of this chapter proposes a fitting conceptual model.

3.1 Formed hypotheses

Sub question 1: **Which venture capital network position is most beneficial for startup performance in a collectivistic society?**

In a collectivistic society, actors tend to rely on social groups and be interdependent between one another. To achieve such relationships, a great amount of trust and harmony is needed, which takes time and effort to create (Hofstede, 1980). These characteristics are rather similar to strong ties, where mutual trust evolves due to the intensity and reciprocity of a relationship (Larson, 1992). In essence, venture capital firms need to gain market knowledge to increase the performance of the startups they invest in, gaining this knowledge is also one of the most important drivers for network syndication (Hopp & Rieder, 2011). In a collective society, Dai et al. (2012) describes that only when a venture capital firm is embedded in one or more social groups, it is able to syndicate with other firms, hereby gaining knowledge that ought to be valuable for the startups they invest in. Having a lot of strong ties may therefore be important in a collective culture. This is also speculated by the study of Yang et al. (2018), where strong ties for venture capital firms prove to work best in China, possibly due to China's collectivistic culture.

H1: In a highly collectivistic society, the amount of strong ties is positively related to the performance of venture capital backed startups.

On the other side of the spectrum, weak ties prove to be beneficial for a diverse information flow due through a large amount of (superficial) relationships (Granovetter, 1973). These type of relationships ensure a lot of bridges and structural holes between groups and ought to be beneficial for a firms performance (Burt, 1992). Xiao & Tsui (2007) however proposed that when being present in a typical collectivistic society, the effect of structural holes will be damped. Because in collectivistic societies, valuable knowledge and social capital is only acquired by facilitating trust, commitment and reciprocity. Therefore, even though a venture capital firm could have a large amount of structural holes in its network, the gained knowledge ought to be limited in a collectivistic society. Furthermore, Bizzi (2013) theorized how structural holes do not work in a network on a high trust social group level. Herein, he finds a negative relation of these structural holes on the individual performance. Reasoning that when being nested in a limited amount of high trust social groups, having arm-length relationships with outsiders might cause friction within the original social groups one is embedded in. Lastly, while trust and harmony characterizes social groups in a collectivistic society, conflict and tension is expected between these social groups (Thiessen, 1997). In conclusion, it is hypothesize that having weak ties in a collectivistic society will not be of great value for venture capital firms.

H2: In a highly collectivistic society, there is no significant relationship between the amount of weak ties and the performance of venture capital backed startups.

Sub question 2: **Which venture capital network position is most beneficial for startup performance in an individualistic society?**

In an individualistic society, venture capital investments are generally executed based on the financial feasibility and an objective look in the business plan (Thiessen, 1997). Relationships are therefore considered formal and actors try to remain independent from one. By creating a venture capital syndication network with other firms, it ought to be better to take these characteristics into account. Furthermore, what typically indicates an individualistic society, is that actors look out for their own interest. When a relationship is formed, actors tend to analyze what they can gain from it, why would one help someone and what can be expected in return (Han & Shavitt, 1994). Hofstede (1980) therefore describes relations in an individualistic society as rather transactional. For this reason, venture capital firms may reconsider building strong relationships with other firms. A high level of trust and intensity does not seem to be that beneficial in the investment process since there remains a very low tolerance for information asymmetry in individualistic societies (Dai et al., 2012). Therefore, even though one builds high trust relationships with other firms, it would only influence the deal flow and the investment process to a limited extent. Firms tend to focus on their own interest and accomplishments, so sharing tacit and high trust information is generally not desired (Thiessen, 1997), especially in the venture capital market, where market information is a key element to success (Hopp & Rieder, 2011). From the information above, we can speculate that the amount of strong ties will only have limited value for a venture capital network in individualistic societies.

H3: In a highly individualistic society, there is no significant relationship between the amount of strong ties and the performance of venture capital backed startups.

As explained earlier, what characterizes relationships in an individualistic society is independence, objectivity and mutual transactions (Hofstede, 1980; Han & Shavitt, 1994). A high level of trust between one another is therefore seems less important, firms tend to exchange knowledge while expecting something in return (Hofstede, 1980). Moreover, the transactional arm length relationships do seem to be preferable for venture capital firms in individualistic societies. As Burt (1992) stated, structural holes in a network can lead to more non-redundant and diverse information flow. The diversity in information can be highly valuable for the funded startups of venture capital firms. Also, in a venture capital market, firms tend to search for radical breakthrough innovations (Zider, 1998), innovations that really bring something new to the table. Having more weak ties in a venture capital syndication network might therefore lead to a higher performance of the funded startups.

H4: In a highly individualistic society, the amount of weak ties is positively related to the performance of venture capital backed startups.

3.2 Conceptual model

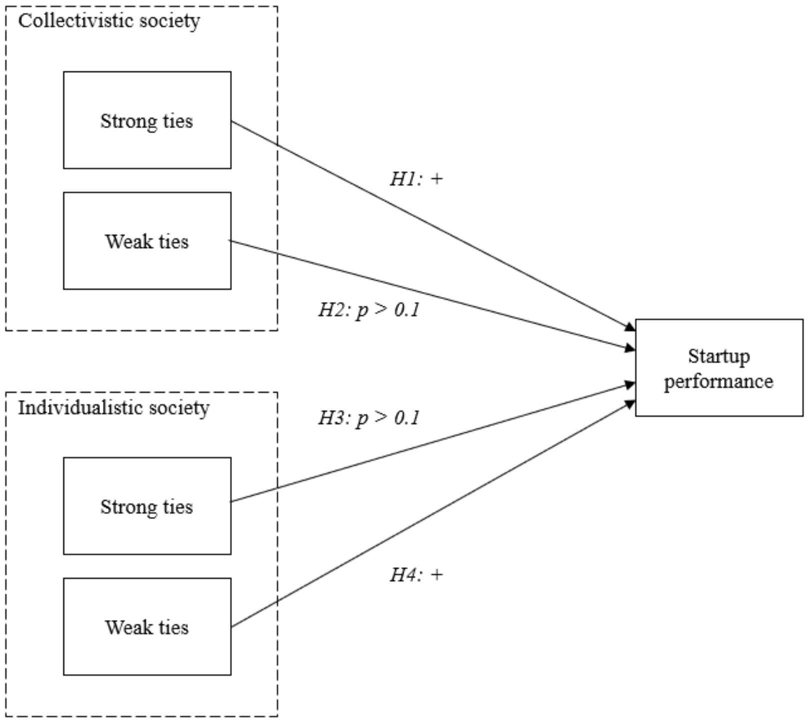
Based on the formed hypotheses in this chapter. Figure 1 below visualizes the conceptual model for this research. It is important to highlight the different structural levels in this model. A collectivistic- and individualistic society are core concepts that operate on a societal level.

The venture capital network position is measured on a network syndication level. In this case, it is important to highlight that the network position of a venture capital firm is determined through its relations between it, and other firms, which is expressed in strong- and weak ties. The amount of strong- and weak ties can therefore be seen as the independent variables in this research.

Lastly, startup performance is measured on an organizational level. The performance, or outcome, is in this research determined by the network position of its venture capital investors.

Startup performance is therefore the dependent variable in this research. The next chapter will go more in depth about the measurement of these variables and the research approach.

Figure 1: Conceptual model



4: Research methodology

4.1 Introduction

To test the formed hypotheses in this research, the methodology strategy will consist of separate parts as shown in figure 2. First, to create two different samples that represent a collectivistic setting and an individualistic setting, a comparative study will be conducted via desk research. In this study, two countries will be described that fit the best profile for this research. After the comparative study, the two samples can be drawn from the provided database. For both samples, a regression analysis will be executed. More details about the desk- and quantitative research will be provided in the coming sections.

Figure 2: Setup methodology strategy

4.2 Desk research

To measure the venture capital network positions in different cultural settings, two samples will be drawn. One of these samples contains venture capital backed startups in a country that is embedded in a highly collectivistic country, while the other sample relates to startups in an individualistic country. To determine which countries to use, a method is used that is referred to as a comparative study. Such a study is used by scholars to measure the differences within two polar opposite theoretical constructs. Thiessen (1997) for example provided an extensive framework for an international comparative analysis for entrepreneurship between collectivistic- and individualistic societies. The goal of this comparative study is to ensure that the two samples, when compared to each other, will present a difference caused by national culture. Such an analysis will increase the validity of the research by making it more likely that national culture is a significant moderator. In chapter five, the culture, along with other important aspects as will be described for two countries. These countries should differ extremely on the collectivism versus individualism spectrum, but share market characteristics that could also be determinative factors for the preferred network position of venture capital firms. These characteristics are described in table 1. Because the selected countries will have a different culture, but similar market characteristics, it will be likely that any statistical differences in these countries are caused by national culture.

Table 1: Criteria comparative study

Characteristic	Reasoning	Emphasized by
National culture	Sample 1: description of a highly collectivistic country Sample 2: description of a highly individualistic country	
Market strength		
Country development	A developed country assures stability to operate freely. An instable environment ensures the need for more trust between actors, therefore influencing the network structure.	Yang et al. (2018)
Financial markets	An established venture capital market lays the foundation to operate freely and to partner up with any actors.	Pukthuanthong & Walker, (2007)
IP Protection	A lack of IP protection by the government results in the need for more trust between the venture capital firm and the startups	Manigart & Sapienza (2000); Yang et al. (2018)

4.3 Quantitative research

After two countries are selected in the comparative study, two samples can be drawn from the provided database. In this section, the proposed variables for the quantitative analysis will be explained. In the regression model, two independent variables will measure network position while one dependent variable will operationalize the performance of venture capital backed startups. Also, three control variables are added to provide a higher quality regression model. The operationalization of these six variables is shown below in table 2, coming paragraphs will give more justification why these variables will be used in the analysis.

Table 2: Variables operationalized

Theoretical construct	Measured via	Level	Emphasized by
Dependent variable			
Startup performance	Revenue	Metric	Zider (1998)
Independent variables			
Strong ties	Average degree centrality	Metric	Opsahl et el. (2010); Zhang & Luo (2017)
Weak ties	Average betweenness centrality	Metric	Opsahl et el. (2010); Onnela et al. (2007)
Control variables			
Synergy effect	Number of investors	Metric	Brander et al. (2002)
Financing cycle	Age of the startup	Metric	Wright & Stigliani (2012)
Size	Number of employees	Metric	Davilla & Foster (2007); Schwarz & Schöneborn (2002)

Lastly, table 2 also shows which researchers emphasized why these measurements should be used to express the theoretical constructs. The conformation by previous researchers surrounding this topic adds to the validity of this research.

