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Network position and market maturity: how to be innovative?

Analyzing the role that market maturity plays as a moderator on the effect that a venture capital firms' network position has on innovativeness of backed firms

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Abstract

The findings of multiple studies suggest that the network position of venture capital firms (VCs) can stimulate innovativeness of their backed firms. However, there is an ongoing debate in the academic field regarding which specific network position stimulates innovativeness most. Possibly, the level of market maturity is the underlying reason for when, which specific type of network position is most valuable for enhancing innovativeness. The aim of this study was to find out to what extent this is the case. In order to accomplish this, two different samples were drawn from a database of Crunchbase. One sample contained VCs with their backed firms operating in an emerging market, while the other sample included VCs with their backed firms active in a mature market. For each sample, a multiple regression analysis was conducted. The results of these analyses led to the conclusion that there is not a specific network position of VCs that significantly enhances the innovativeness of backed firms in both types of markets. Thereby, the findings indicate that the level of market maturity does not moderate the effect that a VC's network position has on the innovativeness of VC-backed firms.

1. Introduction

The development of innovative products plays a primary role within society, as it contributes to the global economy, economic growth and employment (Ahlstrom, 2010; Hitt, Ireland, Sirmon, & Trahms, 2011). Economic growth is the most important mechanism for raising the world's living standard (Helpman, 2009), showing the importance and value that innovations bring. This all implies that bringing innovations to the market successfully, is something that everyone reaps the benefits from. For this reason, it is important to determine how innovativeness can be stimulated.

Research indicates that venture capital activity is one of these stimulating factors for innovativeness (Kortum & Lerner, 2001; Lerner & Nanda, 2020). Investing is not the only way in which venture capital firms (VCs) have a positive impact on innovativeness, as it is found that on-site involvement of VCs also is an important determinant of innovation in the backed firms (Bernstein, Giroud, & Townsend, 2016). Multiple studies confirm this view by finding that a VCs' business network, assistance, and provided input are important ways in which VCs add value to their backed firms apart from investments (Kaplan & Strömberg, 2004; Stuart, Hoang, & Hybels, 1999). In essence, the findings of these studies suggest that the value gained from, inter alia, VCs' networks leads to an increase in innovativeness within the backed firms. The idea of networks influencing innovativeness is supported by another study. This study found that innovativeness depends positively on internal and external networks (Farace & Mazzotta, 2015). However, this does raise the question what type of VC network specifically contributes most to innovativeness.

A VC syndication network is comprised of VCs investing in a project together (Yang, Li, & Wang, 2018). The act of jointly investing is interesting for VCs, as it allows them to share expertise and financial risk among other things (Bygrave, 1987; Gompers, 1995). Different types of syndication networks can be distinguished. Strong and weak ties represent the relationships between actors within a network, and are often used to identify these different types of networks (Han, 2008). Strong and weak ties are both found to be important for innovation, despite fulfilling different roles (Lowik, van Rossum, Kraaijenbrink, & Groen, 2012). This leads to the interesting debate which one of these types of ties is actually most beneficial for which firms (Mariotti & Delbridge, 2001).

The amount of time, emotional intensity and intimacy, and the reciprocal service of the relationship determine the strength of a tie (Granovetter, 1973). Strong ties are characterized by high levels of interaction, communication, emotional attachment, and trust. Strong ties reduce the risks of opportunism and are needed for facilitating complex knowledge transfer (Lowik et

al., 2012). On the contrary, weak ties are characterized by the opposite traits. Weak ties are network relationships that provide access to non-redundant information (Levin & Cross, 2004), which is argued to be important for innovativeness. Weak ties are closely related to structural holes. These structural holes are gaps in information flows between actors linked to the same network but not to each other. Weak ties are used to bridge structural holes and allow disconnected groups to get in touch with each other (Burt, 1997).

There are contradictory empirical evidences revolving around the debate between which of the two different types of networks is most beneficial for innovativeness. For instance, research found that a network rich in structural holes facilitates product development (Batjargal, 2010). On the contrary, a study found that strong ties showed a positive relationship with innovation performance (Shuang & Zeng, 2019).

When looking at this debate in the light of VCs specifically, facing either an emerging or mature market might be one of the reasons for the contrasting results. Ahlstrom & Bruton (2006) found that in the studied emerging markets, VCs need to make strong personal networks more important. The results showed that these strong personal networks are necessary in order to efficiently carry out activities like selecting, monitoring, adding value and exiting from the backed firms. The authors argue that the presence of an emerging market in the studied countries, was the determinant reason for why strong personal networks were found to be of great importance for VCs.

Yang et al. (2018) concluded that the strong ties gained from social closure matters most in determining the performance of the VC-backed firms. It was argued that the emerging market that these studied VCs and backed firms were facing, made it relevant for VCs to build trust, and thus make use of strong ties in the network. Thereby the results and argumentation of Yang et al. (2018) harmonize with those of Ahlstrom & Bruton (2006). Furthermore, the former authors suggest that future research perhaps should look into whether in mature markets weak ties and structural holes are a more potent factor to influence performance.

The argumentation of Ahlstrom & Bruton (2006), and Yang et al. (2018) that strong ties are more important for operating in an emerging market is interesting. However, both these two studies were only conducted in countries with an emerging market, and did not focus on innovativeness specifically. This does raise the question whether the argumentation also holds for innovativeness in countries facing an emerging market. Additionally, finding out if a network rich in weak ties and structural holes would be more beneficial for innovativeness in countries containing a mature market is intriguing.

In the study of Xiao & Tsui (2007) it was concluded that, on an individual level,

structural holes were detrimental in the studied emerging market. However, the authors do provide a different reason than the emerging market influencing this outcome. Namely, it is argued that the presence of a collectivistic culture is the main reason why structural holes had a detrimental effect. Although this explanation is focusing on the individual level and leaves VCs out of the occasion, it might still be a relevant moderator for the effect that VC networks have on innovativeness.

To summarize, innovativeness plays a key role for firms and society in general. Innovativeness is found to be significantly stimulated by VCs. VCs often invest together which is called syndication. The activity of syndicating leads to different network positions of VCs. Research has found contradictory results regarding which of these network positions stimulates innovativeness most. One of the reasons could be the maturity of a market playing a role in whether strong or weak ties are most beneficial. However, it remains unclear whether this is actually the case and what the effect of this is on innovativeness in particular. Due to the major importance that innovativeness has for VCs, their backed firms, economic growth and society in general, gaining insight in this would provide significant value. Therefore the purpose of this study is to examine this burning issue. The main research question is formulated as follows:

To what extent does market maturity moderate the effect that a VC's network position has on the innovativeness of a VC-backed firm?

In order to answer the main research question, two sub-questions are formulated. These two sub-questions are:

1. Which VC's network position is most beneficial for innovativeness of the VC-backed firms in an emerging market?

2. Which VC's network position is most beneficial for innovativeness of the VC-backed firms in a mature market?

This study aims to extend the existing literature by giving insight if and how the maturity of a market influences which VC's network position is most beneficial for innovativeness. The results will contribute in the ongoing debate between strong and weak ties. Additionally, the knowledge provided by this study will help VCs to determine how to position themselves in a network. This for the reason that it helps to take into account how the combination of network position and market maturity may jointly increase the innovativeness in the backed firms. Also when deciding in which firms to invest, this new knowledge can be helpful. It namely provides VCs to opportunity to look into whether their network position allows for effectively bringing

about innovations in the particular settings a specific potential backed firm faces. Ultimately, this new knowledge might lead to an overall increase in innovativeness. This in turn may contribute to global economy, economic growth and employment. Meaning this research is of great value and relevant to multiple groups of interest.

To answer the research question, a quantitative study will be conducted. For this study, a database of Crunchbase containing information of more than 700.000 VC-backed firms is available. The database provides information about the network position of VCs, as well as the amount of patents and trademarks that were obtained by the VC-backed firms. These patents and trademarks will be added up, and can together be seen as the proxy indicator for innovativeness. Comparing two different types of markets can be done by conducting two distinct regression analyses. The results of these regression analyses will show the relationships between the different variables, making it possible to answer the main research question. By answering the main research question, this study will contribute to the academic field.

Reviewing the existing literature and coming up with a conceptual model in the next chapter, is the first step in answering the research question. Hereafter, the methodology will be described, after which the results of the regression analyses will be discussed. This is followed by the conclusion, and theoretical implications. Afterwards, the managerial and societal implications will be described. Finally, the limitations, and possibilities for future research are discussed.

2. Theoretical framework

In order to define hypotheses and to come up with a conceptual model, the existing literature on this topic needs to be assessed. It is important to zoom in on VC syndication in general, the two different mechanisms revolving around network positions, and to provide an overview of what an emerging market and a mature market comprises.

2.1 VC syndication

In this paragraph, the major aspects revolving around VC syndication will be described. Also the ways in which VC syndication is responsible for value creation will be addressed. Thereby, it will become clear how VC syndication may ultimately stimulate innovativeness in the backed firms.

VCs can be defined as: *intermediaries in capital markets that provide funding for startup companies that have potential for high growth* (van Pottelsberghe de la Potterie & Romain, 2004). VCs play a determinant role in providing growth capital to young and innovative firms. Providing this necessary capital to constrained entrepreneurs is not the only way in which VCs are helping out these firms (Hopp & Rieder, 2011). Being involved on-site in the firms, providing input, and giving the opportunity to make use of the VC's business network are all important ways in which VCs provide value for the firms (Bernstein et al., 2016; Kaplan & Strömberg, 2004; Stuart et al., 1999). VCs invest in firms and perform all these activities in the hope of generating superior returns which will compensate the VCs for the taken risks (Van Osnabrugge, 2000). Innovativeness of the VC-backed firms is important in generating these superior returns, as it has a direct positive effect on financial position and firm value (Rubera & Kirca, 2012). This makes it relevant for VCs to stimulate innovativeness in the backed firms, since it allows for an increased chance in generating superior returns. Thereby innovativeness is of major importance for both the VC and the backed firm.

In some cases, VCs benefit from combining their expertise regarding investments when risks are more salient (Hopp & Rieder, 2011). The phenomenon that VCs are jointly investing in a project, is called syndication. Syndication simply means that two or more VCs share in financing a particular firm (Brander, Amit, & Antweiler, 2002). For VCs, syndicating leads to an increase of their social networks (Chen & Qiu, 2019).

A syndication network has more benefits for VCs than only sharing expertise. It namely also helps to diversify risks (Lockett & Wright, 2001). It is argued that these risks are both shared and reduced by syndication. VCs namely try to share the risk associated with a particular investment by involving another VC in the financing. Next to that, VCs attempt to reduce the

risk by sharing information with another VC. The aim of this is to obtain a superior selection and management of the investments made.

Another benefit that syndication brings for VCs is the expansion of the scope of operation (Sorenson & Stuart, 2001). It is found that a VC is more likely to invest in a far-off target when it has co-invested in the past with other members of the syndicate financing that target. Thereby, the geographical scope of investment of VCs can be increased by getting involved in a syndicate.

Finally, syndication also limits the entries of competing VCs. Hochberg, Ljungqvist, & Lu (2010) namely found evidence that markets in which incumbent VCs maintain syndication networks, are indeed associated with reduced entry of new VCs. The found effect was large, and thus showing another important reason why syndication can be beneficial for VCs.

All the mentioned benefits show that syndication is something that might provide significant value for VCs. Nevertheless, the VC itself is not the only party gaining from syndication. As Tian (2012) found that the backed firms experience significant benefits when being backed by VC syndicates compared to individual VCs. The study shows that VC syndication creates value for the backed firms in two ways. First, the product market value is found to be significantly higher. Innovation is nurtured by VC syndicates, and it helps to achieve a better post-IPO operating performance. Second, VC syndication is responsible for creating financial market value for the backed firms.

As described previously, syndication leads to an increase of VCs' social networks (Chen & Qiu, 2019). This raises questions about how to manage these in an efficient manner. It might be of high strategical importance to determine in what kind of social networks VCs want to be included in. This can namely be crucial to effectively reap all the mentioned benefits from syndication. The value gained from syndication leads to an increased performance, and possibly innovativeness, in the VC-backed firms. Hochberg, Ljungqvist, & Lu (2007) namely found that better-networked VCs experience significantly better performance in their backed firms.

More specifically, the results indicate that possessing a central network position as a VC yields better results for the backed firms in the form of successfully exiting through an IPO or an acquisition. The authors also argue that indirect relationships have a less prominent role in the venture capital market. These results of Hochberg et al. (2007) can already be seen as a tentative indication which network position might provide most value. Nevertheless, it remains unspecified how VCs should concretely position themselves within a network in order to spur innovation.

All the above lays a foundation in order to grasp of what a VC syndication network

comprises. Also how value creation due to syndicating takes place for both VCs and the backed firms was touched upon. Next to that, it was described how VC syndication may ultimately help in stimulating innovativeness in the backed firms. However, the act of syndicating also raises questions. It remains opaque which network position is most beneficial. Especially, how these network positions specifically contribute to innovativeness is still an important issue. Delving further into the different network positions might give more insight, and might also help with understanding of what effective VCs' networks should look like for specific purposes and under particular circumstances.

2.2 Network positions

In this paragraph, it will be explained how the two main mechanisms regarding network positions relate to each other. Especially the way in which both network positions may stimulate innovativeness will be addressed. Although both strong and weak ties have been briefly described, a further understanding of the core ideas is essential. Also finding out the underlying reasons why each network position is supported, extends the knowledge that is required in order to formulate well-grounded hypotheses.

2.2.1 Strong ties

As was described in the introduction, strong ties are defined by high levels of interaction, communication, emotional attachment, and trust. Strong ties are also referred to as dense and redundant connections between actors. Such connections are argued to provide substantial benefits for the actors involved in the network (Coleman, 1988; 1990).