4.3.1 Dependent variable

To measure venture capital backed startup performance, revenue will be used as a dependent variable (table 3). Reasoning that the basic goal of a venture capital firm is to maximize its financial return of the projects they invest in (Zider, 1998). When a venture capital firm invests, it is in their interest that the startup generates as much revenue as possible, therefore making it an adequate performance indicator in this research. The database provides an estimated revenue range of each individual startup. These estimations are based on categories as presented in table 3 below. Initially, the dependent variable can be considered as ordinal level. However, it will be transformed to a categorical number as seen in table 3. By making it a metric variable, it can be used to perform a multiple regression analysis (Hair et al., 2010). It is also important to highlight that it is beneficial to start this new metric variable at 1 instead of 0. Reasoning that when the variable experiences an abnormal distribution, it can still be transformed.

Table 3: Parameters dependent variable

Estimated revenue (ordinal)	**Category (metric)**
Less than \$1 million	1
\$1 million – \$10 million	2
\$10 million – \$50 million	3
\$50 million – \$100 million	4
\$100 million – \$500 million	5
\$500 million – \$1 billion	6
\$1 billion – \$10 billion	7
More than \$10 billion	8

4.3.2 Independent variables

Within the notion of a network position, two core concepts can operationalize the amount of strong- and weak ties in such a network. *Degree centrality* refers to the amount of unique ties a firm has in its network (Hochberg et al., 2007). One could describe these ties as a direct relationship between actors (Zhang & Luo, 2017). For this reason, an increase in strong ties as described in the social network theory, leads to an increase of degree centrality (Opsahl et al., 2010). On the other hand, *betweenness centrality* can be defined as a node having a mediating role in a network (Freeman, 1977), thereby making structural holes and information spillover possible (Bloodgood et al., 2017; Burt, 1992). Onnela et al. (2007) further argued that betweenness centrality is therefore highly linked with weak ties. This adds up when referring back to social network theory. Zhang & Luo (2017) for example outline how a high degree centrality combined with a low betweenness centrality results in a redundant communication flow and a lack in diverse information. Granovetter (1973) emphasizes the same conclusion when referring to a network that lack weak ties. In conclusion, the network position of a firm consists of both a determined degree centrality as well as betweenness centrality.

From the information derived above, degree centrality and betweenness centrality can be used to measure the theoretical constructs strong- and weak ties. For this reason, these type of centralities will serve as independent variables in this research. In the database, each venture capital firm has been assigned its network position by calculating its degree- and betweenness centrality. Python provides the function to calculate the two types of centrality. Their database, NetworkX, gives a transparent indication how the calculations are set to be. Regarding degree centrality, NetworkX noted that; '*The values are normalized by dividing by the maximum possible degree in a simple graph n-1 where n is the number of nodes in G.*' (NetworkX, 2020).

For the calculation of betweenness centrality, NetworkX refers to an article created by Brandes (2008), who provided extensive research on how betweenness centrality can be calculated. A brief summary of the formula is visualized below in figure 3.

Figure 3: Calculation betweenness centrality (Brandes, 2008)

$$c_B(v) = \sum_{s,t \in V} \frac{\sigma(s,t|v)}{\sigma(s,t)}$$

V = set of notes

σ(s,t) = number of shortest paths

σ(s,t|v) = number of paths passing through some note V other than s,t

If s = t,σ (s,t) = 1

If v ∈ s,t,σ (s,t|v) = 0

The database from Crunchbase is provided with the top five biggest venture capital investors from each startup. To make the centralities a useful measurement, each startup will be given one score per type of centrality, which is the average of its top five investors. Thus, the data will show the average of both degree- and betweenness centrality from the investors that influenced the operations of the startup. In conclusion, this way the network position of the venture capital firms can be observed on a startup level. An example is shown below in table 4, where the variable can be created by calculating the average centrality of the top 5 investors. In this example, ‘startup 1’ has four investors and ‘startup 2’ only two. The calculation for the average betweenness centrality is calculated in the exact same way.

Table 4: Fictional example calculation average degree centrality (DC)

Startup	DC investor 1	DC investor 2	DC investor 3	DC investor 4	DC investor 5	Average DC
1	0.025189	0.061568	0.002594	0.088499	-	0.0444625
2	0.022656	0.074896	-	-	-	0.048776

4.3.3 Control variables

In the theoretical framework it became clear that certain aspects within venture capital syndication affect the performance of startups. First of all, venture capital firms initially syndicate to decrease financial risk (Wilson, 1968; Lockett & Wright, 2001), to share knowledge (Hopp & Rieder, 2011) and to gain high quality relationships (Hochberg et al., 2007). Important to note, is that Brander et al. (2002) found empirical evidence that syndication investments have a higher return than non-syndication investments. In their research, they observed a linear relationship, where the more venture capital firms invest in a startup, the higher the overall return. For this reason, it is important to add the number of investors in the regression models as a predictor. This could add to a higher quality model that gives more explanation to the dependent variable. The control variable can be implemented as a ratio variable, considering the amount of venture capital investors each startup has affiliated.

Secondly, Wright & Stigliani (2012) describe the phenomenon ‘valley of death’, where startups need to survive in the founding phase of the company due to the lack of profit. In the early stages, startups generally do not gain as much revenue as in a later, more mature stage. However, the authors also state that the growth process is not always absolutely linear, but it can generally be stated that startups in a mature phase, where operations and cash flows have stabilized, gain more revenue than back when they were starting out. The age of a startup can therefore be a useful control variable for the regression models. This can be implemented as a ratio variable measured in number of years.

Third, the size of an entrepreneurial firm seems to imply what the minimum amount of revenue is to keep the organization up and running. The size of an organization can be expressed in the number of employees (Davilla & Foster, 2007). Thereby indicating that for example a small organization with two employees need less revenue than a firm that has over a hundred workers. Schwarz & Schöneborn (2002) gives the example that a startup needs more resources available each time they hire a new employee. For this reason, the size of the startups will be taken into consideration as a control variable. This is a ratio variable and expressed in the number of employees. In the original database, the number of employees was expressed in brackets, to transform this into a ratio variable, the average of the bracket is taken. For example, a startup with 250-500 employees is transformed into (250+500)/2=375.

Lastly, the type of operating industry can also be taken into consideration. As Rowley et al. (2000) for example suggests, an uncertain industry that relies on radical technological innovation probably requires a different network position than a stable environment. Also, Ter Wal et al. (2016) conducted research regarding venture capital networks in the high-tech sector of the United States, but suggested that the results might be different in a low-tech industry. For this reason it would be fitting that both samples contain approximately an equal amount of startups in a high-tech and low-tech industry. The Organization for Economic Co-operation and Development (2011) provided an extensive research to identify traditional high-tech industries by calculating the R&D intensity for each sector. This intensity is an average of the percentage of total capital that firms in this sector spend on R&D. However, the data used in this study dates back to approximately 2000. For this reason, Rainoldi & Gracia (2015) provided a more recent study that also includes high-tech industries that became larger since the early 2000's. The hight-tech industries from these studies are presented in table 5, the remaining inustries will be classified as low-tech. In the drawn samples for this research, a 50% low-tech and 50% is high-tech distribution would be preferable. However, a deviation of approximately 5% would also be concidered acceptable. If the deviation is larger, random cases of the predominant sector can be deleted to gain a more equal distribution. Some industries in table 5 that are closely alligned, have been merged, examples are health care and pharmaceuticals or software and apps.

Table 5: Definition high-tech versus low-tech industries

R&D intensity	Industry	Emphasized by
High-tech	Aircraft & spacecraft, automotive	OECD (2011), Rainoldi & Gracia (2015)
	Radio, TV, communications	OECD (2011)
	Health care, pharmaceuticals, biotechnology	OECD (2011), Rainoldi & Gracia (2015)
	Machinery, technology hardware, FinTech	OECD (2011), Rainoldi & Gracia (2015)
	Software, computer services, apps, IT	Rainoldi & Gracia (2015)
Low-tech	Miscellaneous	

4.3.4 Analysis method

First, the formulas of degree- and betweenness centrality will be applied in Python. Thereafter, two samples will be drawn from Python and converted into SPSS. As explained, these two samples will be determined during the comparative study in chapter five. For both samples, missing data needs to be accounted for. When at least one value of the predictors or the dependent variable is missing for a startup, the case will be deleted in its entirely. Afterwards, the average degree- and betweenness centrality of the top five venture capital investors can be calculated and made into two new variables.

It is desired that all variables are normally distributed. This is calculated by dividing the skewness and kurtosis by the respective standard error. This value ought to be between -3 and 3. If this is not the case, the variable can be transformed to seek improvement. If the requirement is still not met, the regression analyses can still be conducted, but the result might be less precise (Hair et al., 2010). For both of the samples, a regression analysis will be conducted. The corresponding assumptions for a multiple regression analysis need to be met (Hair et al., 2010);

- There needs to be a linear relationship between the dependent variable and each individual predictor.
- Multicollinearity in a regression model might cause biased and distorted coefficients. Therefore the predictors in the model cannot be highly correlated with one another.
- Homoscedasticity in the data is required so that the residuals in the model are equally distributed, therefore assuring the variance is the same in the entire model.
- The errors of the variables should be normally distributed.

When the requirements above are met, the regression analysis can be executed. This is done by first implementing all control variables in the model. Afterwards, the first independent variable is added to create a second model and lastly the second independent variable is added for a third model. By adding the independent variables stepwise, it can be analyzed precisely what the effect is of each of the independent variables. After creating the models, the adjusted R^2 can be analyzed, along with the corresponding t-values to observe the quality and significance of the model.

4.4 Validity and reliability

In an academic research, one ought to take steps to maximize the validity and reliability to improve the quality of the research. Validity refers to what extent the measurement represents the intended variable. Reliability refers to how consistent a measurement is. If another academic would investigate the same question as this research, it should bring the same results (Field, 2017).

Taking samples from two countries to measure a theoretical construct carries a certain amount of risk regarding the validity of the research. Especially since in this research, where the initial relationship of a venture capital network position on startup performance, is quite unexplored up until this point. It is likely that there are multiple moderating effects in this relationship that are currently unknown. By taking two countries to measure the moderating effect of culture, there need to be justification why these two countries can ensure that. For this reason, the countries will differ extremely regarding collectivism and individualism, but share the same characteristics that might also affect a venture capital network position. By doing so, the validity of this research can be increased.