Dense and overlapping relations are possible when occupying a more central location in a social network. This for the reason that an actor occupying such a central location is likely to be perceived as trustworthy by other actors in the network (Tsai & Ghoshal, 1998). This allows for strong ties to develop between actors positioned in the network. Thus, the main idea is that a more central location in a social network will make people trusting each other more. The developed strong ties that result from this trust, lead to more reliable communication channels (Tan, Zhang, & Wang, 2015). Additionally, strong ties reduce the risks of opportunism and are needed for facilitating complex knowledge transfer (Lowik et al., 2012). Furthermore, strong ties ensure solidarity benefits. This is crucial for the tacit characteristics of innovations, that is, knowledge recognition and realization (Rost, 2011).

The importance of strong ties has been proven in multiple studies, also for innovativeness in particular. Namely, it was found that strong ties showed a positive relationship with innovation performance (Phelps, 2010; Shuang & Zeng, 2019). As was

described in the introduction, regarding business performance it is also shown that strong ties of VCs specifically can be a positively influencing factor for the backed firms (Ahlstrom & Bruton, 2006; Yang et al., 2018).

2.2.2 Weak ties

The studies that showed a positive effect between strong ties and innovativeness are somewhat unexpected. Burt (1997) namely mentions that non-redundant information is most conducive for stimulating innovation. The access to this non-redundant information is provided by weak ties (Granovetter, 1973; Levin & Cross, 2004). Weak ties namely help actors to bridge structural holes which allows for disconnected groups to get in touch with each other. This is important, as Burt (1997) argues that actors on each side of a structural hole have access to different flows of information. Individuals that are able to bridge these disconnected actors at each side of a structural hole can broker the flow of information. Due to this information and resources being non-redundant, it is more powerful for stimulating significant innovation (Burt, 1997; Granovetter, 1973).

This means it is encouraged to diversify the network in which one is active. Diversifying the network results in getting access to more non-redundant information, in a more efficient way. Maintaining a connection with actors who are already connected to each other causes low network efficiency, since the information available in the network is redundant (Yang et al., 2018). Thus, a position between many different type of actors is desired. Freeman (1977) argues that the betweenness is a measure for counting the structural holes to which one has exclusive access. In relation to this, the argument of Burt is that the higher the betweenness, the more powerful the network. Furthermore, Burt (1997) argues that weak ties and structural holes lead to entrepreneurial behavior. It can therefore be argued that this non-redundant information allows innovativeness to come to fruition more, than with the redundant information obtained from strong ties.

The importance of weak ties and structural holes was supported by Choi & Zo (2020), who found a negative effect of embedded networks and a positive one of structural holes on innovation performance. Also other studies found positive effects of weak ties and structural holes on (explorative) innovation and product development (Zang, 2018; Vasudeva, Zaheer, & Hernandez, 2013; Batjargal, 2010).

Unfortunately many of the above mentioned studies did not focus on VC's networks specifically, and what the possible effect of this was on the backed firms' innovativeness. It does however provide an overview of how the two main network mechanisms may contribute

to business performance and innovativeness.

Scratching the surface of both VC syndication and network positions separately has provided a solid understanding of what these topics consist of. Also how these two topics relate to innovativeness has been described.

2.2.3 Underlying reason for the contradiction

Not many researchers have investigated VC syndication, network positions, and innovativeness in one particular study. Nonetheless, worth mentioning are the studies of Yang et al. (2018) and Ahlstrom & Bruton (2006). The former found that for VCs, strong ties generate better results for the backed firms' business performance. The latter found that VCs profit more from strong relationships for successfully performing the activities related to the backed firms. The two studies obtained data from VCs and backed firms that were operating in emerging markets. In both studies the authors argue that the aspect of being active in an emerging market is the determinant reason why strong ties were found to provide more value.

Xiao & Tsui (2007) found structural holes to be detrimental in an emerging market on an individual level. The authors argue however that not the maturity of the market was the underlying reason for this, but that the collectivistic culture that was present explains the findings. It could be a possibility that this also was the underlying reason for the results presented in the studies of Yang et al. (2018) and Ahlstrom & Bruton (2006). This for the reason that the studied countries in these researches also contained a collectivistic culture. However, it can also be argued vice versa. Meaning the results of Xiao & Tsui (2007) were found due to the maturity of the market, instead of the collectivistic culture being an important factor.

Next to market maturity and collectivism, type of industry might also be a possible moderator. Rowley, Behrens & Krackhardt (2000) namely suggested that industry characteristics play a role in the effectiveness a specific network position has. Thus, it can be concluded that multiple factors may be seen as potential moderators.

By comparing two different countries, where one contains an emerging market and one a mature market, it can be assessed whether market maturity indeed may play a role as a moderator. A crucial addition to this, is that the cultures of both countries need to have a similar level of collectivism. Also the possible effect that type of industry has, needs to be taken into account when making this assessment. Undoubtedly, there will still be other factors influencing the fact whether strong or weak ties are most beneficial for the backed firms' innovativeness in a specific country. Nevertheless, controlling for collectivism and taken into account the possible effect of industry type will substantially improve the power regarding the conclusion of this

study. Since with including these other two important arguments, the likelihood increases that the results correctly reflect whether market maturity on its own is a significant moderator of the effect that a VCs' network position has on innovativeness. For now, it is interesting to take a closer look at what market maturity revolves around. Also finding out why market maturity might be a significant moderator is necessary in further understanding the possible effect it has.

2.3 Market maturity

This paragraph will address the concept market maturity. In the introduction it became clear that market maturity possibly is a determinant moderator of the effect that a network position has on innovativeness. Getting more acquainted with the concept market maturity will extend the understanding of why this might be a relevant factor influencing the relationship. Therefore, a further explanation of market maturity will be provided in this section.

In this study, market maturity consists out of two distinct categories: the emerging market and mature market. An emerging market encompasses a country that experiences a rapid economic growth, an increase of liberalization of markets, and underdeveloped formal institutions, while having a promising yet volatile market. (Hoskisson, Eden, Lau, & Wright, 2000; Puffer, McCarthy, & Boisot, 2010; Luo, 2002). On the contrary, a mature market can be defined as one that reached a state of equilibrium marked by the absence of significant growth, and experiences a well-established market mechanism (Ganta, Smith, Knoop, Renly, & Kaufman, 2006; Kotabe & Helson, 2000). It must be made clear that in practice, more distinctions in market maturity can be made. For instance, not every non-mature market will be considered to be a promising market. However, only emerging and mature markets will be taken into account in this study.

When looking at the definitions above, it can be concluded that the establishment of formal institutions and mechanisms are key characteristics. The formal institutions capture the number of written rules (Kaufmann & Feeney, 2012) . These include the written constitution, laws, policies, rights and regulations enforced by official authorities. Formal institutions and mechanisms are important factors in distinguishing an emerging market from a mature market. Also Bruton, Ahlstrom & Pukky (2009) argue that many of the institutions assumed to be present in mature markets, may not actually be present in emerging markets. Fundamental differences exist in countries in the world, which can be traced to the given institutions, and therefore to the maturity of a market. Although this is widely acknowledged, it remains unclear how VCs specifically can seek to efficiently control these institutions to their own benefit (Bruton et al., 2009).

A way for VCs of controlling the market maturity to their benefit might be by efficiently managing the network that it is involved in. This for the reason that networks are found to be more important for new business activity in emerging markets than in mature markets (Danis, De Clercq, & Petricevic, 2011). Chen (2001) argues that the underdeveloped formal institutions, that characterize an emerging market, are one of the underlying reasons for why networks are more valuable in a less developed market. Social networks can help to overcome the inefficient institutions by functioning as sources of advice, emotional support, and business resources (Batjargal, Hitt, Tsui, Arregle, & Webb, 2013). These sources can be seen as a necessary replacement for the lack of developed formal institutions.

Another study also showed that developing social and business network ties positively influences the performance in emerging markets with institutionally-challenged conditions (Boso, Story, & Cadogan, 2013). Although Batjargal et al. (2013) affirm that social networks are more important in emerging markets, it is claimed that also in mature markets a high importance of social networks is to be found. Nevertheless, in the study it remains unspecified how in both type of markets the social networks should be structured specifically.

According to Luk et al. (2008) social networks in emerging markets are more beneficial when consisting of more informal, and thus strong, relationships. The authors namely suggest that weaker relationships in emerging markets are risky and should be used with caution. In the study it is also concluded that culture is less able than institutional context to explain variations in the use of informal social capital. Thereby conforming that market maturity might be an important moderator of the effect that network position has on innovativeness.

Kiss & Danis (2008) found that for entrepreneurs in mature markets with developed institutions, weak ties are more prevalent. Likewise, strong ties were more prevalent when lower levels of institutional development were encountered. The authors suggest that entrepreneurs should adjust their network strategies regarding the present level of institutional development. For instance, relying on weak ties in a mature market might be a prerequisite for successfully doing business.

This section reviewed the most prominent literature regarding networking in emerging and mature markets. It is now clear what distinguishes both type of markets from each other. Also how networks and market maturity are related has been addressed. Additionally, it was described how networks can be a necessity for coping with either an emergent or mature market.

After reviewing the existing literature on how VC's networks relate to the backed firms' innovativeness, it is clear that there is still plenty room left for digging further into this insufficiently researched topic. The concepts in this study (i.e. network position, innovativeness

& market maturity) have been separately analyzed by other researchers. Nevertheless, looking at the effects between the three concepts simultaneously is something that has yet not been studied profoundly. The next step in this study is to come up with a conceptual framework and the accompanying hypotheses. Both these will be described in the following section.

2.4 Conceptual framework

Reviewing the literature provided an interesting overview of the leading train of thoughts regarding the main concepts of this study. Next to that, it served as a starting point from where well-grounded hypotheses and a congruent conceptual model can be developed. In this section, the relationships in the conceptual model will be analyzed more profoundly. The conceptual model is shown in Figure 1 below.

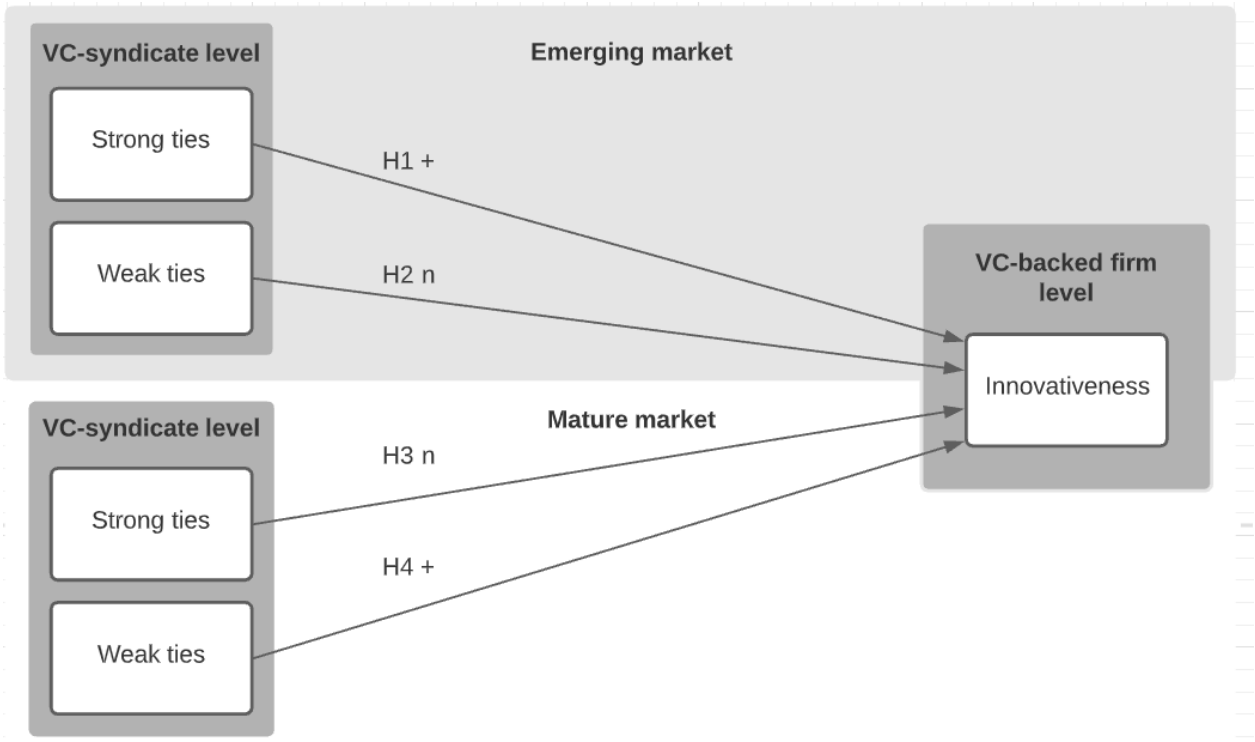

Figure 1: *Conceptual model*

It stands out that there are different sections within the conceptual model. The reason for this is to provide a clear overview at which level the concepts are situated. These different levels are elaborated on further per relationship described below. The ´n´ in the conceptual model means that a neutral relationship between the concepts is expected. In other words, the expectation is that there neither is a significant positive, nor a significant negative relationship between these concepts.

In the previous sections, the two distinct mechanisms revolving around network position

have been analyzed. It was described what they consist of, and how both might positively influence the backed firms' innovativeness and business performance in general. The concepts strong ties and weak ties rank on the VC-syndicate level. This is for the reason that it will be analyzed how the network position of the VC-syndicate influences the innovativeness of the VC-backed firms. Since the innovativeness refers to the innovativeness of VC-backed firms, this concept ranks on the VC-backed firm level.

According to Coleman (1988; 1990), establishing trust and norms between actors within a social network provides most benefits. Having many dense and redundant connections between the actors allows for developing this necessary trust. Occupying a more central location in a network is crucial for achieving these strong ties. As such a location signals trustworthiness to other actors positioned in the network (Tsai & Ghoshal, 1998). Multiple studies found a positive relation between strong ties and innovation performance (Phelps, 2010; Shuang & Zeng, 2019).

On the other hand, it is argued that non-redundant sources of information provide most value. Firms that are able to bridge disconnected actors at each side of a structural hole through weak ties, can broker the flow of information. Since this information and these resources are non-redundant, it is more valuable for innovation (Burt, 1997; Granovetter, 1973). In a more practical sense, this means it is encouraged to diversify the network in which one is active (Yang et al., 2018). This helps with getting access to more non-redundant information, in a more efficient way. Burt (1997) argues that this non-redundant information results in more entrepreneurial behavior. Therefore, it is expected that this type of information leads to an increased innovativeness. The importance of weak ties is emphasized by empirical evidence from multiple studies. Choi & Zo (2020), Zang (2018), Vasudeva et al., (2013), and Batjargal (2010) all found a positive effect of weak ties and structural holes on innovativeness and product development.

It can be concluded that strong and weak ties have both shown to be able to increase innovativeness. A possible explanation for this might be that the mentioned market maturity is the determinant factor for when which network position provides most value. Ahlstrom & Bruton (2006) and Yang et al. (2018) concluded that the emerging market present was the reason for both studies finding that strong personal relationships were more important for VCs and the backed firms. Danis et al. (2011), and Batjargal et al. (2013) conclude that networks are more important in emerging markets than in mature markets. Nonetheless, Batjargal et al. (2013) do point out that social networks are also of high importance in mature markets. It can therefore be assumed that a difference in network position can also significantly influence the

effect on innovativeness in mature markets. The level of market maturity ranks on the country level in the conceptual model. Meaning in this study, all VC-backed firms operating in the same country are facing the same level of market maturity. Inefficient institutions characterize an emerging market, as was described previously. Social networks can replace these inefficient institutions by functioning as sources of advice, emotional support, and business resources (Batjargal et al., 2013). Hence, a social network can help to overcome the lack of developed formal institutions in an emerging market. However, it remains unaddressed which type of network position suits a specific level of market maturity best.

Kiss & Danis (2008) suggest that entrepreneurs should adjust their network strategies regarding the present level of institutional development. For instance, relying on weak ties in a mature market might be a prerequisite for successfully doing business. Luk et al. (2008) found that weaker relationships are risky and can only be used with caution in emerging markets. Hence, it is encouraged to develop strong ties in emerging markets. It was also concluded that culture is less able than institutional context, and thus market maturity, to explain variations in the use of informal social capital. Thereby indicating that market maturity is a more potent moderator compared to a cultures´ level of collectivism.

To summarize, it is found that both strong and weak ties can positively influence innovativeness. The level of market maturity is assumed to be the reason for the contrasting results. When taken all the info above together and looking at VC networks and innovativeness of VC-backed firms specifically, multiple relationships are expected.

The relevant literature leads to the proposition that strong ties provide more value for VCs and the backed firms when innovating in emerging markets. The strong relationships help to overcome the lack of developed formal institutions that characterizes an emerging market. Due to the underdeveloped formal institutions, a need for VCs regarding trustworthy relationships occurs. Since without such strong relationships, there is little certainty to build upon. Obtaining a more central location in a network allows for this type of relationships to flourish. Hence, it is expected that strong ties of VCs have a substantial positive effect on the innovativeness of VC-backed firms operating in emerging markets. This leads to the following proposition:

Hypothesis 1. Strong ties of VCs enhance the innovativeness of VC-backed firms in an emerging market.

Simultaneously, weak ties are not expected to be important in an emerging market. These relationships will namely not help to overcome the lack of developed formal institutions in such a market. Meaning no significant positive relationship is expected between weak ties and innovativeness in an emerging market. Accordingly it is posited:

Hypothesis 2. Weak ties of VCs do not enhance the innovativeness of VC-backed firms in an emerging market.

Finding out whether these two hypotheses can be accepted or rejected, allows for answering the first sub-question. The first sub-question is as follows: *Which VC's network position is most beneficial for innovativeness of the VC-backed firms in an emerging market?*

In mature markets on the other hand, there is a developed market mechanism which contains reliable and mature institutions. Thus, there is no need for VCs to possess a more central location in a network. This necessity is absent, due to the fact that the developed institutions already provide substantial reliability and certainty for VCs and the backed firms. Hence, the necessity for possessing strong relationships in order to overcome weak and unreliable institutions has vanished. Meaning it is expected that strong ties are not a significant factor for increasing innovativeness in mature markets. This leads to the following proposition:

Hypothesis 3. Strong ties of VCs do not enhance the innovativeness of VC-backed firms in a mature market.

Operating in a mature market allows for shifting the focus on using weak ties to bridge structural holes. Bridging structural holes should lead to more entrepreneurial behavior of VC-backed firms. Meaning the more structural holes a VC has, the more opportunities there are to be entrepreneurial, and therefore innovative. Hence, it is expected that using VCs' weak ties to bridge structural holes in a mature market significantly increases the innovativeness of the backed firms. Therefore, the last proposition is as follows:

Hypothesis 4. Weak ties of VCs enhance the innovativeness of VC-backed firms in a mature market.

Accepting or rejecting these latter two hypotheses, provides the opportunity to answer the second sub-question. This sub-question is as follows: *Which VC's network position is most beneficial for innovativeness of the VC-backed firms in a mature market?*

3. Methodology

Before the hypotheses can be tested, it is of importance to describe the research process. In the following two sections, the research method, and the data collection and sample will be addressed. Afterwards, the measurement development will be described. Ultimately, the research ethics, and the data analysis procedure will be discussed.

3.1 Research method

In order to answer the main research question, the most important literature was discussed first in chapter 2. From this qualitative data, the four mentioned hypotheses were determined. For testing these hypotheses, a database of Crunchbase containing info of more than 700.000 backed firms worldwide with their VCs will be worked with. This database allows for a quantitative study in which regression analyses can be used to answer the two sub-questions of this study. Using regression analyses is an appropriate choice, as it allows for investigating functional relationships among metric variables (Chatterjee & Hadi, 2015).

For answering the two sub-questions of this particular study, two different countries will be analyzed. These two countries will be analyzed by conducting two distinct regression analyses. Meaning two different samples that both represent a distinct country are required. The findings of the regression analysis of the first sample will be used for answering the first sub-question. Similarly, the results of the regression analysis of the second sample provide the opportunity to answer the second sub-question of this study. Afterwards, the answers to both sub-questions will be compared. This comparison allows for providing an answer to the main research question.

However, before the regression analyses can be conducted, it is important to verify which country will be used for each sample. Hence, this is the first step in the research process. Afterwards, both samples can be drawn from the database of Crunchbase. Hereafter, the regression analyses can be conducted and the sub-questions and the main research question can be answered. This whole research process is displayed below in Figure 2. The first step of this process, the country selection, will be described in the following sections.

Figure 2: *Research process*

3.2 Data collection and sample

The two different countries that will be compared are selected on the basis of three main criteria that are shown below in Table 1. It is not uncommon in the academic field to select a country for a sample based on a small number of selection criteria. For instance, Tellis, Yin, & Bell (2009) and Zaki & Rashid (2016) have also used three specific selection criteria for studying certain countries.

Table 1 below shows that one of the two samples needs to represent a country that contains an emerging market, while the other sample needs to represent a country with a mature market. Next to that, the cultures of both these countries need to have a similar level of collectivism. This namely allows for controlling the argument that the level of collectivism might play a role as a moderator instead of market maturity. Lastly, it is required that similar opportunities to be innovative are present in both countries. Furthermore, it must be captivating for firms in both countries to focus on bringing about innovations.

Hence, it is important that the two countries strongly differ on their level of market maturity, while being as similar as possible on the other two selection criteria. This namely allows for measuring the effect of market maturity more accurately in the regression analyses.

Table 1: *Selection criteria countries*

Selection criterion	**Detailed criterion**	**Evaluation**
1. Different level of market maturity	Country 1: contains an emerging market Country 2: contains a mature market It is required that this level of market maturity has been stable in both countries for a prolonged period of time. Additionally, the specific characteristics of either an emerging or a mature market must be met by the country.	Triangulation
2. Similar level of collectivism	The level of collectivism in the cultures of both countries needs to be as similar as possible.	Triangulation
3. Similar innovation perspective	For this criterion, the ability and importance regarding innovations in both countries will be compared. In both countries, it is required that significant innovations can come to fruition. Furthermore, in both countries it should be captivating for firms to focus on innovativeness.	Analyzing multiple dimensions

Triangulation will be used in order to assess whether the countries are meeting the first two criteria. Triangulation means that multiple sources are used to look at one phenomenon, or research topic. Triangulation limits methodological biases, and increases the likelihood of reproducing the findings (Abdalla, Oliveira, Azevedo, & Gonzalez, 2018). In order to come to a well-grounded evaluation regarding the third selection criterion, multiple dimensions will be taken into account. After applying the three selection criteria, it became clear that India and Japan met the requirements and thus provide the possibility to study the effect that market maturity plays as a moderator. Therefore, India and Japan are the countries that will be compared in this study. One sample will thus contain Indian VC-backed firms with their VCs, whereas the other sample contains Japanese VC-backed firms with their VCs. The sample representing India contains a sample size of 114, while 305 is the sample size of the sample representing Japan. Both samples meet the requirement of having a ratio of five observations per independent variable (Hair, Black, Babin, & Anderson, 2014), and thus allow for conducting a regression analysis. In the coming sections, it will be described why India and Japan met the different selection criteria.

3.2.1 Different level of market maturity

Recent literature affirms that the market of India may be viewed as an emerging one. This for the reason that all the analyzed studies that revolve around comparing different types of markets include the South-Asian country within the category of emerging markets (Jain, Merchant, Roy, & Ford, 2019; Katti & Raithatha, 2018; Kanwar & Sperlich, 2019; Valiya Purayil & Lukose, 2021; Col & Sen, 2019). On the contrary, Japan contains a mature market according to the literature. As in multiple recent studies, the Japanese market is classified as a mature one (Jain & Sehgal, 2019; Chotimah & Winanti, 2018; Sivapregasam, Selamat, Rahim, & Muhammad, 2020; Shizume, 2018).

However, it is not only important to look at recent literature for determining the level of market maturity. Numerous VC-backed firms in the database were founded decades ago. Therefore, it is important to verify since when India and Japan were considered to contain an emerging and a mature market. In the early 2000's, the market of India was already seen as an emerging one (Bhati, 2002; Patibandla, 2002; Sarkar & Sarkar, 2000). In the same era, Japan was already considered by multiple studies to have a mature market (Blomström, Gangnes, & La Croix, 2000; Sugiura, 2002; Schmiegelow, 2003). Thereby, it is justified to view the market of India since the year 2000 as an emerging one, and the market of Japan as a mature one.

Also when considering the previously described specific characteristics of an emerging

market, it can be concluded that the Indian market can be seen as such a type of market. The market of India is namely one of the fastest growing markets in the world, while at the same time being characterized by inadequately defined regulations (Shukla, 2017; Gupta & Singh, 2018). On the other hand, the market of Japan shifted in the early 1990s from a pattern of excessive economic growth to one of moderate growth (Sarracino, O'Connor, & Ono, 2019). Additionally, Japan has well-established regulations regarding anti-counterfeiting and protecting intellectual property (Groh & Wallmeroth, 2016). Hence, also considering the specific characteristics of an emerging market verifies the view that India contains an emerging market. At the same time, looking at the specific characteristics of a mature market leads to the conclusion that the Japanese market fits the description. It can therefore be concluded that India and Japan meet the first selection criterion that was displayed in Table 1.

3.2.2 Similar level of collectivism

The second selection criterion entails that the cultures of both countries must contain a similar level of collectivism. As described previously, Xiao & Tsui (2007) found that structural holes were detrimental in the studied emerging market. However, the authors argued that the present emerging market is not the reason for the detrimental effect of the structural holes. It is namely concluded that the presence of a collectivistic culture is the main reason for this. Therefore, it is necessary to control for this explanation in order to effectively study the role that market maturity plays. This can be done by comparing two countries that both have a culture with an almost equal level of collectivism.

Both the cultures of India and Japan are found to have an intermediate level of collectivism. The Indian culture scores 48 on collectivism, whereas the Japanese culture is found to score 46 on this cultural pillar according to the commonly used Hofstede´s country comparison tool (Hofstede Insights, n.d.). Due to both cultures having an almost equal level of collectivism, this factor is not able to have an effect as a moderator in this study. Also Bhawuk (2017) and Triandis (2018) consider the cultures of India and Japan to have a similar level of collectivism. Hence, the choice for comparing India and Japan provides the opportunity to control for collectivism as a possible moderator.

3.2.3 Similar innovation perspective

The aim of this section is to provide a well-grounded argumentation for why India and Japan passed the third selection criterion. This will be done by discussing the ability and importance regarding bringing about innovations in both countries. Additionally, this section provides more background information about how the quantitative findings in chapter 4 should

be interpreted.

Although different matters will be controlled for in the analyses (see the upcoming section 3.2.4), it can still be argued that the results possibly do not completely reflect the role that market maturity might play as a moderator. It is namely debatable whether comparing two different countries is an appropriate way for directly measuring the effect that market maturity has. For this reason, a third selection criterion was applied. This third selection criteria entails that the ability and importance regarding bringing about innovations in both countries is as similar as possible. Multiple dimensions will be taken into account in order to make a justified assessment regarding this third selection criterion.