The data is derived from Crunchbase. In essence, investment firms can enter their own data into Crunchbase. This makes the quality of the data questionable. However, Crunchbase manually validates the data with a team of data analysis experts. Also, this team develops AI and machine learning tools to scan the data for abnormalities and conflictions, which increases the validity of the database (Crunchbase Product Team, 2021).

Lastly, statistical tests can ensure a greater validity and reliability in the research. By assessing the assumptions of a linear regression model as described in 4.3.4, the validity and reliability can be increased. When the data meets the set requirements stated by Hair et al. (2010), it can be stated that there are limited biased or distorted coefficients in the regression analysis.

4.5 Research ethics

As explained, the database is provided by Crunchbase and regularly updated. This database will not be shared with any outsiders. To control privacy aspects, no names of any venture capital firm nor startups will be mentioned in this research. Due through the large sample sizes (n>100), it will be nearly impossible to gain any info regarding single organizations by interpreting the results in this research.

4.6 Limitations

The chosen research approach does come with paired limitations. In this research, it is expected that societal culture moderates the relationship of venture capital network positions and startup performance. However, there ought to be more moderators in this relationship that have not yet been brought to light. To minimize this limitation, the most considerable market characteristics will be explained and discussed in the comparative analysis in chapter five. These characteristics derive from previous literature signing the possibility for a moderating effect, therefore increasing the probability that culture moderates the relationship in this research.

Another limitation lies in the dependent variable of the research. While revenue is an adequate performance indicator, it says little about profit or the return on investment. Therefore, there is a possibility that a startup gains a lot of revenue, but still does not break even. At the same time, a startup with relatively little revenue can produce a high return on investment. However, a high revenue may indicate a large scalability and market share, which can also be seen as startup performance.

Moreover, the provided data is only supplemented with the top five venture capital investors of each startup. In some cases a startup has less investors, but it can also occur that a startup has more than five investors. In the case of more than five investors, solely the most important five are shown in the database. The importance is determined by the amount of financial injection. In the case of the provided database, it ought to be a limitation that not all investors and their accompanied network positions are shown. However, the average centralities of the top five investors gives a very decent indication. Also, most startups do not exceed five investors, in that situation, this limitation is not an issue. Furthermore, by taking the average centrality of multiple firms, it is implied that these firms all have an equal amount of influence with their network in the startup, which in reality is not necessarily the case.

Lastly, the location of the startup does not determine the location of the venture capital firms that invests in this startup. This is worth mentioning since the independent variables in this research are determined by the venture capital firms and not the startups itself. Even though that it is likely and most common that a venture capital investor is located in the same country as the startup they invest in, it is not a unconditional fact. It is therefore important to highlight this limitation of the provided database.

5: Comparative study

Two countries were chosen that can enable the measurement of a preferred venture capital network position in different cultural settings. The countries in question for this research are South Korea and the United Kingdom. Coming section will give a comparative analysis on the culture and the market strength of these two countries. The details and reasoning of these characteristics were elaborated on in chapter four.

5.1 Cultural description

Hofstede's (1980) model quantifies the cultural dimensions for each country. Table 6 below shows the discrepancy of the dimension collectivism versus individualism, ranking the top 5 for each opposing site. The selected countries should be economically developed, as explained in chapter 4. Therefore, only economically developed countries are shown in table 6. Whether the countries are developed or not is based on the top 20% of the human development index created by the United Nations (2020).

Table 6: Scale of collectivism (0) versus individualism (100) (Hofstede, 2021)

Top collectivistic countries		**Top individualistic countries**	
Taiwan	17	United States	91
South Korea	18	Australia	90
Singapore	20	United Kingdom	89
Hong Kong	25	Canada	80
Portugal	27	Netherlands	80

Business network culture in South Korea can be described as highly collectivistic. Relationships, often referred to as yongo, cuts close ties with the Chinese guanxi culture as described in chapter two. Notable difference is that in South Korea, networks are very exclusive and generally predefined, partially by birth. For this reason, South Korea is arguably one of the most collectivistic countries in East Asia. The networks are rather homogenous and there exists a hostile and competitive nature between social groups, (Horak & Taube, 2016). This also results in a high degree of information asymmetry between venture capital firms and startups (Kim & Kutsuna, 2014).

The United Kingdom can be seen as the most individualistic society in Europe. There are numerous indications how the United Kingdom show signs of an individualistic society business wise. When seeking for an investment, venture capital firms in the United Kingdom are mostly interested in the startups business plan and the contract that ensures the deal. Even though investors are also interested in the CEO of a funded project, they generally only want to build a stronger relationship when they perceive more risk in the project (Sapienza et al., 1996). So even when there is a desire to form strong relationships, it is mostly to protect one's own interest. Mason (2006) adds to this that it also works the other way; business owners are skeptical to just send out a business plan to venture capital firms. In order to protect one's own interest, both parties are careful in sharing information, which is very characteristic for individualistic societies (Hofstede, 1980).

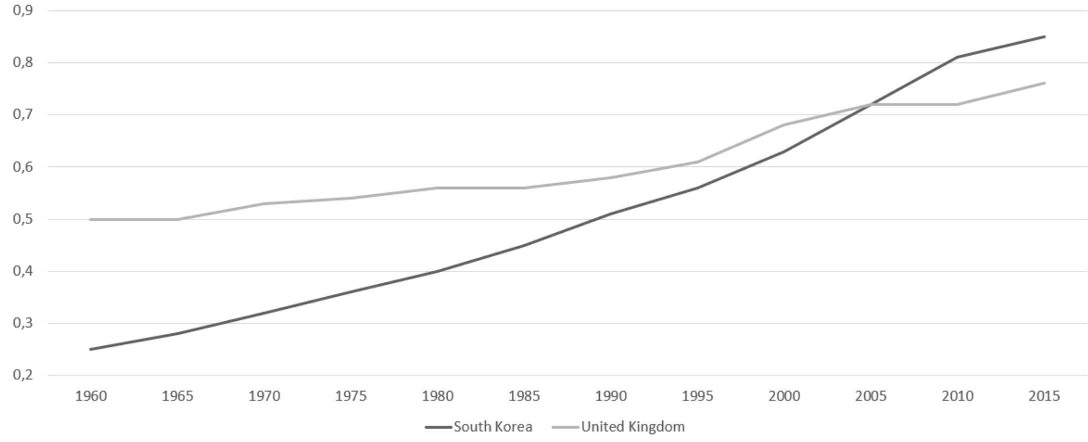
5.2 Market strength

While South Korea and the United Kingdom highly differ in terms of culture, they are aligned with each other on aspects that might also influence the relationship that is being examined in this research. As elaborated in chapter four, three main market characteristics are to be assessed in this comparative analysis. By showing similarities in the market, it is more likely that further quantitative results are caused by the cultural differences as described in 5.1.

Country development

In their research, Yang et al. (2018) provided empirical evidence how strong ties are especially important in China, compared to the United States. Their argumentation partially consisted of how underdeveloped China was as a country at the time they collected their data. For this reason it is important that the development of South Korea and the United Kingdom are taken into account in this comparative study. In figure 4, the growth of the human development index (HDI) is shown for both countries. The HDI was created by the United Nations to assess the development of a country. This is done by taking a quantitative score between 0 and 1 regarding long and healthy life, knowledge and a decent standard of living (UNDP, n.d.). Originating from 1960 until 2015, it is clear that both countries followed the same growth pattern.

Figure 4: Growth pattern of the Human Development Index (Prados de la Escosura, 2021)



Financial markets

South Korea's financial markets are considered to be developed and their venture capital market has been from world class level since its origins in the early 70's (Kim & Kutsuna, 2014). For this reason, South Korea experiences less difficulties regarding uncertainties in the institutional environment. Partially since their economy already experienced a rapid developed in the early 90's and stabilized short after (Naqi & Hettihewa, 2007), but also governmental stimulation towards a stable and secure venture capital market (Kim & Kutsuna, 2014). Regarding the United Kingdom, the venture capital market started to emerge in Europe during the 1970's, with the UK and Ireland being the first to attract the first venture capital investments (Pukthuanthong & Walker, 2007). Since then, the venture capital market in the United Kingdom has been the absolute largest in Europe. The current policies in the United Kingdom, along with the European Commission, are ensuring a decent base for venture capital firms to operate, especially in the early stages of financing startups (Mason & Harrison, 2000).

IP protection

As Manigart & Sapienza (2000) stated, it is essential that intellectual property rights are protected in the institutional environment. If actors in the market cannot rely on the government, there is a greater need for strong ties (Yang et al., 2018) Groh & Wallmeroth (2016) quantified the IP protection in venture capital markets around the world. In this case, IP protection equals the degree of intellectual property protection and also anti-counterfeiting in a country. In their research, South Korea and the United States scored 4.5 and 5.9 respectively on a scale of 0 to 7. According to the World Intellectual Property Organization (2016), these scores are well above world average.

5.3 Conclusion

First, section 5.1 described how South Korea is a great example of a highly collectivistic country, while the United Kingdom is considered extremely individualistic. For this reason, these countries can be represented in this study. Secondly, South Korea and the United Kingdom show a lot of similar market characteristics. They followed the same country development pattern, have established financial markets and a juridical system that is considered above average. Because of these similarities, there is a high probability that the possible differences between these two countries will be determined by national culture.

6: Quantitative results

This chapter shows the outcome of the statistical analysis. As discussed in chapter four, two regression analyses will be conducted. This chapter shows the univariate analysis of the variables, the assumptions for the regression analysis and a review of the model in a transparent matter. Thereby closing the chapter by answering the formed sub questions and hypotheses.

6.1 Introduction

The provided database consists of approximately 930.000 venture capital backed startups. To narrow this down to two usable samples for this research, lots of cases are to be deleted. Table 6 shows the criteria for both samples, by narrowing the data down, both samples end up with zero missing values. As explained in chapter four, two new variables were created by taking the average degree- and betweenness centrality of the top five investors of each startup. For a clear understanding in the provided tables, these two new variables have been abbreviated to 'Average_DC' and 'Average_BC' respectively. Lastly, to keep the option open for variable transformation, the average centrality scale should make a slight move to eliminate absolute 0 values. Therefore, to all average centralities, a value of 0.0001 has been added. By doing so, the distribution of the variables did not change, but now it is possible to perform transformations to improve the distribution of the variables (Hair et al., 2010). Lastly, the most common significance levels are usually considered 95% and 99% (Field, 2017) , however, since this is a rather explorative research, a significance level of 90% will also be taken into account if this makes a difference in the coefficient table.

Table 7: Requirements for the cases in both samples

Sample 1 contains	Sample 2 contains
HQ location: South Korea	HQ location: United Kingdom
High tech / low tech industry, ~50/50% divided	High tech / low tech industry, ~50/50% divided
Estimated revenue	Estimated revenue
Average degree centrality of the top five investors	Average degree centrality of the top five investors
Average betweenness centrality of the top five investors	Average betweenness centrality of the top five investors
Number of investors	Number of investors
Age of the startup	Age of the startup
Number of employees	Number of employees

6.2 Sample 1: South Korea

6.2.1 Univariate analysis

The research consists of six metric variables, the descriptive table of this sample is presented in appendix 2. Hair et al. (2010) gives two guidelines for the amount of cases needed in a regression analysis. The ratio cases to variables should be at least 5:1. Also, the absolute minimum ought to be 100. After narrowing down the cases with the requirements described in 6.1, this sample is unfortunately left with approximately 60 venture capital backed startups. To fix this problem, the control variable 'Size' ought to be excluded from this analysis. The reason for choosing 'Size', is because this variable contains a lot of missing values. After excluding the variable 'Size', the sample increased back to 238 cases. Table 10 in appendix 1 shows that in this sample, 54.6% of the startups is embedded in a high-tech industry, while 45.4% operates in a low-tech industry, which can be considered a decently equal distribution.

It is important to look at the skewness- and kurtosis values, as it is wished that the data is sufficiently normally distributed. The desired skewness and kurtosis score lies between -3 and 3 (Hair et al., 2010). The score is calculated by dividing the score by the standard error. Initially for sample 1, all variables scored outside of the desired skewness and kurtosis range. A suiting remedy for this problem is to transform the variables to seek an improvement. The variables all score the best skewness and kurtosis score by computing the variables with a logarithm (LN) function, this is presented in appendix 1. While most variables are now sufficiently distributed (or are at least very close to the threshold), 'Average_BC_LN', 'Number_of_investors_LN' and 'Age_LN' still underly some problems. In essence, it is not a strict requirement for the analysis that all variables are sufficiently distributed. However, it makes the analysis less precise, it can therefore be seen as a slight limitation of the data.

6.2.2 Assumptions

Chapter four laid the guidelines for conducting a regression analysis. The data has to meet certain requirements. First of all, there ought to be a linear relationship between the dependent variable and the independent/control variables. To assess the linearity of the regression model, the scatterplot can be analyzed. It consists of standard residuals (ZREZID) and the standardized predicted values of the dependent variable in the model (ZPRED). The scatterplot for this sample is visualized in figure 5 of appendix 3, in order to determine linearity, the dots should not form a clear pattern. This has a sense of multi interpretability, Hair et al. (2010) emphasized that there should not be a clear curve or triangle in the model. Even though there is a slight density in the lower side of the middle in the scatterplot of sample 1, there is no clear pattern to be found. Therefore, we can state linearity in the regression model and no polynomial variables need to be included.

Secondly, multicollinearity indicates a significant relationship between the independent variables. This means all variables except 'Revenue_LN' should not have a high correlation with each other. To test for multicollinearity, the tolerance score ought to be analyzed, which cannot be below 0.10. Table 13 in Appendix 3 shows the relevant tolerance- and VIF scores for sample 1. The VIF equals 1 divided by the tolerance score, which therefore cannot exceed a score of 10. 'Number_of_investors_LN' and 'Age_LN' show an excellent score that has no indication of any multicollinearity. Both 'Average_DC_LN' and 'Average_BC_LN' score a rather low tolerance score and seem to be in the danger zone. To go more into the origin of the low tolerance, a bivariate analysis has been made (table 14). Hair et al. (2010) gives the guideline that in the bivariate analysis, the Pearson score cannot be above 0.5. As shown in the bivariate analysis, most variables do correlate with each other, but score below the 0.5 threshold. Except for the relation between average degree centrality and average betweenness centrality. These are highly positively related to each other. At this point, it could be formally considered to either combine both variables or remove one of the two variables. However, the tolerance threshold in the regression assumption has not been exceeded and taking such actions highly disregards the outcome of the study. Therefore, the low tolerance score can be accepted.

Next, a constant variance of the residuals is referred to as homoscedasticity. This criteria is important to analyze because to execute a regression analysis, an equally distributed error is desired. This can be done by looking at the scatterplots in figure 5 of appendix 3, a clear pattern ought to be absent and the dots should be evenly divided over de axis. For both samples, these requirements seem to be met, there is an absence of a clear pattern and therefore we can assume homoscedasticity.

Lastly, the errors should be normally distributed in the model. This can be analyzed by looking at the normal probability plot and the histogram in appendix 3. The dots in the normal probability should be closely aligned with the linear line in the graph. Moreover, the histogram shows a bell-curve, it is desired that the histogram values match this bell-curve pattern. For sample 1, the normal probability plot looks promising, the dots are very closely aligned in the graph. Also the histogram shows a decent normal distribution aside from the fact that it seems to be slightly positively skewed.

6.2.3 Regression analysis

This analysis for sample 1 has four predictors, the first model contains solely two control variables. In the upcoming models, the independent variables will be added once at a time to observe a possible significant change. In model 2, the first independent variable, ‘Average_DC_LN’ is added. Lastly, in the third model, ‘Average_BC_LN’ is also added as the final independent variable.

Appendix 4 shows the output of the regression model. Firstly, the ANOVA table shows the F-test. The F-test shows whether the predictors show a significant change in effect in regard of the dependent variable. When the F-test is significant, it can be concluded that there is a good model fit. For sample 1 this seems to be the case since all models show a significant p value ($p<0.001$).

Secondly, appendix 4 also shows the model summary and coefficients table. A summary of the most important findings is presented further down in this chapter in table 8. The quality of the regression model is observed through the adjusted R^2. In contrast to the regular R^2, the adjusted R^2 gives a more precise indication of the actual quality of the model. This is due to the fact that the adjusted R^2 takes the complexity of the regression model into consideration and compensates for potential flaws. The first model shows an explanation of 10,4%, which is solely due to the two control variables. After adding the average degree centrality in model 2, the R^2 increases significantly to 14,2%. Finally, in model 3 the average betweenness centrality is added, which ensures an insignificant change, the R^2 even decreases in the third model to 14,0%. For this reason, the second model seems to explain the most about the dependent variable ‘Revenue’. In this model, both control variables, as well as the average degree centrality, show a significant positive effect when calculating with an alpha of 5%. The average betweenness centrality does not seem to have an effect at all on the dependent variable in the third model.

6.3: Sample 2: United Kingdom

6.3.1 Univariate analysis

The descriptive table of sample 2 is presented in table 18 of appendix 5. Just as in the first sample, the database is narrowed down to the startups that fit the requirements of paragraph 6.1. After deleting the cases without these requirements, the database is left with 1215 venture capital backed startups, which is an eligible amount according to the guidelines of Hair et al (2010). In contradiction to the first sample, all three control variables can be taken into account.

This does mean that the two analyses in this research differ regarding one control variable. However, Schjoedt & Sangboon (2015) state the importance of including every significant control variable that is theoretically relevant, but they also mention it might affect the generalizability of s study. Furthermore, Brunetti & Weder (1998) also provided an exploritive comparative study, where they compare two samples with different predictors. They mention that the independent variables need to be equal in both samples, while one can explore with different control variables to look for significant results. In the case of this research, because the number of employees does seem to be a significant predictor, it is valuable to take it into account despite this predictor being absent in the first sample.

Appendix 1 shows the distribution of startups in high-tech and low-tech industries. In this sample, 52.8% of the cases is operating in a high-tech industry, while 47.2% is embedded in a low-tech industry, which can be regarded as a fairly equal distribution. Sample 2 does seem to carry more complications regarding the distribution of the variables. Again, all variables have been transformed with a logarithm (LN) function. Even after transformation, most variables score outside of the desired skewness and kurtosis range (table 19). Especially 'Average_BC_LN' and the remaining control variables. Again, it is not a strict requirement to conduct a regression analysis, however, the results should be interpreted more carefully.

6.3.2 Assumptions

Appendix 6 shows the relevant figures and tables to assess the assumptions for sample 2. The first assumption to be discussed is the linearity between the dependent variable and the predictors in the regression model. Just as in sample 1, the scatterplot is taken into consideration to ensure linearity in the model (figure 8). When observing this plot, a clear curve or triangle pattern seems to be absent, therefore linearity in this model can be assumed.

Next, the tolerance and VIF score is observed in table 20 to assess multicollinearity between the five predictors in the model. The same phenomenon seems to happen as in the first sample, where the control variables show excellent tolerance levels above 0.5 and VIF scores below 2. The independent variables on the other hand, show some concerning values. 'Average_DC_LN' shows a tolerance level of 0.164 and a VIF score of 6.097. Furthermore, 'Average_BC_LN' has closely aligned values, the tolerance level is 0.172 and the VIF score 5.808. As in the first sample, an extra bivariate analysis is made (table 21) to observe the relationships between the predictors. While most variables show a significant score, most do not exceed the 0.5 threshold as stated by Hair et al. (2010). However, the average degree centrality and average betweenness centrality show a very high positive correlation, just as in sample 1. The same conclusion can be applied; the tolerance scores in the regression model are not below 0.1 and deleting or merging variables is a possibility that is not suitable in this research. For this reason, the regression analysis can be conducted, but the results ought to be interpreted with more care.

As in the first sample, the homoscedasticity of the model is assessed by interpreting the scatterplot in figure 8. The distribution of the residuals gives a promising impression of homoscedasticity in the model. Even though there is a slight density in the left side of the model, a clear concerning pattern seems to be absent. For this reason, it can be concluded that the assumption of homoscedasticity is met.

For the last assumption, which is the normal distribution of the error terms, the normal probability plot and the histogram are observed (figure 9 & 10). The P-P plot shows very good results, where the dots are closely aligned on the linear line. Furthermore, the histogram does show an unusual second peak on the left side of the graph. The distribution also seems to be slightly positively skewed. However, the pattern of a bell curve is clearly present, the assumption for a regression analysis is therefore met.

6.3.3 Regression analysis

The same interpretation strategy as the first sample is applied. However, this sample contains three control variables instead of two. The first model contains these three control variables. The second model is supplemented with the first independent variable, which is 'Average_DC_LN' . Lastly, in the third model, 'Average_BC_LN' is also added, making the model complete.

The ANOVA table, model summary and coefficients table are presented in appendix 7. Again, before interpreting the coefficients, it is important to look at the model fit and the quality of the regression model. The ANOVA table shows the F-test, indicating the model fit (table 23). For all three models, the F-test shows a significant value when applying an alpha of 5% ($p<0.001$), for this reason, there is a good model fit.