The first of these, is the innovation index. Groh & Wallmeroth (2016) concluded that the score on the innovation index is substantially higher for Japan compared to India: 5.68 against 4.05 on a scale of 1 to 7. A high innovation index means a high innovation performance of a country. The innovation index is measured through five pillars: ´Institutions and Policies´, ´Human Capacity´, ´Infrastructure´, ´Technological Sophistication´, ´Business Markets and Capital´. It is positive that both countries score intermediate to high results on the innovation index. This namely means that innovations come to fruition in both countries. Therefore, it is unlikely that extreme differences in innovativeness will be found between the VC-backed firms per country. Nevertheless, the fact that Japan scores substantially higher might lead to finding a marginally higher level of innovativeness in the VC-backed firms in Japan.

Additionally, the shareholders are found to be highly protected in both countries. This is beneficial, as this results in shareholders being more confident at innovation investment (Hsu, Tian, & Xu, 2014). Therefore, it is assumed that backed firms in either country have similar possibilities regarding attracting equity in the form of shareholders. This can be an important factor, as it can be argued that these investments significantly contribute to the innovativeness of the backed firms within a certain country.

Lastly, both India and Japan are known to have innovative consumers (Tellis et al., 2009). This means there is a strong demand from consumers for innovative products. Thereby, it can be assumed that for the backed firms in both countries it is captivating to bring innovative products to the market.

To summarize, both countries having intermediate to high scores for the innovation index is favorable. Also the fact that shareholders in both countries are highly protected, and the presence of innovative consumers in both India and Japan is advantageous. Since the countries are rather similar on these aspects, it can be assumed that these matters will not be a reason for a possible found large contrast in innovativeness of VC-backed firms in both

countries.

Due to the difference in market maturity and the described similarities regarding the second and third selection criteria between both countries, there is an increased likelihood that the results of the regression analyses will correctly reflect the role that market maturity plays as a moderator. Therefore, it can be concluded that the choice for comparing India and Japan is a well-grounded one. In Table 2 below, the selection criteria and references are shown that were used to describe the strong difference in market maturity, and the clear similarities regarding the level of collectivism and the innovation perspective between India and Japan.

Table 2: *Selection criteria including used references*

Selection criterion	**References**
1. Different level of market maturity	India: Bhati, 2002; Patibandla, 2002; Sarkar & Sarkar, 2000; Jain, Merchant, Roy, & Ford, 2019; Katti & Raithatha, 2018; Kanwar & Sperlich, 2019; Valiya Purayil & Lukose, 2021; Col & Sen, 2019. Specific characteristics: Shukla, 2017; Gupta & Singh, 2018 Japan: Blomström, Gangnes, & La Croix, 2000; Sugiura, 2002; Schmiegelow, 2003; Jain & Sehgal, 2019; Chotimah & Winanti, 2018; Sivapregasam, Selamat, Rahim, & Muhammad, 2020; Shizume, 2018. Specific characteristics: Sarracino et al., 2019; Groh & Wallmeroth, 2016
2. Similar level of collectivism	Hofstede Insights, n.d.; Bhawuk, 2017; Triandis, 2018
3. Similar innovation perspective	Groh & Wallmeroth, 2016: innovation index Hsu et al., 2014: shareholder protection Tellis et al., 2009: innovative consumers

3.2.4 Type of industry

Besides meeting the selection criteria described in the previous sections, there are other requirements that the samples must meet. One of these, is that the samples need to contain VC-backed firms that are active in distinct industries. This namely allows for taking into account the role that type of industry might play. By comparing the effects for different types of industries, it can be assessed more accurately whether market maturity actually is a significant moderator. However, not all industries are relevant for this study. In this study, innovativeness will be measured by the amount of patents and trademarks per VC-backed firm. While patents and trademarks may play a key role for protecting the VC-backed firms innovative activity, researchers have argued that these are more important in certain industries (Artz, Norman, Hatfield, & Cardinal, 2010; Orsenigo & Sterzi, 2010). Meaning not all industries can be taken into account in the study. Cockburn & Long (2015) presented a survey that shows the extent to which patents are considered to be important per industry. In the survey, respondents active in different industries were asked to rate the importance of patents in their industry. The respondents had to choose between: not important, mildly important, moderately important, and extremely important. The rating 'extremely important' was given by 73% of the respondents in the electronics and software industry, by 79% of the respondents in the energy and chemicals industry, and by 89% of the respondents in the healthcare industry (including biotechnology, pharmaceuticals and medical devices).

According to Antonipillai & Lee (2016), there are more industries where patents and/or trademarks are highly valued. The authors mention the importance of patents and/or trademarks in the industries of technical consulting, technical services, and semiconductors. Lastly, patents and/or trademarks were found to be important in the apps, artificial intelligence, robotics, and automotive industry (Blind, Edler, Frietsch, & Schmoch, 2006; Haney, 2019; Vishnubhakat, 2015; Yun, Jeong, Lee, & Kim, 2018). Since patents and/or trademarks are highly valued in the above mentioned industries, only VC-backed firms operating in one of these industries will be included in the samples. Thereby, innovativeness and its importance for firms is measured more accurately. In Table 3 on the next page, a clear overview of the included VC-backed firms per industry for both samples is shown.

Table 3: *VC-backed firms per industry*

Type of industry	**VC-backed firms India**	**VC-backed firms Japan**	**Academic support for the importance of patents and/or trademarks per industry**
AI & Technology	23	46	Antonipillai & Lee, 2016; Haney, 2019
Apps & Software	34	82	Cockburn & Long, 2015; Vishnubhakat, 2015
Automotive	6	8	Blind et al, 2006
Biotechnology & Healthcare	42	118	Cockburn & Long, 2015
Chemicals & Energy	Not present	15	Cockburn & Long, 2015
Electronics & Robotics	7	33	Cockburn & Long, 2015; Yun et al., 2018
Semiconductor	2	3	Antonipillai & Lee, 2016

3.2.5 Founding year

Furthermore, the samples will only contain VC-backed firms founded since the year 2000. As mentioned previously, this provides the opportunity to control for possible changes in the past regarding the level of market maturity in India and Japan. Second, this allows for analyzing the number of patents and trademarks per backed firm in a more unbiased way. This for the reason that the earlier a backed firm was found, the more time this backed firm had to obtain patents and trademarks.

3.3 Measurement development

In this section, the measurement development of the different variables will be explained. Only when all variables are measured in a correct manner, the research question can be answered appropriately. The measurement of the concepts network position, market maturity, and innovativeness will be described in this order. An overview of how these concepts are measured is provided on the next page in Table 4.

Table 4: *Operationalization*

Concept	**Variable**	**Indicator**	**Academic support for the measurement**
Network position	Strong ties	Average degree centrality of the VCs per backed firm	Cainelli et al., 2015
	Weak ties	Average betweenness centrality of the VCs per backed firm	Everett & Borgatti, 2005 Takagi & Toyama, 2009
Market maturity	Emerging market	India	See paragraph 3.2.1
	Mature market	Japan	
Innovativeness	Innovativeness	Number of patents and trademarks of the VC-backed firm taken together	Heimonen, 2012 Hasanov et al., 2015 Vasudeva et al., 2013

3.3.1 Network position

Strong and weak ties were described as the two main mechanisms revolving around network position. The former one is characterized by high levels of interaction, communication, emotional attachment, and trust. In order the achieve these strong ties, a VC must obtain a more central position in its network. As such a central location is crucial for signaling trust to other actors in the network (Tan et al., 2015; Tsai & Ghoshal, 1998). Degree centrality measures the amount of relationships an actor in the network possesses (Hochberg et al., 2007). Cainelli, Maggioni, Uberti, & De Felice (2015) argue that the relationships measured by degree centrality can be seen as strong ties. Therefore, also in this study degree centrality will be used in order to measure the strong ties a VC has. An important remark to this approach however, is that degree centrality simply shows how many connections an actor has. An actor can be connected to lots of other actors at the heart of the network, but these other actors might also be far-off on the edge of the network. Meaning degree centrality accurately shows the amount of connections, but it does not necessarily show how strong these connections are (Golbeck, 2015). This remark is important to take into account when drawing conclusions from the results of the regression analyses.

Betweenness centrality examines to what extent an actor is positioned between all other actors within a network. If an actor is positioned between two different actors, then there is not

a connection between the alters on the path connecting them (Freeman, 1977). One way of measuring the extent to which a VC has structural holes in its network can be measured by the betweenness centrality (Everett & Borgatti, 2005). Takagi & Toyama (2009) mention that only actors with a high betweenness centrality can be considered to have substantial weak ties. Therefore, it is expected that the betweenness centrality will give an adequate indication of the amount of weak ties per VC. Nevertheless, it is important to be completely aware that betweenness centrality does not exactly reflect the amount of weak ties a VC has. Meaning the results of the analysis should be interpreted cautiously.

Both degree centrality and betweenness centrality will be calculated based on the scores of all the network positions of the VCs that are taken into account in the database. This will be done in Pythons' library named 'NetworkX'. According to the official NetworkX documentation (n.d.), the degree centrality for a node (i.e. VC) is the number of nodes (i.e. other VCs) it is connected to. The values for the degree centrality are normalized by dividing by the maximum possible degree in a simple graph n-1 where n is the number of nodes (VCs) in the graph.

Furthermore, in the official NetworkX documentation (n.d.) it is described that the betweenness centrality of a node v (i.e. VC) is the sum of all-pairs shortest paths that pass through v. This betweenness centrality is calculated in NetworkX with the formula shown below in Figure 3.

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

Figure 3: *Formula betweenness centrality*
(NetworkX, n.d.)

In the database, the number of VCs per backed firm with a score on both degree centrality and betweenness centrality ranges from one to five. In order to analyze one score on degree centrality, and one score on betweenness centrality per VC-syndicate, the average for these scores of all included VCs per backed firm will be taken into account. It is important to be aware of the fact that both degree centrality, as well as betweenness centrality are thus averages. Another important aspect to keep in mind, is that there is a maximum of five VCs per backed firm with a network position in the database. Nevertheless, in reality there might be more than five VCs investing in the backed firm. Meaning the network position might slightly

differ from the reality. Both the degree centrality average, and betweenness centrality average are metric variables.

3.3.2 Market maturity

As described previously, the emerging market of India will be compared to the mature market of Japan. In this study, market maturity should be seen as a dichotomous variable; a country either has an emerging market (i.e. India), or it has a mature market (i.e. Japan). For each country, an independent regression analysis in SPSS will be conducted. Meaning within SPSS itself, there will not be a difference made in the variable market maturity.

3.3.3 Innovativeness

In the database, the number of patents and trademarks per VC-backed firm is provided. In the quantitative analysis, these patents and trademarks will together form the proxy for innovativeness. Patents and trademarks can be used by companies to protect their new critical technologies and know-how (Manzini & Lazzarotti, 2016). It can be argued that new critical technologies and specific know-how lead to innovations. Therefore it is a logical train of thought to see these as an adequate proxy for innovativeness. It is not uncommon to use patents and trademarks as a proxy for innovativeness, as for example Heimonen (2012), Hasanov, Abada, & Aktamov (2015), and Vasudeva et al. (2013) have used this same approach. The exact number of patents and trademarks per backed firm can be found in the database. This leads to innovativeness being a metric variable in the study.

3.3.4 Control variables

As was discussed in the theoretical framework, both collectivism and type of industry might also play a role as moderators. Controlling for these matters provides the opportunity to look more accurately at the effect that market maturity has as a moderator. The similar level of collectivism in the Indian and Japanese culture justifies the act of controlling for the former potential moderator. As both cultures are almost equally collectivistic, the results from the regression analyses cannot be moderated by a difference in degree of collectivism.

Taking into account the effect that type of industry has, is a more complicated task. Due to the minor sample sizes for some industries, it is not possible to include type of industry as a dummy variable into the analyses. Nevertheless, the influence that type of industry has can still be partly analyzed in this study. If the regression analysis of both samples indicate that market maturity plays a significant role as a moderator, the effect of type of industry needs to be taken into account. This for the reason that it is otherwise not possible to state with certainty that a

difference in market maturity was the underlying reason for the significant results. The effect of type of industry can be analyzed by performing a third analysis. This third analysis will compare the three most frequently represented industries from the sample representing Japan. The sample size of those three industries is namely large enough to compare the effect per industry with a PLS-analysis. When concluding that these three different industries show similar effects, it can be assumed that type of industry does not play a significant role. With this approach, type of industry can still be taken into account in this study. This is crucial, as it leads to an increased likelihood that the final results correctly reflect the effect that market maturity has as a moderator. In the case that the regression analysis of both samples lead to the conclusion that market maturity certainly does not play a significant role as a moderator, the third analysis will not be conducted. This for the reason that the results of this analysis would be redundant for answering the main research question.

Two other relevant control variables for this study are the size and age of the VC-backed firm. This for the reason that Laforet (2013) found that innovativeness positively depends on the size and age of an organization. Therefore, the concepts size and age of the VC-backed firm should be included in this study as control variables.

Lastly, the number of VCs investing in the backed firm will be included as a control variable. Not every firm in the database is backed by multiple VCs. It is however important to control for this, as it is found that firms backed by a syndicate perform better than firms backed by just one VC (Tian, 2012). The number of VCs per backed firm is a metric variable and can thus be included in the analysis.