Table 8 below shows a summary of the results, the quality of the regression model is analyzed by interpreting the adjusted R^2. It appears that the three initial control variables already explain 19,6% in the model. All three control variables show an significant effect, with 'Size_LN' having the highest standardized β. The independent variables do not seem to have a significant impact on the dependent variable when analyzing the results of models two and three. This also shows as the adjusted R^2 stays the same in the second model. In the third model, the adjusted R^2 even decreases to 19,5%.

Table 8: Summary coefficient table and model summary

	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
	Collectivistic society			Individualistic society		
(Constant)	-0.199	0.378	0.258	-0.266***	-0.222*	-0.222*
Number of investors	0.264***	0.192**	0.195**	0.072*	0.062*	0.062*
	(3.869)	(2.795)	(2.826)	(2.538)	(1.982)	(1,982)
Age of the company	0.323***	0.323***	0.330***	0.147***	0.149***	0.149***
	(4.757)	(4.896)	(4.909)	(4.858)	(4.903)	(4.900)
Number of employees				0.382***	0.383***	0.383***
				(13.896)	(13.909)	(13.869)
Average degree centrality		0.234***	0.318*		0.023	0.026
		(3.699)	(1.980)		(0.769)	(0.411)
Average betweenness centrality			-0.091			-0.004
			(-0.570)			(-0.061)
R^2	0.104	0.153	0.154	0.198	0.198	0.198
Adjusted R^2	0.096	0.142	0.140	0.196	0.196	0.195
N	238	238	238	1215	1215	1215
Degrees of freedom	235	234	233	1211	1210	1209
F-value	13.569***	14.096***	10.622***	99.602***	74.824***	59.811***
Sig. F change	0.000	0.000	0.569	0.000	0.442	0.951

*Dependent variable: Revenue, $p < 0.001$***, $p < 0.01$**, $p < 0.05$*, $p < 0.1$ not present. Model shows standardized β (t-value 2 way)*

6.4 Hypotheses

After interpreting the regression results, the coefficients can be linked to the formed sub questions and hypotheses of this research. As a recap, the initial theoretical construct that ought to be measured is strong- and weak ties. In the analysis, these were measured by degree- and betweenness centrality respectively.

Hypothesis 1*: In a highly collectivistic society, the amount of strong ties is positively related to the performance of venture capital backed startups.*

Previous literature indicated that strong ties of venture capital firms ought to be beneficial for the performance of startups they invest in when measured in a collectivistic society. In the regression model, the average degree centrality of venture capital firms seems to have a significant effect on the revenue of startups. Remarkably, when the average betweenness centrality is added in model 3, the significance of average degree centrality decreases from 0.000 to 0.049. This is an indication that the variables correlate with each other, which was already observed when the assumptions were assessed in 6.2.2. Nevertheless, even in the third model, degree centrality shows a significant effect. Herein, the corresponding t-value ($t=1.980$) lies outside of the -1.96 and 1.96 threshold. Furthermore, the p-value ($p<0.05$) shows a significant result when applying an alpha of 5%. For this reason, the first hypothesis can be accepted. Because the variables were transformed with a logarithm function, it is hard to interpret the beta coefficient. However, by interpreting the standardized beta, it can be compared to the other significant predictors. It appears that the average degree centrality ($\beta=0.318$) does show a higher explanation regarding revenue of the startup in contradiction to the number of investors ($\beta=0.195$) the venture capital firm has. Furthermore, the age of the startup is also a significant predictor and shows a slightly larger explanation ($\beta=0.330$) than the average degree centrality.

Hypothesis 2*: In a highly collectivistic society, there is no significant relationship between the amount of weak ties and the performance of venture capital backed startups.*

It was hypothesized that weak ties are not useful in a collectivistic society, where business networks are generally build on strong relationships. After adding the average betweenness centrality in the third model, the adjusted R^2 decreases by 0.2%. The corresponding t-value ($t=-0.570$) and p-value ($p=0.569$) of the variable show no significant effect on the revenue of startups while applying a significance level of 10%. In conclusion, betweenness centrality does not seem to have an impact on revenue in a collectivistic society, for this reason, there is support for hypothesis 2.

Hypothesis 3*: In a highly individualistic society, there is no significant relationship between the amount of strong ties and the performance of venture capital backed startups.*

In an individualistic society, it is expected that strong ties are not of much use. Therefore it is hypothesized that there is no relationship between degree centrality of the venture capital firms and the revenue of the startups they invest in. When analyzing the second regression analysis, in the second model, where degree centrality is added, the adjusted R^2 stays the same at the initial 19,6%. The average degree centrality does not seem to have a significant impact on the dependent variable. The t-value ($t=0.411$) lies well within the established threshold and the p-value (p=0.681) does not show a significant effect when maintaining an alpha of 10%. As this was expected, the third hypothesis can be accepted.

Hypothesis 4*: In a highly individualistic society, the amount of weak ties is positively related to the performance of venture capital backed startups.*

The network position that ought to make a positive difference in an individualistic society, is through the use of weak ties. After the average betweenness centrality was added in the third model, the adjusted R^2 once again maintained the same value of 19.6%. When looking more closely at the impact of the average betweenness centrality, it is clear that the predictor shows no significant impact on the dependent variable with a t-value of -0.061 and a p-value of 0.951. The highly insignificant result shows that the fourth hypothesis needs to be rejected.

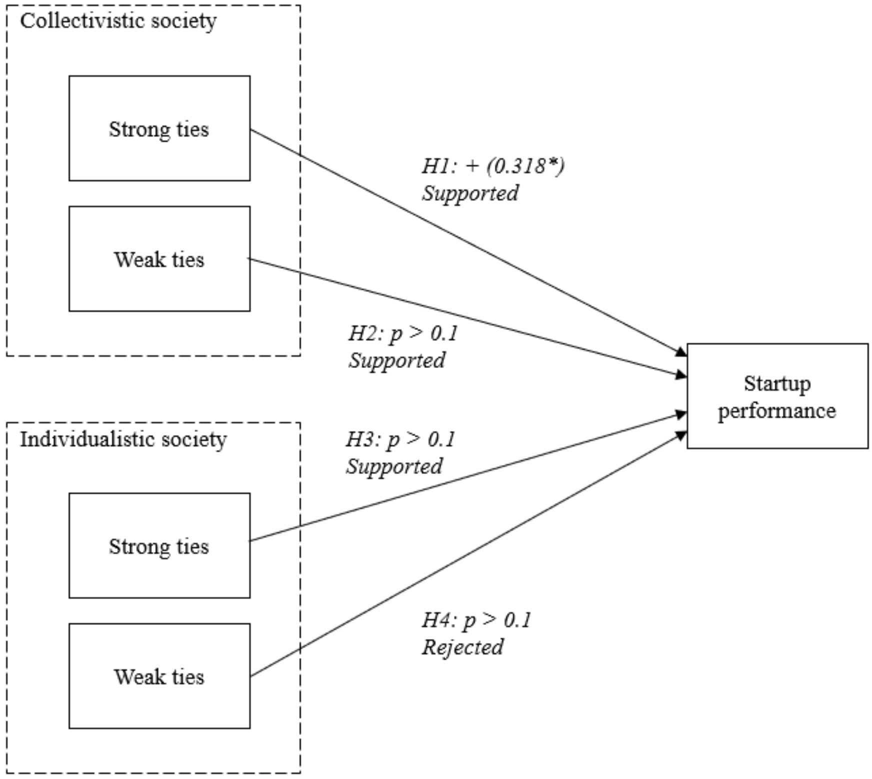
Table 9 below shows a brief overview of the four tested hypotheses.

Table 9: Summary hypotheses results,

Hypothesis	Conclusion
Sample 1: ***Collectivistic culture***	
H1: Strong ties positively affect startup performance	Supported
H2: Weak ties do not affect startup performance	Supported
Sample ***2: Individualistic culture***	
H3: Strong ties do not affect startup performance	Supported
H4: Weak ties is positively affect startup performance	Rejected

By rejecting and accepting the hypotheses created in this research, the conceptual model below (figure 4) can be presented with the fitting results. In conclusion, there is support for hypothesis one, two and three, while the fourth hypothesis needs to be rejected. As explained in the beginning of this chapter, a significance level of 90% would also be considered acceptable since this research is rather explorative. Therefore, the results in the conceptual model are determined at an alpha of 10%. The only significant result (H1) is set at a p-value of 0.49, therefore it is valuable to mention it is significant at an alpha of 5%.

*Figure 4: Conceptual model results, *significant at an alpha of 5%*



6.5 Other sample possibilities

As explained in chapter five (comparative analysis), there were multiple developed countries that would fit the profile in this research. However, the problem of multicollinearity was also present in the dataset of these other countries. As an example, collinearity statistics from the United States and Australia are presented in appendix 8, these two countries belong to the most individualistic societies in the world. The appendix shows the tolerance scores, VIF scores and bivariate analyses. Clearly, the same phenomenon happens as in the samples used for this research. The multicollinearity is even more present here, where the sample in the United States for example has a tolerance score below 0.1. Moreover, the bivariate analyses show how this is mostly caused by the average degree- and betweenness centrality, which are highly positively correlated. With these extra analyses, it seems that the positive correlation between the centralities is more generalizable. Lastly, in the bivariate analysis of the United States sample, the control variable 'number of investors' also exceeds the threshold of 0.5 as set by Hair et al. (2010) regarding the Pearson's correlation score.

7: Conclusion

This chapter provides a conclusion regarding this research. The research question, as well as the sub-questions will be answered. Thereafter, the theoretical- and managerial implications will be described along with a discussion regarding the research results. Lastly, a reflection regarding the limitations in this research will be shown and possibilities for future research will be given.

7.1 Research question

The main research question of this study was: *'To what extent does national culture affect the relationship between venture capital network position and startup performance?'* Before answering this question, the sub questions ought to be answered. First one being; '*Which venture capital network position is most beneficial for startup performance in a collectivistic society?*'. As explained, it seems that strong ties provide great value for the performance of startups in a collectivistic setting. The regression model showed a significant effect for strong ties, while weak ties do not seem to carry a significant value for the performance of startups. Secondly, to dive into the next question; '*Which venture capital network position is most beneficial for startup performance in an individualistic society?*'. Unfortunately, neither strong nor weak ties show any effect on the performance of startups in an individualistic setting. Therefore, a concrete answer to this second question is absent since the most beneficial network position remains unknown. To conclude that venture capital syndication has no effect in individualistic societies based on this study may be too short sighted since numerous scholars emphasize the performance benefits when building a syndicating network as a venture capital firm. Possible reasons for the surprising outcome will be mentioned in the discussion.