3.4 Validity and reliability

In order to measure the variables accurately, it is important to take the validity and reliability into account. Validity is described by Hair et al. (2014) as the extent to which a measure correctly represents the concept of the study. In order to achieve a high validity, the measure should be free from any systematic or nonrandom error. Reliability differs from validity in that it relates not to what should be measured, but instead to how it is measured. Meaning the reliability is high in the case that when multiple measurements are taken, the measures will be consistent in their values (Hair et al., 2014). The validity and reliability are overall considered to be sufficiently high, as the measurement items used in this study are common to use in the academic field. Furthermore, the moderation effect of market maturity can be analyzed more accurately due to including multiple control variables. This means that the internal validity of the study increases. Nevertheless, the results cannot simply be

generalized since this study only takes into account two different countries. Meaning the external validity is low.

Lastly, multiple statistical tests will be taken into consideration in order to improve the validity and reliability of this study. For example, meeting the different assumptions for a multiple regression analysis increases the external validity (Field, 2018). These different assumptions are described in more detail in chapter 4. Furthermore, the distribution of the data will be analyzed by looking at the skewness and kurtosis of the different variables. This is also important for ensuring a greater validity and reliability, as a normal distribution of the data increases the accuracy of the analysis (Field, 2018).

3.5 Research ethics and database

Unfortunately, it is not possible to determine the research ethics revolving around the data collection procedure, as the database was downloaded from the external source Crunchbase. What can be controlled however, is to guarantee anonymity of the exact VCs and backed firms that are included in the database. Thereby this study does not disturb the privacy of the VCs and firms, of which data was used. Furthermore, the data available in the database is considered to not be extremely sensitive data. Meaning no detrimental revelations of firms and VCs can be found and mentioned in the first place.

As described previously, the database originates from Crunchbase. Crunchbase is crowd-sourced, which means that executives, entrepreneurs, and investors enter the data on themselves and others. This community ensures that the datasets are always being updated (Crunchbase, n.d.). Although Crunchbase also uses AI and machine learning algorithms to validate data accuracy, it cannot simply be assumed that the entire dataset is completely accurate. Therefore, it is important to be aware that the data might not be entirely reliable. Furthermore, Crunchbase makes use of other resources to enrich their data. In the database that is used for this study, the information regarding the granted patents and trademarks per VC-backed firm is abstracted from IPqwery. The information of IPqwery is used frequently by Crunchbase users for comparing patents and trademarks across companies with respect to innovativeness (Crunchbase, n.d.).

3.6 Data analysis procedure

After the calculation process in Pythons' library 'NetworkX', the data will be cleaned in Python and Excel. Afterwards, the cleaned dataset will be downloaded into SPSS. Missing data will be analyzed first, as well as whether other important requirements are met. If the missing data of an item is crucial for the analysis, this item will be deleted from the sample.

Extreme outliers in the data will also be considered and, if necessary, deleted from the sample. In SPSS, two distinct regression analyses will be conducted: one will analyze the emerging market of India, while the other one does the same for the mature market of Japan. These regression analyses will be multiple regression analyses, as they contain multiple metric independent variables (Hair et al., 2014). These metric independent variables are namely the degree centrality average and betweenness centrality average. The dependent variable is, just like the independent variables, a metric variable. The variables being metric is an important requirement for using regression analyses. Additionally, the required ratio of observations to variables for a regression analysis is 5:1. Both samples are large enough to achieve this ratio. Thereby the use of the multiple regression analyses is justified (Hair et al., 2014).

For the regression analyses, it is important to meet different assumptions. These assumptions are linearity, constant variance, independency of residuals, and normal distribution of the residuals (Hair et al., 2014). These assumptions will be explained in detail in chapter 4. After meeting these assumptions, the results can be analyzed. Therefore, the adjusted R^2, the standardized coefficients, and the t-values with the accompanying p-values will be taken into consideration.

4. Results and findings

As described previously, the relationship between the independent variables and the dependent variable for both samples will be analyzed with two distinct multiple regression analyses. The results of these two analyses will be discussed in this chapter.

4.1 Outliers

Both samples were checked for outliers. Taking into account the z-score per variable for each case is a justified method for detecting outliers (Field, 2018). When a case shows a z-score for a variable of 3.29 or higher, it is considered to be an extreme case (Field, 2018). Such extreme cases (i.e. outliers) were present numerous times in both samples. These extreme cases were responsible for excessive levels of skewness and kurtosis. Furthermore, these outliers made it hard to correctly interpret the scatterplots of both samples. This is unfavorable, as interpreting the scatterplots correctly is crucial for determining whether the assumptions for a multiple regression analysis are met.

In order to interpret the scatterplots correctly, it was decided to delete the problem-giving cases. The method that was used for this, was standard deviation based trimming. This simply means that cases with a z-score that is a certain number of standard deviations greater than the mean, are deleted (Field, 2018). Both samples contained one extreme case that was more than 10 standard deviations greater than the mean. These two extreme cases were deleted first from the samples. Although more extreme cases were present in the samples, deleting the two most extreme ones led to a substantial improvement regarding the possibility to interpret the scatterplots correctly. Therefore, only the two most extreme cases were deleted. Meaning one case from the sample representing India was deleted, as well as one case from the sample representing Japan. Deleting these outliers was a permitted act. Grace-Martin (2008) namely argues that it is allowed to delete outliers for a regression analysis if these outliers affect meeting the assumptions, but do not change the outcome of the results.

To make sure that deleting the outliers did not affect the outcome of the results, two distinct regression analyses per sample were conducted. One regression analysis per sample included the extreme outlier, whereas the other regression analysis excluded it. The results of the regression analyses that did include the outlier are displayed in Tables A1 & A2 in Appendix A. From the results of the different analyses, it can be concluded that excluding the two outliers did not result in major changes of the results for the different models and variables for both samples. Nevertheless, it is important to note that the independent variable ‘degree centrality average’ changed from clearly not significant, to almost significant in model 2 of the sample

representing India. It is remarkable that such a big difference is caused by only excluding one outlier. Despite this contrast in the results between excluding and including the outlier, 'degree centrality average' is still not a significant variable when considering a threshold for the p-value of < .05. Meaning the outcome of the results did not greatly change. Hence, it is allowed to interpret the results from the regression analyses that excluded the outliers. These regression analyses will be described in the remaining sections of this chapter.

4.2 Control variables

In both analyses, only the variable 'number of investors' will be included as a control variable. As was described in section 3.3.4, the possible effect of type of industry cannot be analyzed directly due to an insufficient amount of cases per industry. Therefore, the effect of this variable will, depending on the results of the analyses, be studied in a final separate analysis.

In section 3.3.4, also the concept 'size' was mentioned as a possible important control variable. This concept can be measured by the number of employees a VC-backed firm has (Hashim, Guan, Talib, & Tamrin, 2021). Unfortunately, the variable 'number of employees' had a high amount of missing values. Roughly half of the cases in the samples had a missing value for this variable. This leads to a trade-off between the gains from including this as a control variable, and a reduction in sample size (Hair et al., 2014). Due to the already minor sample sizes, it was decided that including ´number of employees´ as a control variable did not outweigh the disadvantage of reducing approximately half of the cases from the samples. This is a fair choice to make, as Hair et al. (2014) even argue that variables with 50 percent or more missing data should always be deleted. Which also means that considering options like filling missing values with either the median or mean is not even allowed.

Additionally, it was argued in section 3.3.4 that innovativeness positively depends on the age of a firm. Therefore, also the possibility of including 'age' of the VC-backed firm as a control variable was assessed. Unfortunately, including this control variable in the model led to problems with meeting the assumption for homoscedasticity of the data in both samples. This can be derived from Figures A1 & A2 in Appendix A. It can namely be seen in these figures that there is no constant variance, and that the residuals form a clear triangle pattern. Hair et al. (2014) advice to transform variables in order to deal with homoscedasticity. However, the variables were already transformed due to the high levels of skewness and kurtosis (see the next section). Meaning transforming the variable 'age' again is not an option, and the assumption of homoscedasticity of the data cannot be met when including this control variable in the analyses. This is a major drawback, as meeting this assumption is a requirement for conducting a

regression analysis (Hair et al., 2014). For this reason, ´age´ of the VC-backed firm was unfortunately also excluded as a control variable in both analyses. Favorably however, is the fact that only VC-backed firms founded since the year 2000 are included in both samples. Which means the difference in age for all VC-backed firms is already limited.

Only including the 'number of investors' as a control variable is clearly not an ideal scenario. Including more control variables namely allows for a more perspicuous demonstration of how the independent variables relate to the dependent variable. Meaning the internal validity would be higher when including more control variables. Nevertheless, it can be concluded from this section that including the desired control variables was not possible. In the coming sections, the results regarding the analysis of the Indian sample are discussed. Afterwards, the results of the analysis of the sample representing Japan will be described.

4.3 Results sample India

In this section, the results of the sample representing India will be discussed. The descriptive statistics, the assumptions, and the regression model and fit are described in this order.

4.3.1 Descriptive statistics sample India

For conducting a multiple regression analysis, it is important that the sample size is sufficiently large. The database contains 41,005 VC-backed firms that are located in India. However, it is not possible to include all these firms in the sample representing India. It is namely required that the VC-backed firms do not have any missing values for 'degree centrality average', 'betweenness centrality average', 'number of investors', and 'innovativeness'. Furthermore, only VC-backed firms operating in certain industries can be included in the final sample. The reason behind this was described in section 3.2.4. After excluding VC-backed firms active in irrelevant industries and deleting missing values and one extreme outlier, the sample for India contains 114 cases. The minimum ratio for the sample in relation to the number of independent variables is 5:1 (Hair et al., 2014). In this analysis, only two independent variables, and one control variable are taken into account. Meaning the sample size is sufficiently large.

Afterwards, the distribution of the scores per variable were taken into consideration. The distribution of the scores can be analyzed by looking at the z-scores for skewness and kurtosis of the different variables (Field, 2018). The z-scores can be calculated by dividing the estimates of skewness and kurtosis by their standard errors. The resulting z-scores must not be higher than absolute 1.96 in order to expect an approximately normal distribution of the scores

(Field, 2018). Unfortunately, the skewness and kurtosis of all original variables showed that a normal distribution cannot be expected. A remedy for this is to transform the data. This simply means that mathematical functions can be applied to all cases in a dataset to correct for distributional abnormality such as skewness or kurtosis (Field, 2018). For this sample, a log(x+1) transformation was most favorable. This is explained in more detail in Appendix B.

Using transformed data means that interpreting the results of the analysis becomes more complex (Feng et al., 2014). This for the reason that a regression model with normal, non-transformed will have unit changes between the independent and dependent variables. A single unit change in the independent variable will then coincide with a constant change in the dependent variable. With transformed data, this is not the case anymore. For a log(x+1) transformation, the data will effectively change the case from a unit change to a percent change (Andy, 2019). This is important to take into account when analyzing the standardized regression coefficient.

Although the skewness and kurtosis have been improved considerably after the transformation, the variables are still not normally distributed. This is a serious limitation for this study, and something to keep in mind when interpreting the results. The skewness and kurtosis of the transformed variables that were used in the multiple regression analysis are shown below in Table 5.

Table 5: *Skewness and kurtosis sample India*

	Z-score skewness	**Z-score kurtosis**
Number of investors	4.765	1.911
Degree centrality average	8.398	5.457
Betweenness centrality average	12.752	18.940
Innovativeness	4.381	3.552

4.3.2 Assumptions sample India

Before the results of the regression analysis can be interpreted, it is important to look whether the four assumptions for a multiple regression analysis have been met. These assumptions are: linearity, constant variance, independency of residuals, and normal distribution of the residuals (Hair et al., 2014).

In order to check the linearity of the regression model, the scatterplot based on the standard residuals and on the standardized predicted values of the dependent variable will be

taken into consideration. Additionally, the partial plots can be analyzed for the linearity of the independent variables in combination with the dependent variable. Linearity can be assumed in the case that no curvilinear patterns are found, and if all the residuals are spread equally around the horizontal zero-line (Hair et al., 2014). When looking at Figures B1-B4 in Appendix B, it can be concluded that this is mainly the case. It is clear that there are a few extreme cases located in the upper region, and on the right side in the plot. Nevertheless, the vast majority is spread equally around the horizontal zero-line. Furthermore, the majority of the residuals are randomly presented in the plots, and are also not concentrated in a specific area in the plots. Hence, there is a linear relationship in this model and the first assumption has been met.

The second assumption entails that there is a constant range of the error terms of the independent variables, which is called homoscedasticity (Hair et al., 2014). If there is not a constant range of the error terms, then heteroscedasticity is present. From Figure B1 in Appendix B, it can be derived that, apart from a few extreme cases, the residuals have a constant variance and no clear pattern can be found. Meaning the data is homoscedastic, and the second assumption for a regression model has been met as well.

The third assumption requires that the error terms are independent. This means that each predicted value is independent, and does not relate to any other prediction. According to Field (2018), this assumption can be tested with the Durbin-Watson test. This test sheds light on the serial correlations between errors. The test statistic ranges from 0 to 4, where a value of 2 means the error terms are independent. Table 6 on the next page shows the Durbin-Watson test has a value of 2.067. Therefore, the assumption of independence of the error terms has been met.

Lastly, a multiple linear regression analysis requires a normal distribution of the errors between the observed and predicted values. This assumption can be checked by looking at the normal probability plot, which is a plot of the standardized residuals (Hair et al., 2014). If all the residuals lay on or around the diagonal line, there is a normal distribution. As can be seen in Figure B5 in Appendix B, this is the case. Hence, all assumptions are met, and it is allowed to look at the results of the multiple regression analysis in the next section.

4.3.3 Regression model and fit sample India

Three different models were used in this multiple regression analysis. Model 1 only contained the ‘number of investors’ as control variable. In model 2, ‘degree centrality average’ was added as independent variable. Lastly, ‘betweenness centrality average’ was included as an independent variable in model 3. The purpose of model 1 is to control for the ‘number of investors’ in the final results. The first step of interpreting the results is to evaluate the F-test.

The F-test displays if a model successfully predicts variance in the dependent variable. Table 6 on the next page shows that none of the models was significant, as $p > .05$. This means that the independent variables per model together did not significantly explain variance in the dependent variable.

Table 6 on the next page also displays that the independent variables individually were not significant, as $p > .05$. It does stand out that when applying a threshold of $p < .10$, 'degree centrality average' is found to be a significant variable in model 2. However, it must be mentioned that a threshold of .10 is not often worked with in the academic field. The values .01 and .05 are namely the most commonly used critical thresholds (Stankov, Glavinić, & Grubišić, 2004; Tu, 2007; Ding & Fang, 2016; Field, 2018). Therefore, also in this study only variables with a p-value that is at least below .05 are considered to be truly significant predictors. Nevertheless, also considering a p-value threshold of < .10 does provide the opportunity to nuance the outcome of the analysis.

However, the finding that 'degree centrality average' is significant in model 2 when considering a threshold of .10, must be interpreted slightly different for three different reasons. First, as was described in section 4.1, 'degree centrality average' was clearly insignificant when the outlier for the sample was included. This can also be derived from Table 1 in Appendix A. However, deleting this one outlier led to a change regarding the p-value for 'degree centrality average'. Meaning it became a significant variable with a p-value of < .10, and it almost became a significant variable with a p-value of < .05. Nonetheless, the fact that 'degree centrality average' was undoubtably insignificant when the outlier was included, means it is questionable whether it is fair to perceive it as being a significant predictor at a p-value of < .10 now. Second, the adjusted R^2 for model 2 is extremely low, while the F-test of this model was not significant. This leads to the conclusion that the independent variables that were used in this model (i.e. 'number of investors' and 'degree centrality average') did not explain much variance in the dependent variable. Third, when 'betweenness centrality average' was added in model 3, 'degree centrality average' showed to clearly not be a significant predictor of the innovativeness of VC-backed firms. These three arguments taken together lead to the conclusion that it is not fair to perceive 'degree centrality average' as an important predictor of innovativeness.

An explanation for the mentioned third argument, is that 'betweenness centrality average' takes away part of the variance that was explained by the 'degree centrality average'. This could suggest that there might be a presence of multicollinearity in the analysis.

To verify this, the tolerance and VIF values for the variables must be considered. If the value for tolerance is higher than .20, and the value for VIF is lower than 5, then there are no

serious concerns regarding multicollinearity between the variables (Menard, 1995; Gujarati, 2003). From the results, it can be concluded that the thresholds for both the tolerance and VIF were met. These values can be seen in Table B6 in Appendix B. This means there are no serious concerns about high levels of multicollinearity between the variables in this analysis. However, it must me mentioned that the thresholds were just met. Which leads to the interpretation that there certainly was a minor presence of multicollinearity between the variables 'degree centrality average' and 'betweenness centrality average' in the analysis. Additionally, the correlation matrix in Table B8 in Appendix B shows that 'degree centrality average' and 'betweenness centrality average' had a correlation coefficient of -.886. Field (2018) argues that a correlation coefficient of absolute .5 is considered high. Thus, it can be concluded that the variables had a high correlation. This means both variables were not independent of each other. This would explain why 'degree centrality average' was an even less significant predictor of innovativeness when 'betweenness centrality average' was added in model 3.

Table 6: *Summary table regression analysis sample India*

	Model 1	Model 2	Model 3
	Emerging market		
(Constant)	(6.099)***	(5.861)***	(5.826)***
Number of investors	.080	.036	.034
	(.848)	(.376)	(.348)
Degree centrality average		.187*	.253
		(1.949)	(1.219)
Betweenness centrality average			-.074
			(-.362)
R^2	.006	.039	.040
Adjusted R^2	-.002	.022	.014
N	114	114	114
Degree of freedom	112	111	110
Sig. F-test	.398	.108	.207
Durbin-Watson			2.067

Table showing the standardized regression coefficient per variable; *** $p < .01$; ** $p < .05$; * $p < .10$; accompanying t-values are displayed in parentheses

4.4 Results sample Japan

The results of the sample representing Japan will be described in this section. First, the descriptive statistics will be discussed. Afterwards, the assumptions and the regression model and fit are described.

4.4.1 Descriptive statistics sample Japan

The database contains 15,357 VC-backed firms that are located in Japan. Nevertheless, also for this sample it is required that there are no missing values for 'number of investors', 'degree centrality average', 'betweenness centrality average', and 'innovativeness'. Cases that did have missing values for at least one of these variables were deleted first. Afterwards, VC-backed firms active in irrelevant industries were excluded from the sample. After deleting the missing values and excluding VC-backed firms operating in irrelevant industries, the Japanese sample contains 305 cases. Thereby the sample size is large enough to conduct a multiple regression analysis. It is important to note that the sample representing Japan is much larger than the sample representing India. The sample representing India namely contained 114 cases. This is not favorable, as unequal sample sizes strongly decrease the power of a study (Rusticus & Lovato, 2014).

Hereafter, the distribution of the scores were taken into account. For this, the z-scores for skewness and kurtosis of the different variables were analyzed. Unfortunately, also in this sample the variables were not normally distributed. This variables namely showed high levels of skewness and kurtosis, which means the data needed to be transformed. Also for this sample, a log(x+1) transformation was superior compared to the other type of transformations. This is described in more detail in Appendix C.

Unfortunately, also after the log(x+1) transformation almost all z-scores for skewness and kurtosis are higher than 1.96. Meaning the variables are still abnormally distributed, which forms a serious limitation for this study. Especially the independent variable 'betweenness centrality average' deals with extreme levels of skewness and kurtosis. The skewness and kurtosis of each variable can be seen in Table 7 on the next page. The fact that transformed data is used in this analysis, means that the standardized regression coefficient must be interpreted consciously.

Table 7: *Skewness and kurtosis sample Japan*

	Z-score skewness	**Z-score kurtosis**
Number of investors	1.807	2.755
Degree centrality average	12.976	22.313
Betweenness centrality average	38.321	154.813
Innovativeness	6.229	2.266

4.4.2 Assumptions sample Japan

Also for the second sample the different assumptions for a multiple regression analysis have to be taken into consideration. Only when the four assumptions are met it is allowed to look at the results of the analysis.

In Figure C1 in Appendix C, a scatterplot based on the standard residuals and on the standardized predicted values of the dependent variable is displayed. From this figure, it can be concluded that the bivariate relationship follows a linear relationship. It can namely be seen that the residuals are mainly spread equally around the horizontal zero-line. In addition to that, no curvilinear patterns can be found. Figures C2-C4 in Appendix C are showing the partial plots that can be analyzed for the linearity of the different variables separately. As can be seen from the partial plots, linearity can be assumed. There are a few extreme cases visible from the plots, however these do not form a serious reason for concern. Thereby, the first assumption for a multiple regression analysis is met, and there is no need to include polynomial terms.

For the second assumption, Figure C1 in Appendix C will be taken into account once more. In this figure, it can be seen that there is a constant range of the error terms of the independent variables. The residuals do namely not form a clear pattern, and are showing a constant variance which means that homoscedasticity of the data is assumed. This leads to the conclusion that also the second assumption has been met.

For the third assumption, the independence of the error terms will be considered. As described previously, a value of approximately 2 for the Durbin-Watson test means that the error terms are independent. Table 8 on page 42 shows that the model has a value of 2.176 for the Durbin-Watson test. Hence, there is an independence of the error terms and the third assumption has been met.

Ultimately, a normal distribution of the errors between the observed and predicted values is required for interpreting the results of the multiple linear regression analysis. In order to check whether this is the case, the p-p plot of the standardized residuals will be taken into

account. The p-p plot in Figure C5 in Appendix C shows that all the residuals lay on or around the diagonal line. This means there is a normal distribution of the errors. Meaning also the final assumption is met, and it is allowed to look at the results of the multiple regression analysis.

4.4.3 Regression model and fit sample Japan

Also for this multiple regression analysis, three different models were used. Model 1 only contained the control variable 'number of investors'. Model 2 additionally contained 'degree centrality average' as an independent variable. In model 3, 'betweenness centrality average' was added as a second independent variable. With this approach, the effect of the control variable 'number of investors' can be taken into account. Additionally, this allows for considering the effect per variable in an unbiased way.

In order to correctly interpret the results, the F-test of the different models will be evaluated first. Table 8 on the next page leads to the conclusion that none of the models was significant. This for the reason that the F-test of all models have a significance level of > .05. Meaning the independent variables used in the models together, were not able to significantly explain variance in the dependent variable. Table 8 also displays the independent variables individually did not significantly explain variance in the dependent variable, as also here $p >$ .05. In the analysis, there was no serious multicollinearity present. The independent variables namely all have a value higher than .20 for tolerance, and a value lower than 5 for VIF, which is shown in Figure C6 in Appendix C. Nevertheless, it must be mentioned that the correlation matrix in Table C8 in Appendix C shows that 'degree centrality average' and 'betweenness centrality average' have a high correlation coefficient of -.856. This means that these variables were not independent of each other.

Table 8: *Summary table regression analysis sample Japan*

	Model 1	Model 2	Model 3
	Mature market		
(Constant)	(10.940)***	(10.914)***	(10.797)***
Number of investors	.027	.030	.027
	(.462)	(.482)	(.437)
Degree centrality average		-.009	.033
		(-.148)	(.274)
Betweenness centrality average			-.048
			(-.410)
R^2	.001	.001	.001
Adjusted R^2	-.003	-.006	-.009
N	305	305	305
Degree of freedom	303	302	301
Sig. F-test	.645	.889	.940
Durbin-Watson			2.176

Table showing the standardized regression coefficient per variable; *** $p < .01$; ** $p < .05$; * $p < .10$; accompanying t-values are displayed in parentheses

4.5. Answering the sub-questions

The results from the multiple regression analyses provide the opportunity to answer the two sub-questions of this study. The results from the regression analysis of the sample representing India, will be used to answer the first sub-question. This sub-question was as follows: *Which VC's network position is most beneficial for innovativeness of the VC-backed firms in an emerging market?*. In order to answer this first sub-question, two different hypotheses were formulated. Finding out whether these hypotheses are supported or rejected is necessary for answering this first sub-question. Therefore, this will be described first in this section.

Hypothesis 1: *Strong ties of VCs enhance the innovativeness of VC-backed firms in an emerging market.*

As was described in section 4.3.3, ´degree centrality average´ was not a significant independent variable when considering a threshold for the p-value of < .05. However, it was found to be a significant predictor when applying a less critical threshold of < .10. Nonetheless, it must be mentioned that this was only the case when the variable 'betweenness centrality average' was not included in the model. This in combination with other reasons, which were described in section 4.3.3, made it not fair to perceive 'degree centrality average' as an important predictor. Besides these reasons, only variables that have a p-value below .05 are considered to be truly significant in this study. This for the reason that thresholds of .05 and .01 are most commonly used in the academic field (Stankov et al., 2004; Tu, 2007; Ding & Fang, 2016; Field, 2018). Hence, the variable 'degree centrality average' is not considered to be a significant predictor of innovativeness.

Since 'degree centrality average' is considered to have an insignificant effect on the innovativeness of Indian VC-backed firms, hypothesis 1 must be rejected. Meaning the results indicate that strong ties of VCs do not enhance the innovativeness of VC-backed firms in an emerging market.

Hypothesis 2: *Weak ties of VCs do not enhance the innovativeness of VC-backed firms in an emerging market.*

Also 'betweenness centrality average' was found to have an insignificant effect on the innovativeness of Indian VC-backed firms. Which means there is no significant relationship between weak ties of VCs and the innovativeness of VC-backed firms in an emerging market. Thereby hypothesis 2 is supported, as the results point out that weak ties of VCs do not enhance the innovativeness of VC-backed firms in an emerging market. With these findings, sub-question 1 must be answered with a different angle of approach. The insignificant effects of 'degree centrality average' and 'betweenness centrality average' namely suggest that no specific network position of VCs is beneficial for the innovativeness of VC-backed firms in India. Hence, the results lead to the tentative interpretation that the network position of VCs does not significantly influence the innovativeness of VC-backed firms operating in an emerging market.

The results of the second multiple regression analysis allow for providing an answer to the second sub-question. The second sub-question was the following: *Which VC's network position is most beneficial for innovativeness of the VC-backed firms in a mature market?.*

For answering this sub-question, it is necessary to figure out whether the third and fourth hypothesis are either supported or rejected.

Hypothesis 3: *Strong ties of VCs do not enhance the innovativeness of VC-backed firms in a mature market.*

In the second multiple regression analysis, it was found that 'degree centrality average' did not have a significant effect on the innovativeness of Japanese VC-backed firms. Which means that the results suggest that strong ties of VCs do not enhance the innovativeness of VC-backed firms in a mature market. This means hypothesis 3 is supported.

Hypothesis 4: *Weak ties of VCs enhance the innovativeness of VC-backed firms in a mature market.*

Similarly, 'betweenness centrality average' did also not significantly influence the innovativeness of the Japanese VC-backed firms. In essence, this means the results indicate that weak ties of VCs do not enhance the innovativeness of VC-backed firms in a mature market. Therefore, hypothesis 4 must be rejected. Hence, the findings of this multiple regression analysis indicate that there is not a specific network position of VCs which significantly stimulates the innovativeness of VC-backed firms in a mature market. Thereby, also the second sub-question has been answered. In Table 9 below, an overview of the outcome per hypothesis is shown. The final conceptual model showing the different hypotheses can be found in Figure 4 on the next page.