Previous paragraph can give an answer to the main research question of this research. It can be stated that national culture overall does have an impact on the preferred venture capital network position. The quantitative results show that especially strong business relationships are important in a highly collectivistic society since an increase of strong ties ensured an increase of revenue from the venture capital backed startups. Compared to the individualistic society, where no preference regarding strong- or weak ties is shown. Not only is no preference present, neither strong nor weak ties in a network seem to significantly improve the performance of venture capital backed startups. In conclusion, a highly collectivistic setting makes a difference. However, in this research, solely two polar opposite settings were examined. Hofstede (1980) did quantify the degree of collectivism in countries. As of right now, it is not clear that an increase for Hofstede's quantification implies an increase of importance regarding strong ties. What can be stated, is that a highly collectivistic society shows a significant sign that strong ties are more important than weak ties.

7.2 Theoretical implications

The intention of this research was to bring more clarity in the relationship of a venture capital network position and the startups they invest in. By doing so, it can add value to the general social network theory, but also to the application for venture capital firms. Previous scholars such as Hochberg et al. (2007) and Brander et al. (2002) did find how the network position of a venture capital firm influences performance. The past decade, other studies showed more concrete empirical evidence such as the study of Ter Wal et al. (2016) and Yang et al. (2018), speculating how the type of operating industry and the economic/juridic development of a country influences the impact of a venture capital network position. With this study, I would like to propose how societal culture does impact the optimal venture capital network structure. When new scholars further investigate this relationship, the national culture can be taken into account, especially how in a highly collectivistic society, strong ties clearly show to be an advantage opposing to weak ties. Moreover, this proves to be an additional value to the study of Yang et al. (2018), who found empirical evidence how strong ties are especially beneficial in China. They speculated numerous reasons for their findings, including the collectivistic culture in China. This research gives a stronger argumentation to this statement and more explanation to their insightful research.

7.3 Managerial and societal implications

Regarding a managerial approach, venture capital firms can take the importance of syndication in mind when investing in startups. Depending on where the startup is located, it can decide whether it should have a network of mainly strong- or weak ties. The findings showed that in a highly collectivistic society, where business relationships thrive on a high amount of trust, reciprocal services and emotional intensity, venture capital firms could benefit by creating strong ties with the actors in its network. This is of course, not applicable to all regions in the world since some countries are mainly stuck in the middle regarding a collectivistic- or individualistic society. Examples of these countries are Japan, Spain and Israel (Hofstede, 1980). In a societal sense, as stated in the introduction of this research, venture capital firms contribute to the wealth and innovation of a society (Dagogo & Ollor, 2009; Kortum & Lerner, 2000) of a society. This research ought to give more directions for venture capital firms on how to operate and build a network syndication structure, therefore being able to add more value on a societal level.

7.4 Discussion

In the end, three out of four hypotheses were accepted. Therefore the results are decently aligned with the expectations derived from previous literature. Especially in the sample that represented a collective society, where both hypotheses were accepted. Due to the transformation in the data, the unstandardized beta should not be interpretated to measure the absolute strength of the effect. Instead, the standardized beta can be observed, which is comparable with other significant predictors. Degree centrality showed an increase in strength after betweenness centrality was added in the third model. Here, it showed a higher coefficient than the variable 'number of investors', the variable 'age' however, had a slightly higher coefficient.

The results in an individualistic society leaves a sense of surprise. A lot of previous literature does describe how venture capital firms syndicate in these type of societies. From the biggest venture capital markets in the west, Sapienza et al. (1996) even emphasized how firms the United States and the United Kingdom are the most involved in the startups they invest in, which are considered the most individualistic places in the world. The data shows that a lot of firms do indeed syndicate, but it does not show that an increase of syndication leads to an increase of business performance of the startups.

To conclude that venture capital syndication has no effect in individualistic societies based on this study is too bluntly and short sighted. Previous scholars did show a lot of empirical evidence of syndication and the performance of startups (Hochberg et al., 2007; Brander et al., 2002). These authors did however, used different measures for startup performance such as IPO, acquisition or the annual rate of return. There are some possible explanations for the surprising results in the individualistic society to be found in the used data. There seemed to be an indication of multicollinearity between degree- and betweenness centrality. The tolerance score was however not low enough to completely disregard the analysis, but it is good to be aware of the possible complications. The extra samples in section 6.5 did show that the occurrence of multicollinearity is common in other samples too. The presence of multicollinearity may be explained due of the following; when a venture capital firm does not syndicate, they immediately score a zero for both type of centralities. In situations like this, the variables are linked to each other, which is not ideal in a regression model since it can create biased and distorted coefficients. This is for example visible in the regression analysis of the first sample. When betweenness centrality is added in the third model, the significance of degree centrality decreases from $p<0.001$ to $p<0.05$. The multicollinearity may very well be the reason for this radical decrease. Moreover, while the variables were transformed to get a suitable distribution, the skewness- and kurtosis score were sometimes still very much outside of the preferred threshold as described by Hair et al. (2010). This also means the results ought to be interpreted with more care.

Notable to say, is that all control variables showed a significant effect. They also contributed to the quality of the regression models. Especially the number of employees in a startup showed a high standardized beta compared to the other predictors. In the end, even though the regression models only contained four to five predictors, they explained 14.2% and 19.8% of the dependent variable in sample one and two respectively.

7.5 Reflection limitations

Initial limitations regarding the research methodology were discussed in section 4.6. Most notable example was that the database only contained the top five venture capital investors of each startup. Also, by conducting a explorative study in a relationship that is rather unexplored, other possible moderators besides national culture may be present that the researcher is unaware of.

After conduction the research, other limitations occurred. First of all, as explained in the discussion, multicollinearity was very present in both samples, the bivariate analyses showed that this was mostly due to the high positive correlation between the average degree- and betweenness centralities.

Moreover, while the variables were transformed to get a suitable distribution, the skewness- and kurtosis score were often still very much outside of the preferred threshold as described by Hair et al. (2010). This means the variables were not always sufficiently distributed. Even though this is not a strict requirement for a regression analysis, it does make the results les precise. This can be considered a limitation regarding the data.

Also, the second sample contained one more control variable opposed to the first sample. It can be seen as a limitation since these samples were to be compared with each other. It was a conscious choice in the research to take the control variable 'size' into the second sample even though it was absent in the first sample. While Schjoedt & Sangboon (2015) state it impacts the generalizability of the research, it does bring more power to the second sample. Moreover, in an exploratory research such as this, it is important to take all significant control variables into account (Brunetti & Weder, 1998).

Lastly, while both samples had enough cases to perform a regression analysis according to Hair et al. (2010), the samples did not have the exact same amount of cases. Rusticus & Lovato (2014) state how the power of the analysis increases when the sample size increases. However, they also state that when comparing two samples, the power will be higher when both samples are supplemented with the same amount of cases. In this research, it was decided tho maintain a maximum sample size for both analyses. Especially the power for the second sample (United Kingdom) increased due to this since it has approximately 1000 more cases than than the first sample. However, the unequality in sample sizes does ensure a decrease in analysis power.

7.6 Future research

It is important to suggest future directions for more research regarding the topic presented in this research. Firstly, it ought to be interesting to figure out what the reason is for the highly positive relationship between degree- and betweenness centrality. It is also currently unknown if the phenomenon happens in every setting, as of right now, it was tested in four samples that score very high regarding collectivism or individualism. Calculating the degree- and betweenness centrality as NetworkX suggests may not be the only way to operationalize strong- and weak ties. Perhaps another way can decrease the high multicollinearity between these two theoretical constructs. A completely different research strategy was executed by Petróczi et al. (2007), where the scholars measured tie strength with a qualitative approach. By using a survey, the researchers could quantify ties on a more detailed level. This gives the possibility for more in-depth knowledge why venture capital firms choose their network position. Their method could be applied to gain more knowledge and take a different approach regarding national culture as a moderator. However, applying this method would carry great complexities since one would probably need to gather qualitative data in multiple countries.

Secondly, as suggested in this research, there is a high probability that the economic development of a country also influences the relationship of the venture capital network position and the business performance of startups (Yang et al., 2018). To measure this, the same research setup like this can be enforced. For example, one can use two highly collectivistic societies for this research, as a significant result was find in this research in a collectivistic setting.

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Appendices

Appendix 1: Deviation high-tech / low-tech industries

Table 10: Cases of high-tech and low-tech industries per sample

R&D intensity	Industry	Sample 1 (Cum%)	Sample 2 (Cum%)
High-tech	Aircraft & spacecraft, automotive	5 (2.1%)	40 (3.3%)
	Radio, TV, communications	4 (3.8%)	62 (8.4%)
	Health care, pharmaceuticals, biotechnology	15 (10.1%)	119 (18.2%)
	Machinery, technology hardware, FinTech	23 (19.7%)	130 (28.9%)
	Software, computer services, apps, IT	83 (54.6%)	290 (52.8%)
Low-tech	Miscellaneous	108 (100%)	547 (100%)
Total (N)		238	1215

Appendix 2: Sample 1 – Univariate analysis

Table 11: descriptive table sample 1

Variable	N	Mean	St. dev.	Min	Max
Dependent variable					
Revenue _LN	238	0.669	0.512	0.000	2.08
Independent variable					
Average_DC_LN	238	-6.261	1.389	-9.210	-3.222
Average_BC_LN	238	-7.740	1.216	-9.210	-4.344
Control variable					
Number_of_investors_LN	238	0.952	0.892	0.000	2.996
Age_LN	238	2.311	0.527	1.099	4.511

Table 12: Skewness and Kurtosis score sample 1

Variable	Skewness	SE skewness	Skewness score	Kurtosis	SE Kurtosis	Kurtosis score
Dependent variable						
Revenue _LN	0.404	0.158	2.557	-0.101	0.314	-0.322
Independent variable						
Average_DC_LN	-0.224	0.158	-1.418	-0.202	0.314	-0.643
Average_BC_LN	0.889	0.158	5.627	0.262	0.314	0.834
Control variable						
Number_of_investors_LN	0.440	0.158	2.785	-1.066	0.314	5.147
Age_LN	1.065	0.158	6.740	2.364	0.314	7.529

Appendix 3: Sample 1 – Assumptions

Figure 5: Residual plot sample 1

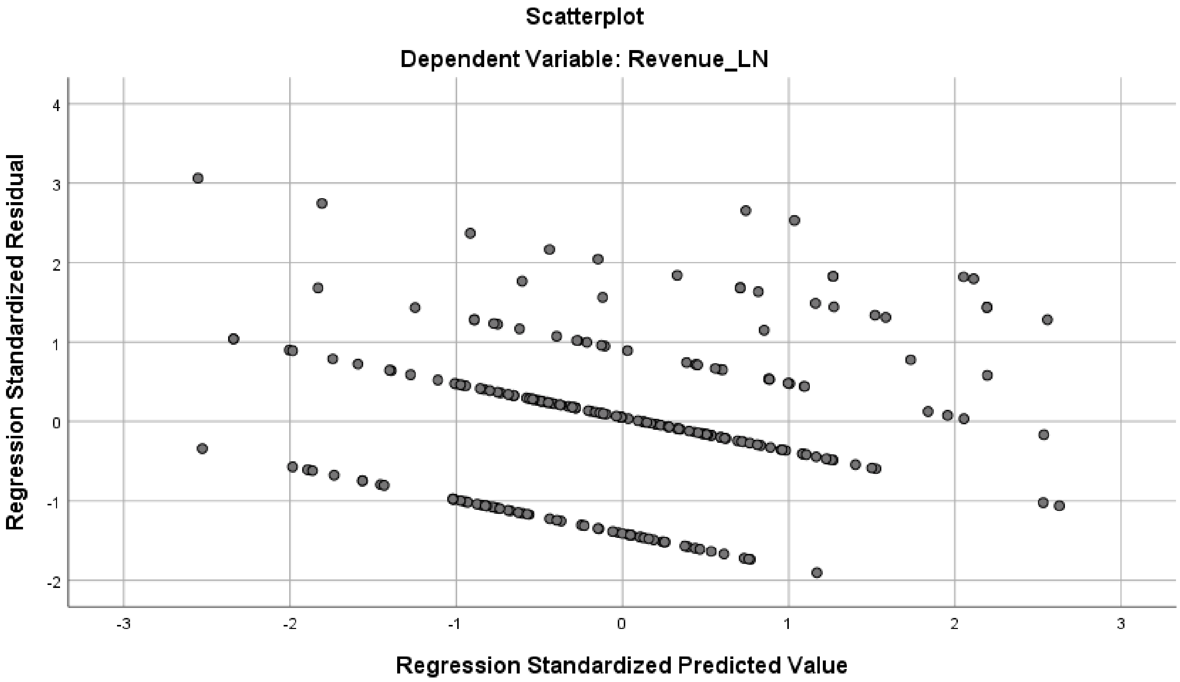


Table 13: Multicollinearity sample 1

Variable	Tolerance	VIF
Average DC	0.141	7.103
Average BC	0.142	7.033
Number of investors	0.760	1.316
Age	0.801	1.249

*Table 14: Bivariate analysis sample 1, , p < 0.001***, p < 0.01**, p < 0.05**

		1	2	3	4
1	Average DC	1			
2	Average BC	0.923***	1		
3	Number of investors	0.308***	0.285***	1	
4	Age	-0.130*	-0.055	-0.412***	1

Figure 6: Normal probability plot sample 1

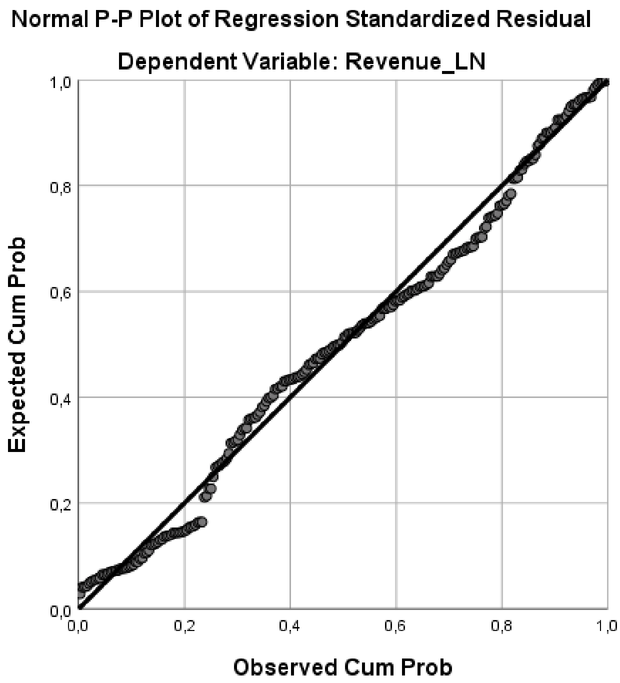
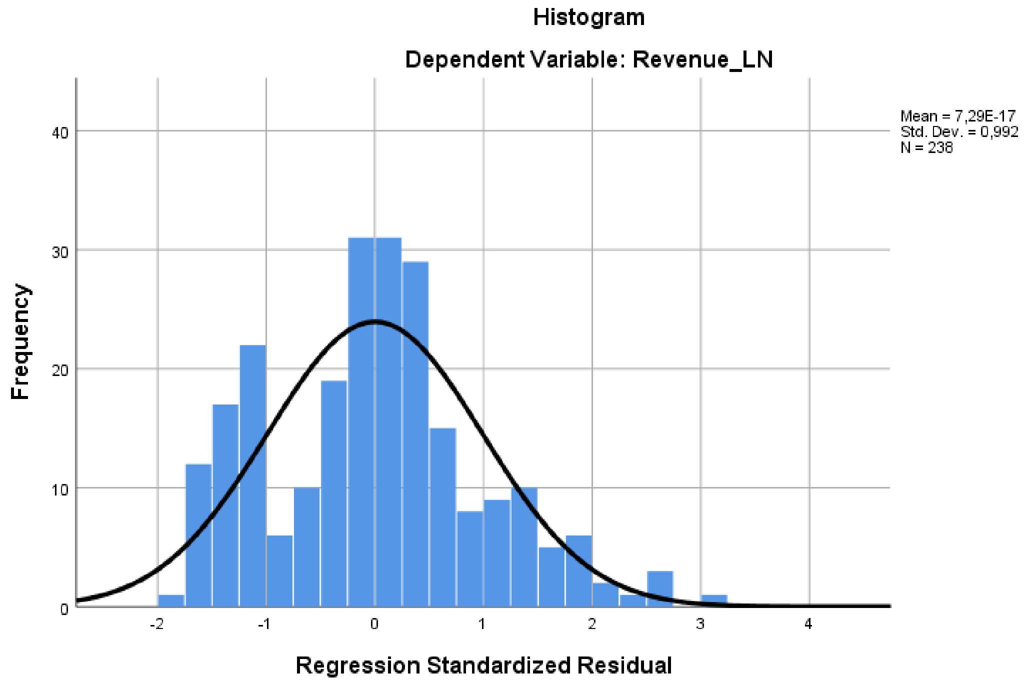


Figure 7: Histogram sample 1



Appendix 4: Sample 1 – Regression results

Table 15: Model summary sample 1

Model summary[d]

Model	R	R square	Adjusted R square	St. Error of the estimate	R square Change	df1	df2	Sig. F Change
1	,322	,104	,096	,48651	,104	2	235	,000
2	,391	,153	,142	,47389	,050	1	234	,000
3	,393	,154	,140	,47457	,001	1	233	,569

a. Predictors: (Constant), Age_LN, Number_of_Investors_LN
b. Predictors: (Constant), Age_LN, Number_of_Investors_LN, Average_DC_LN
c. Predictors: (Constant), Age_LN, Number_of_Investors_LN, Average_DC_LN, Average_BC_LN
d. Dependent Variable: Revenue_LN

Table 16: Model fit sample 1

ANOVA[a]

Model		Sum of squares	df	Mean square	F	Sig.
1	Regression	6,423	2	3,212	13,569	,000[b]
	Residual	55,623	235	,237		
	Total	62,046	237			
2	Regression	9,496	3	3,165	14,096	,000[c]
	Residual	52,549	234	,225		
	Total	62,046	237			
3	Regression	9,570	4	2,392	10,622	,000[d]
	Residual	52,476	233	,225		
	Total	62,046	237			

a. Dependent variable: Revenue_LN
b. Predictors: (Constant), Age_LN, Number_of_Investors_LN
c. Predictors: (Constant), Age_LN, Number_of_Investors_LN, Average_DC_LN
d. Predictors: (Constant), Age_LN, Number_of_Investors_LN, Average_DC_LN, Average_BC_LN

Table 17: Coefficients table sample 1

Coefficients[a]

Model		Unstandardized B	Coefficients Std Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-,199	,174		-1,145	,253
	Number_of_investors_LN	,152	,039	,264	3,896	,000
	Age_LN	,313	,066	,323	4,757	,000
2	(Constant)	,378	,230		1,643	,102
	Number_of_investors_LN	,110	,039	,192	2,795	,006
	Age_LN	,314	,064	,323	4,896	,000
	Average_DC_LN	,086	,023	,234	3,699	,000
3	(Constant)	,258	,312		,825	,410
	Number_of_investors_LN	,112	,040	,195	2,826	,005
	Age_LN	,321	,065	,330	4,909	,000
	Average_DC_LN	,117	,059	,318	1,980	,049
	Average_BC_LN	-,038	,067	-,091	-,570	,569

a. Dependent Variable: Revenue_LN

Appendix 5: Sample 2 – Univariate analysis

Table 18: descriptive table sample 2

Variable	N	Mean	St. dev.	Min	Max
Dependent variable					
Revenue _LN	1215	0.851	0.466	0.000	2.079
Independent variable					
Average_DC_LN	1215	-6.277	1.517	-10.131	-2.759
Average_BC_LN	1215	-8.363	2.434	-19.341	-3.442
Control variable					
Number_of_investors_LN	1215	0.959	0.963	0.000	3.611
Age_LN	1215	2.685	0.692	1.099	6.861
Size_LN	1215	5.274	1.148	4.317	9.210

Table 19: Skewness and kurtosis score sample 2

Variable	Skewness	SE skewness	Skewness score	Kurtosis	SE Kurtosis	Kurtosis score
Dependent variable						
Revenue _LN	-0.111	0.070	-1.586	-0.086	0.140	-0.614
Independent variable						
Average_DC_LN	-0.300	0.070	-4.286	-0.402	0.140	-2.871
Average_BC_LN	-1.273	0.070	-18.186	2.465	0.140	17.607
Control variable						
Number_of_investors_LN	0.579	0.070	8.271	-0.862	0.140	-6.157
Age_LN	0.869	0.070	12.414	1.813	0.140	12.950
Size_LN	1.494	0.070	21.343	2.000	0.140	14.286