Table 9: *Overview outcome hypotheses*

Sample	**Hypothesis**	**Outcome**
India: Emerging market	1. *Strong ties of VCs enhance the innovativeness of VC-backed firms in an emerging market.*	Rejected
	2. *Weak ties of VCs do not enhance the innovativeness of VC-backed firms in an emerging market.*	Supported
Japan: Mature market	*3. Strong ties of VCs do not enhance the innovativeness of VC-backed firms in a mature market.*	Supported
	4. Weak ties of VCs enhance the innovativeness of VC-backed firms in a mature market.	Rejected

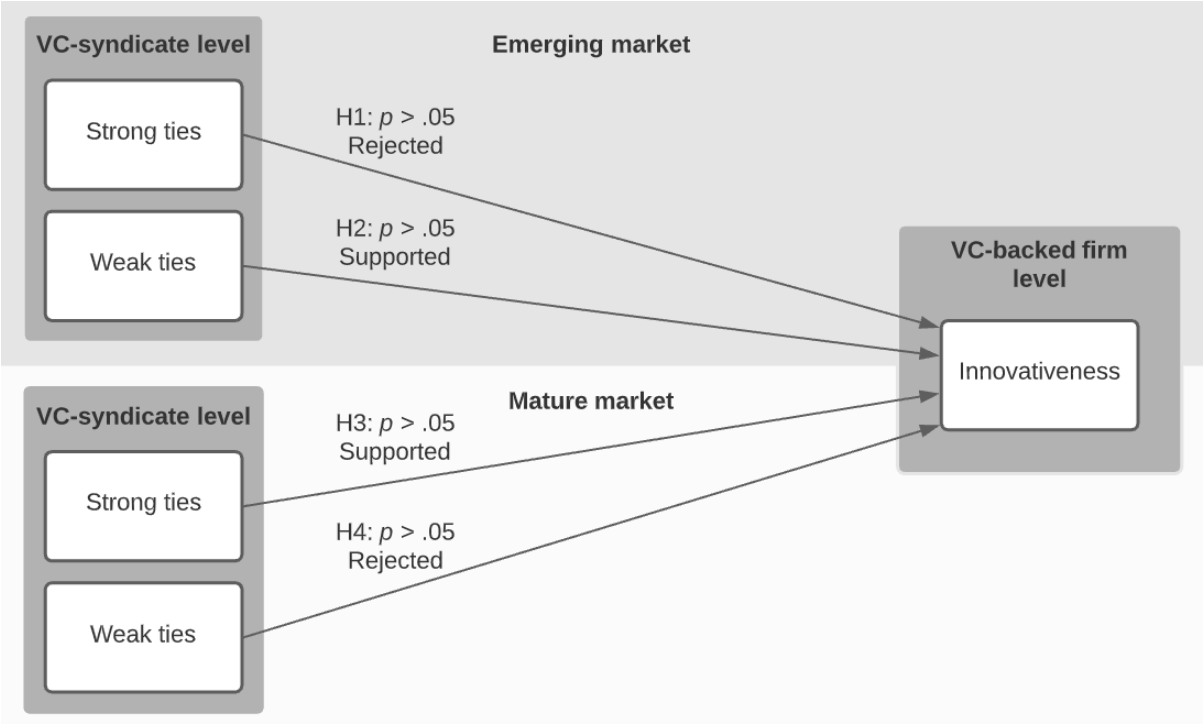

Figure 4: *Conceptual model including results*

4.6 Analysis type of industry

Due to the found insignificant results, the third analysis revolving around the possible moderator type of industry will not be conducted. As was described in section 3.3.4, a third analysis would have been conducted if the results indicated that market maturity was a possible moderator of the effect that network position has on innovativeness. This third analysis would have provided insight into whether type of industry might actually be the underlying reason for the found results, instead of market maturity. Nevertheless, from the results it can be derived that market maturity does not play a significant role as a moderator. Thereby, this third analysis becomes redundant for answering the main research question. Hence, the third analysis will not be conducted.

5 Conclusion

In this chapter, the conclusion of this study will be described. The main research question will be answered first. Afterwards, the theoretical, and managerial and societal implications will be discussed. Ultimately, the limitations and possibilities for future research will be described.

5.1 Answering the main research question

Assessing the literature revealed a debate in the academic field revolving around how the network position of VCs impacts the innovativeness of VC-backed firms. The aim of this study was to provide relevant information to this debate by giving an answer to the following research question: *To what extent does market maturity moderate the effect that a VC's network position has on the innovativeness of a VC-backed firm?.*

Looking at the relevant literature regarding this subject leads to the conclusion that both strong and weak ties were proved in multiple studies to be important. Possibly, the market maturity is the underlying reason for when which type of network position provides most value. Ahlstrom & Bruton (2006) and Yang et al. (2018) namely concluded that the presence of an emerging market, was the reason for both studies finding that strong personal relationships were most valuable. The explanation for this, is that a strong social network can help can help to overcome the lack of developed formal institutions in an emerging market (Batjargal et al., 2013). Also Luk et al. (2008) and Kiss & Danis (2008) encourage to develop strong ties in emerging markets. On the other hand, Yang et al. (2018) suggest that weak ties of VCs potentially can be more fruitful for enhancing the business performance of their backed firms in a mature market.

The findings of these authors let to multiple propositions in this study. First, it was hypothesized that strong ties of VCs enhance the innovativeness of VC-backed firms in an emerging market. Second, it was expected that weak ties of VCs do not enhance the innovativeness of their backed firms in such a type of market. Third, it was proposed that for VC-backed firms operating in a mature market, strong ties of VCs do not enhance the innovativeness. Fourth, it was hypothesized that weak ties of VCs enhance the innovativeness of their backed firms in a mature market.

Two different multiple regression analyses were conducted to figure out whether support could be found for these hypotheses. This was important to find out, as this provided the opportunity to answer the two sub-questions. These two sub-questions were the following:

1. Which VC's network position is most beneficial for innovativeness of the VC-backed firms in an emerging market?
2. Which VC's network position is most beneficial for innovativeness of the VC-backed firms in a mature market?

The findings from the multiple regression analyses demonstrated that strong and weak ties of VCs did not significantly influence the innovativeness of their backed firms in both types of markets. Thereby, the answer to the two sub-questions is that there is not a VC's network position that is most beneficial for enhancing the innovativeness in either type of market.

The results lead to the conclusion that no difference is found between an emerging market and a mature market for the effect that strong and weak ties of VCs have on the innovativeness of VC-backed firms. Which means that the answer to the main research question is, that market maturity does not moderate the effect that a VC's network position has on the innovativeness of a VC-backed firm. Besides this conclusion, it is interesting that the results might even suggest that a VC's network position is actually not an important factor influencing the innovativeness of VC-backed firms whatsoever. There are a few possible explanations for this surprising latter finding. These explanations will be described in the next section. Nonetheless, the results of this study should be interpreted cautiously due to multiple limitations. These limitations are discussed in section 5.4.

5.2 Theoretical implications

When taking into account the relevant literature, there are a few possible explanations for the surprising finding that a VC´s network position is not an important factor influencing the innovativeness of VC-backed firms. One of these might be that the network position of VCs is only important for business performance, instead of for innovativeness specifically. The studies of Ahlstrom & Bruton (2006) and Yang et al. (2018) did namely not focus on innovativeness, but on business performance.

Another argumentation can be that not the level of market maturity, but the type of industry is the underlying reason for when a certain type of network position is most beneficial for enhancing innovativeness. Rowley et al. (2000) namely argued that industry characteristics play a role in the effectiveness a specific network position has. Due to the fact that both samples included a wide range of distinct industries, it is possible that the effects of strong and weak ties were neutralized.

Lastly, the study of Xiao & Tsui (2007) leads to the indication that the level of collectivism might be the underlying reason for the effectiveness of a specific network position.

This argumentation might also be a relevant factor for correctly interpreting the results. Both the cultures of India and Japan have an intermediate level of collectivism. This means the results might only indicate that solely for countries with a culture that is intermediately collectivistic, the network position of VCs does not play a significant role. Meaning for countries with a lowly or highly collectivistic culture, the network position of VCs possibly does impact the innovativeness of the VC-backed firms operating in such a country.

5.3 Managerial and societal implications

The insights of this study are valuable for VCs that are seeking ways to alter their network position with the aim of increasing the innovativeness of their backed firms. The results namely suggest that market maturity is not a potent moderator of the effect that a VC's network position has on the innovativeness of VC-backed firms. This means VCs should not try to adjust their network position based on the level of market maturity of the country in which the backed firm is operating, in order to enhance innovativeness. Nevertheless, this managerial implication must be interpreted cautiously. This for the reason that there were several important limitations relevant for this study.

For two reasons, it is unfortunately not possible to state that the insignificant effects of strong and weak ties lead to the managerial implication that a VC's network position is not important for increasing innovativeness in VC-backed firms whatsoever. First, it can namely be the case that the act of including VC-backed firms from distinct industries account for neutralized effects that the strong and weak ties had in this study. Second, both studied countries contained a culture with an intermediate level of collectivism. Therefore, it can be argued that different results might be found for countries containing a culture with either a low or high level of collectivism. Hence, the managerial implications from this study are confined.

Innovativeness plays a primary role for society, as was described in the introduction of this study. Therefore, it was important to find out how innovativeness can be stimulated. Unfortunately, the results of this study did not reveal how to stimulate innovativeness. Thereby, also the societal implications are restricted. Nevertheless, identifying ways that certainly do not stimulate innovativeness is also valuable. This for the reason that the focus can now be shifted on investigating other potential factors that possibly do enhance innovativeness.

5.4 Limitations

Several limitations regarding this study must be discussed. First, the measurements of the concepts strong and weak ties. As was described in chapter 3, the variable strong ties was measured through the degree centrality of VCs. Although accurately showing the amount of

connections, degree centrality does not necessarily reveal how strong these connections are. Meaning degree centrality not precisely reflects the amount of strong ties a VC has. Also the measurement of the concept weak ties must be discussed. The amount of weak ties of VCs were namely measured via the betweenness centrality of the VCs. However, betweenness centrality measures the extent to which there are structural holes in a network. While the amount of structural holes in a network provides an adequate indication of the amount of weak ties a VC has, it does not exactly show the amount of weak ties. Hence, a limitation of this study is that the measurements do not exactly reflect the concepts strong and weak ties. Nevertheless, it is expected that the measurements provide an adequate indication of strong and weak ties.

The second limitation of this study is the fact that both samples contained numerous extreme cases. This led to an abnormal distribution of the data, which means that the results must be interpreted cautiously. These extreme cases can namely be highly influential, and thus potentially provide a distorted view. This was for example also the case with the deleted outlier in the sample representing India. Deleting this one outlier led to a remarkable difference in the significance level of the variable ‘degree centrality average’. Therefore, it must be concluded that it is questionable to what extent the dataset is reliable.

Third, the fact that only one control variable was used might lead to the results being less accurate. This for the reason that including more control variables allows for a more clear demonstration of the relationship between the independent variables and the dependent variable. Hence, including more control variables would have allowed for interpreting the relationships between the variables more accurately.

Fourth, the network position per VC-syndicate is calculated based on the five most important VCs per backed firm. However, in reality there might be more VCs involved per syndicate than these five. This means the network position might not be completely reflected in a correct way. Therefore, it is possible that for some VC-syndicates, a marginally distorted view of the network position might been given in both samples.

The final limitation is the extent to which the results of the multiple regression analyses display the role that market maturity has. It is debatable whether a comparison between two countries analyses market maturity accurately. Possibly, other influential factors than the level of market maturity might be different between India and Japan. Thus, making it difficult to state with absolute certainty that the results are completely reflecting the effect that market maturity had as a moderator. Nevertheless, the similarities between India and Japan that were described in chapter 3 help to diminish this final limitation.

5.5 Future research

This study provides interesting possibilities for future research. First of all, it would be interesting to see future studies delve further into the impact that market maturity has on the relationship between a VC´s network position and the innovativeness of their backed firms. Finding out whether the same results are found when analyzing two different countries in a similar type of study would be interesting. This would especially be interesting, if more control variables like 'size' and 'age' of the VC-backed firm are included in the analysis of such a future study. Innovativeness namely depends positively on the size and age of an organization (Laforet, 2013). Hence, including such concepts as control variables allows for analyzing the relationship between network position and innovativeness more accurately.

Also conducting a qualitative study to further dig into this subject might provide additional value. This for the reason that more in-depth knowledge can be gained from such a qualitative approach. This knowledge might help with understanding and explaining the findings from this study.

Furthermore, it would be intriguing to see whether the type of industry is an important moderator for the effect that a VC´s network position has on innovativeness. This was namely suggested by Rowley et al. (2000). If this seems to be the case, finding out which type of ties per industry are conducive for enhancing innovativeness would lead to valuable information. The insights gained from such a study would namely provide a lot of value for VCs and their backed firms that are seeking ways to increase their innovativeness.

Another suggestion for future research, is to further investigate a culture's level of collectivism as a possible moderator. As described previously, Xiao & Tsui (2007) concluded that structural holes had a detrimental effect due to the presence of a collectivistic society. Therefore, also the level of collectivism might be a possible moderator for the effect that a VC´s network position has on the innovativeness of VC-backed firms. Finding out whether this argumentation holds, would extend the knowledge in the academic field regarding how VC's network positions can spur innovativeness of their backed firms.