Appendix 6: Sample 2 – Assumptions

Figure 8: Residual plot sample 2

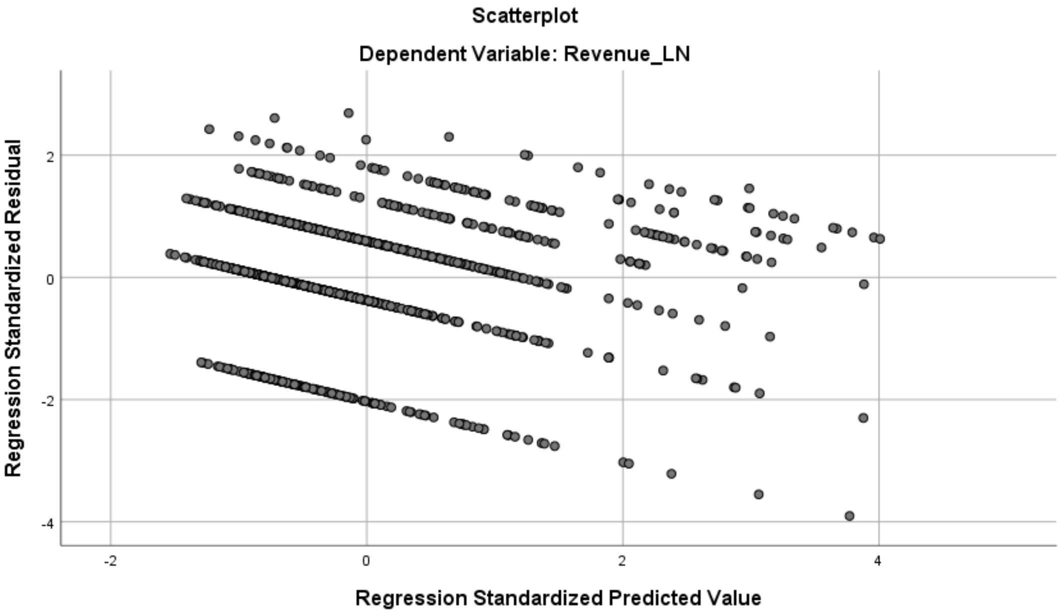


Table 20: Multicollinearity sample 2

Variable	Tolerance	VIF
Average DC	0.164	6.097
Average BC	0.172	5.808
Number of investors	0.676	1.480
Age	0.721	1.387
Size	0.871	1.147

*Table 21: Bivariate analysis sample 2, p < 0.001***, p < 0.01**, p < 0.05**

		1	2	3	4	5
1	Average DC	1				
2	Average BC	0.909***	1			
3	Number of investors	0.481***	0.441***	1		
4	Age	-0.278***	-0.249***	-0.420***	1	
5	Size	-0.092**	-0.107***	-0.086**	0.346***	1

Figure 9: Normal probability plot sample 2

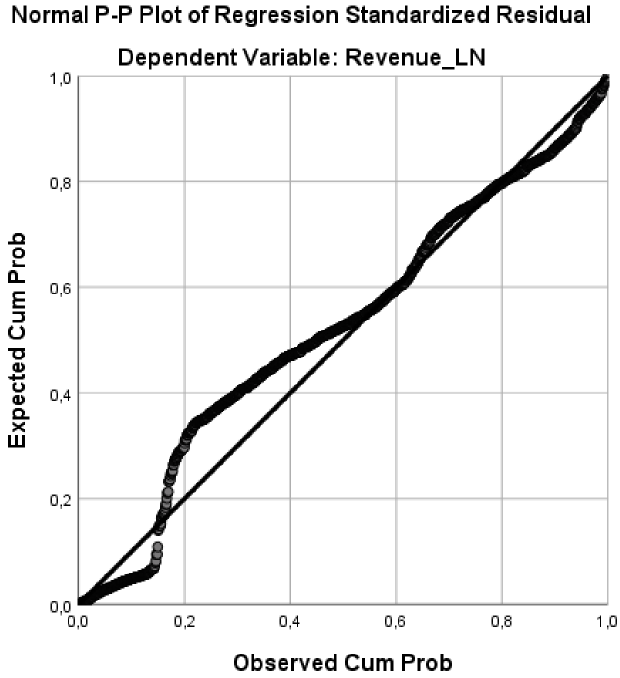
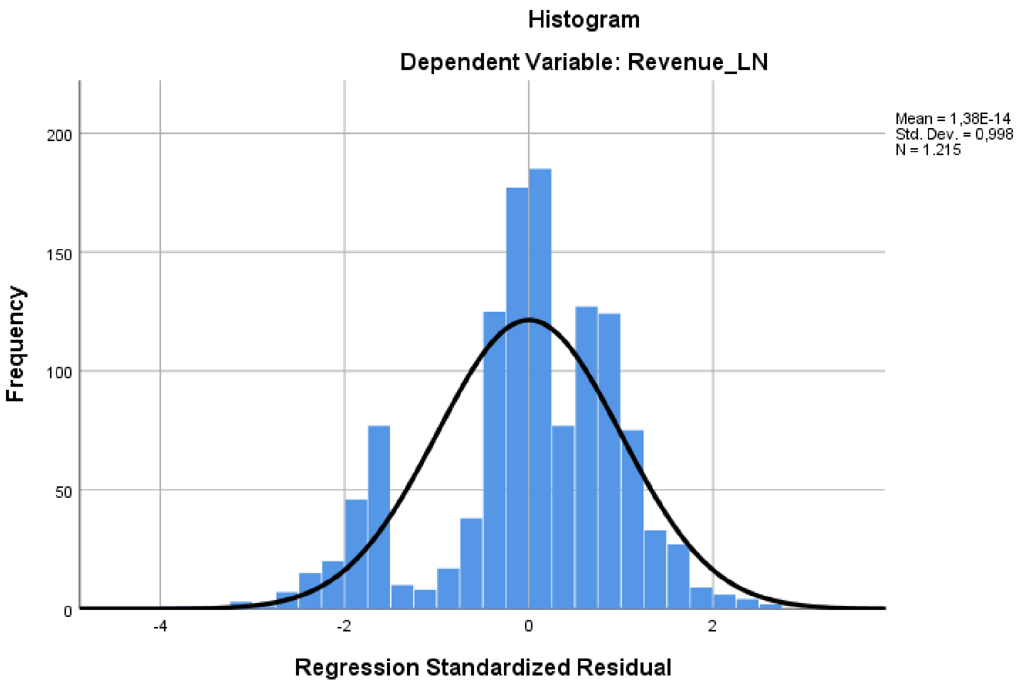


Figure 10: Histogram sample 2



Appendix 7: Sample 2 – Regression results

Table 22: Model summary sample 2

Model summary[d]

Model	R	R square	Adjusted R square	St. Error of the estimate	R square Change	df1	df2	Sig. F Change
1	,445[a]	,198	,196	,41801	,198	3	1211	,000
2	,445[b]	,198	,196	,41808	,000	1	1210	,442
3	,445[c]	,198	,195	,41825	,000	1	1209	,951

a. Predictors: (Constant), Age_LN, Number_of_Investors_LN, Size_LN
b. Predictors: (Constant), Age_LN, Number_of_Investors_LN, Size_LN, Average_DC_LN
c. Predictors: (Constant), Age_LN, Number_of_Investors_LN, Size_LN, Average_DC_LN, Average_BC_LN
d. Dependent Variable: Revenue_LN

Table 23: Model fit sample 2

ANOVA[a]

Model		Sum of squares	df	Mean square	F	Sig.
1	Regression	52,211	3	17,404	99,602	,000[b]
	Residual	211,603	1211	,175		
	Total	263,814	1214			
2	Regression	52,315	4	13,079	74,824	,000[c]
	Residual	211,499	1210	,175		
	Total	263,814	1214			
3	Regression	52,315	5	10,463	59,811	,000[d]
	Residual	211,499	1209	,175		
	Total	263,814	1214			

a. Dependent variable: Revenue_LN
b. Predictors: (Constant), Age_LN, Number_of_Investors_LN, Size_LN
c. Predictors: (Constant), Age_LN, Number_of_Investors_LN, Size_LN, Average_DC_LN
d. Predictors: (Constant), Age_LN, Number_of_Investors_LN, Size_LN, Average_DC_LN, Average_BC_LN

Table 24: Coefficients table sample 2

Coefficients[a]

Model		Unstandardized B	Coefficients Std Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-,266	,071		-3,747	,000
	Number_of_investors_LN	,035	,014	,072	2,538	,011
	Age_LN	,099	,020	,147	4,858	,000
	Size_LN	,155	,011	,382	13,896	,000
2	(Constant)	-,222	,091		-2,441	,015
	Number_of_investors_LN	,030	,015	,062	1,982	,048
	Age_LN	,100	,020	,149	4,903	,000
	Size_LN	,155	,011	,383	13,909	,000
	Average_DC_LN	,007	009	,023	,769	,442
3	(Constant)	-,222	,092		-2,416	,016
	Number_of_investors_LN	,030	,015	,062	1,982	,048
	Age_LN	,100	,020	,149	4,900	,000
	Size_LN	,155	,011	,383	13,869	,000
	Average_DC_LN	,008	,020	,026	,411	,681
	Average_BC_LN	-,001	,012	-,004	-,061	,951

a. Dependent Variable: Revenue_LN

Appendix 8: Remaining multicollinearity statistics

Table 25: Multicollinearity sample 3 (USA)

Variable	Tolerance	VIF
Average DC	0.099	10.107
Average BC	0.113	8.880
Number of investors	0.514	1.946
Age	0.699	1.431
Size	0.850	1.176

*Table 26: Bivariate analysis sample 3 (USA), p < 0.001***, p < 0.01**, p < 0.05**

		1	2	3	4	5
1	Average DC	1				
2	Average BC	0.941***	1			
3	Number of investors	0.660***	0.600***	1		
4	Age	-0.328***	-0.284***	-0.423***	1	
5	Size	-0.030**	-0.012	-0.081***	0.372***	1

Table 27: Multicollinearity sample 4 (Australia)

Variable	Tolerance	VIF
Average DC	0.119	8.434
Average BC	0.122	8.197
Number of investors	0.714	1.400
Age	0.756	1.323
Size	0.800	1.250

*Table 28: Bivariate analysis sample 4 (Australia), p < 0.001***, p < 0.01**, p < 0.05**

		1	2	3	4	5
1	Average DC	1				
2	Average BC	0.934***	1			
3	Number of investors	0.471***	0.450***	1		
4	Age	-0.101	-0.112	-0.296***	1	
5	Size	-0.076	-0.012	-0.091	0.403***	1