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Appendix A – Relevant output outliers and excluding control variable 'age'

Table A1: *Summary table sample India including outlier*

	Model 1	Model 2	Model 3
	Emerging market – including extreme outlier		
(Constant)	(6.028)***	(5.818)***	(5.784)***
Number of investors	.025	-.010	-.012
	(.263)	(-.101)	(-.120)
Degree centrality average		.144	.194
		(1.494)	(.929)
Betweenness centrality average			-.056
			(-.272)
R^2	.001	.020	.021
Adjusted R^2	-.008	.003	-.006
N	115	115	115
Degree of freedom	113	112	111
Sig. F-test	.793	.320	.504
Durbin-Watson			2.209

Table showing the standardized regression coefficient per variable; *** $p < .01$; ** $p < .05$; * $p < .10$; accompanying t-values are displayed in parentheses

Table A2*: Summary table sample Japan including outlier*

	Model 1	Model 2	Model 3
	Mature market – including extreme outlier		
(Constant)	(10.939)***	(10.929)***	(10.894)***
Number of investors	.029	.036	.027
	(.512)	(.616)	(.424)
Degree centrality average		-.035	.022
		(-.598)	(.147)
Betweenness centrality average			-.061
			(-.411)
R^2	.001	.002	.003
Adjusted R^2	-.002	-.005	-.007
N	306	306	306
Degree of freedom	304	303	302
Sig. F-test	.609	.734	.852
Durbin-Watson			2.179

Table showing the standardized regression coefficient per variable; *** $p < .01$; ** $p < .05$; * $p < .10$; accompanying t-values are displayed in parentheses

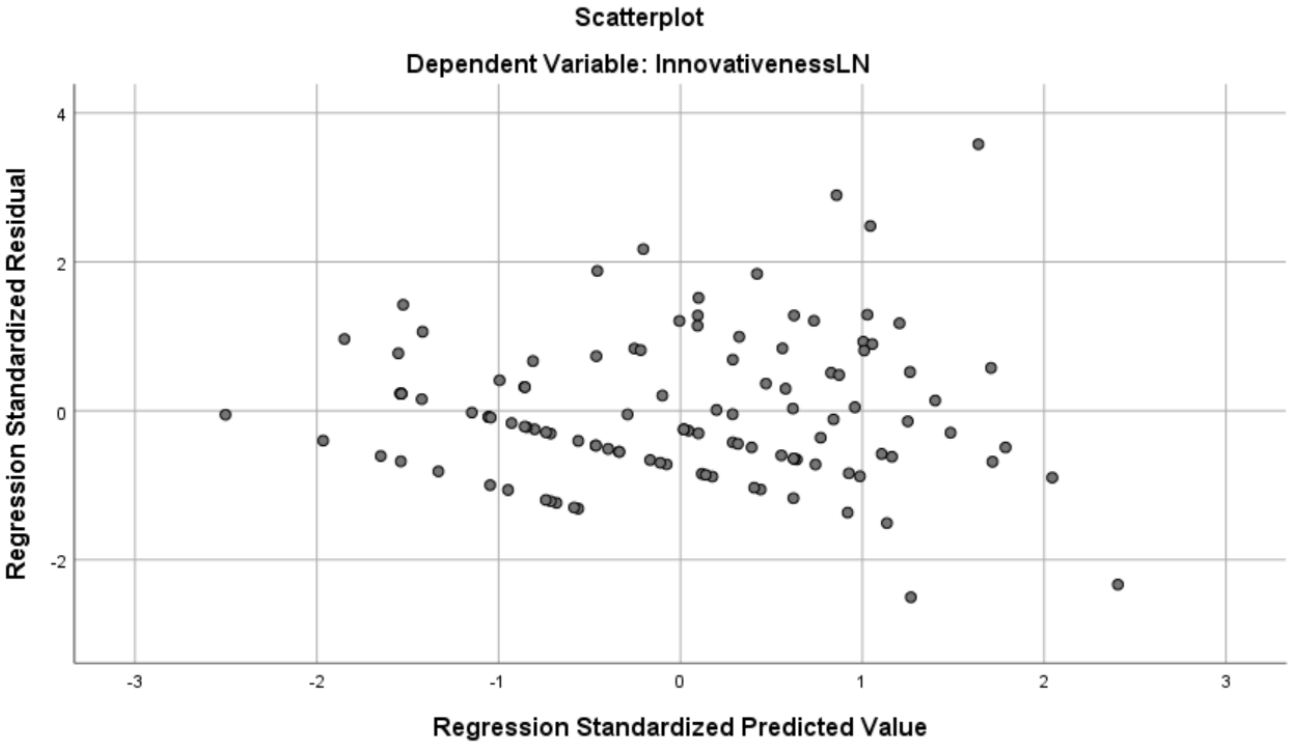

Figure A1: *Scatterplot showing heteroscedasticity sample India*

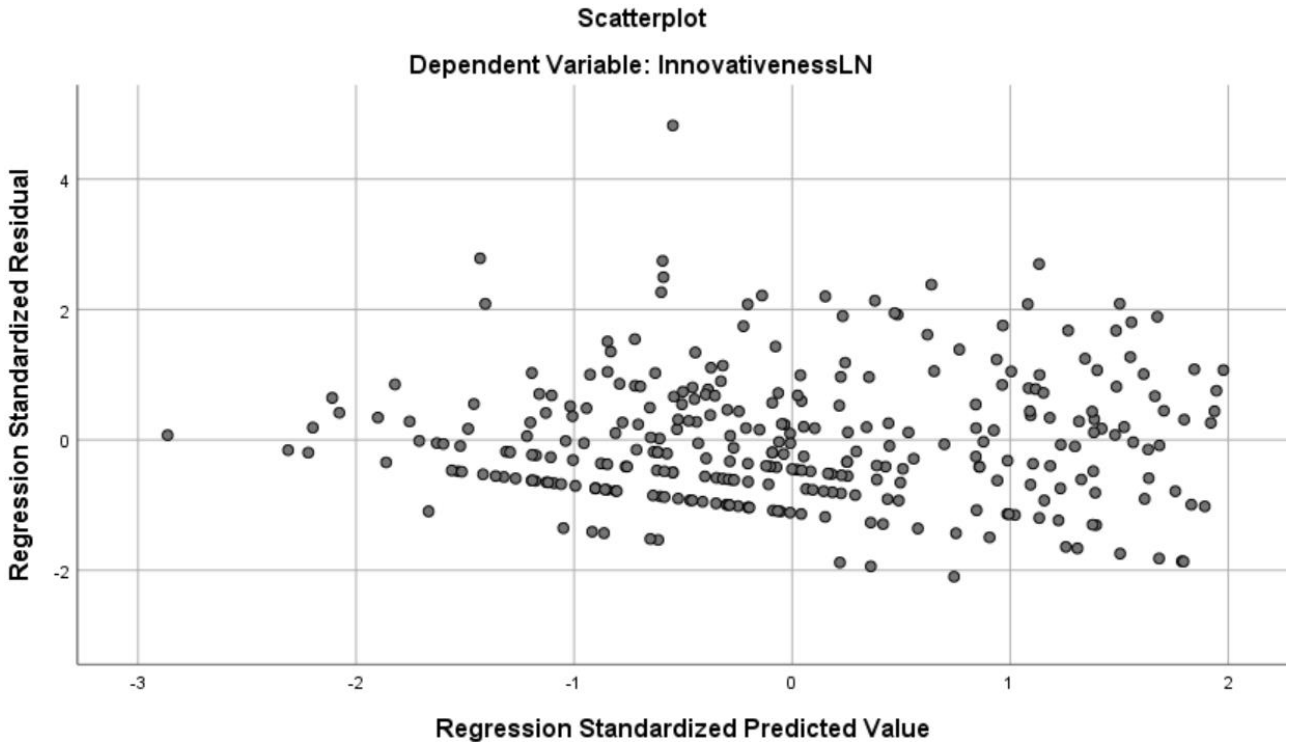

Figure A2: *Scatterplot showing heteroscedasticity sample Japan*

Appendix B – SPSS output sample India

For the sample representing India, four different transformations per variable have been conducted. These are the square root (SQRT), exponentiation (M2), log(x+1) (LN), and inverse (INV). After applying these different transformations, it became clear that the skewness and kurtosis for the control variable 'number of investors', and for the dependent variable 'innovativeness' are reduced most with either the inverse or the log(x+1) transformation. The normality of distribution for the independent variables 'degree centrality average', and 'betweenness centrality average' is improved best by using a square root transformation. This can be seen in Tables B1-B4 on the next page. Unfortunately, the same transformation must be applied to all variables (Field, 2009). The inverse transformation made the skewness and kurtosis worse of both 'degree centrality average' and 'betweenness centrality average'. Hence, the inverse transformation is not an option. Compared to the square root transformation, applying the log(x+1) transformation to all variables led to more favorable results regarding meeting the assumptions for a multiple regression analysis. Therefore, the log(x+1) transformation was applied instead of the square root transformation.

A log(x+1) transformation was required, as a regular log transformation would have led to missing values. This for the reason that a log transformation cannot take into account zero values. Since the value zero is present numerous times for 'innovativeness', 'degree centrality average', and 'betweenness centrality average', the log(x+1) transformation was applied. This means that a constant of 1 is added to all scores before taking the log transformation (MaCurdy & Pencavel, 1986; Field, 2018).

For reasons of convenience, the different variables are abbreviated in all tables and figures in the Appendices B and C. The control variable ´number of investors´ is abbreviated to ´Investors LN´, while the independent variables ´degree centrality average´, and ´betweenness centrality average´ have been abbreviated to ´Degree LN´ and `Betweenness LN´. The dependent variable ´innovativeness´ is displayed as `Innovativeness LN´. The `LN´ included in all variables' names stands for the log(x+1) transformation that was applied.

Table B1: *Transformation 'Degree centrality average' sample India*

	Degree orig.	**Degree SQRT**	**Degree M2**	**Degree LN**	**Degree INV**
Skewness	1.919	.822	3.608	1.898	4.358
Kurtosis	3.556	-.078	14.610	3.450	20.457

Table B2: *Transformation 'Betweenness centrality average' sample India*

	Betweenness orig.	**Betweenness SQRT**	**Betweenness M2**	**Betweenness LN**	**Betweenness INV**
Skewness	2.890	1.358	4.267	2.882	10.101
Kurtosis	8.556	1.803	18.737	8.504	102.330

Table B3: *Transformation 'Number of investors' sample India*

	Investors orig.	**Investors SQRT**	**Investors M2**	**Investors LN**	**Investors INV**
Skewness	3.889	1.998	7.041	1.077	.365
Kurtosis	19.225	5.284	55.926	.858	-1.449

Table B4: *Transformation 'Innovativeness' sample India*

	Innovativeness orig.	**Innovativeness SQRT**	**Innovativeness M2**	**Innovativeness LN**	**Innovativeness INV**
Skewness	7.272	2.875	10.166	.996	1.040
Kurtosis	62.256	14.211	106.093	1.595	.535

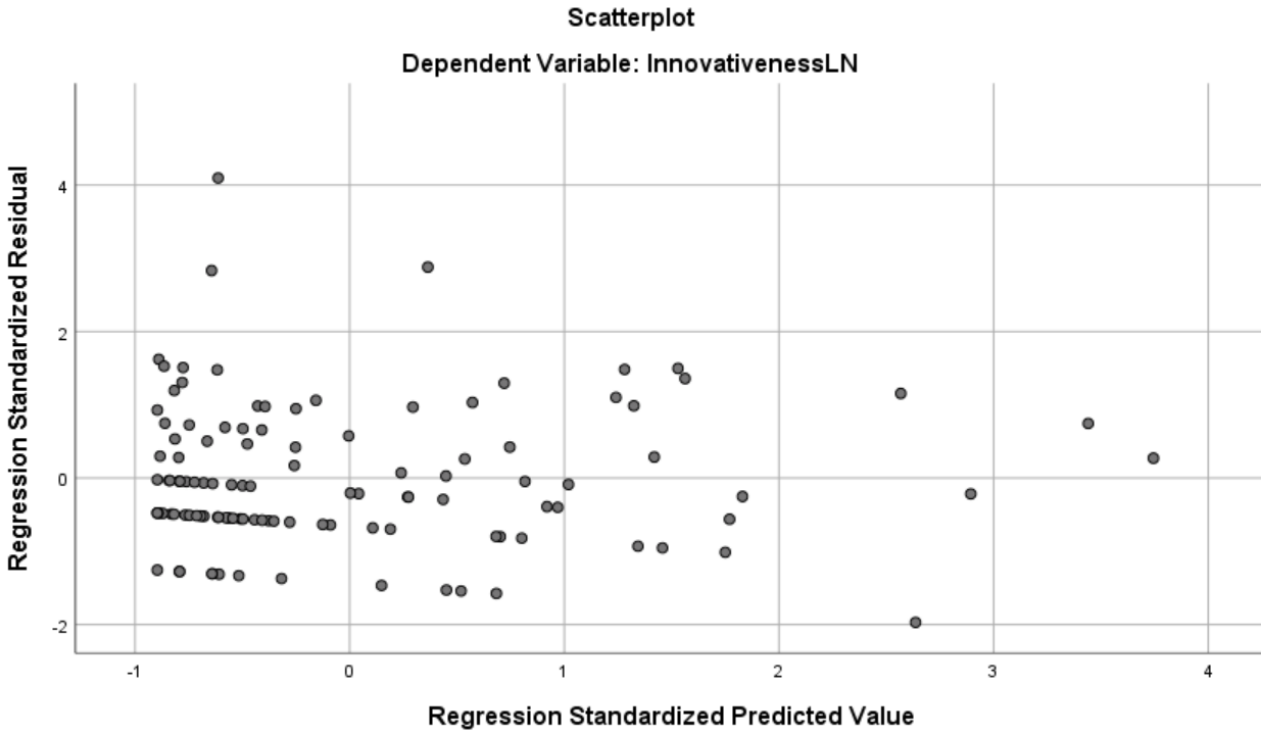

Figure B1: *Scatterplot sample India*

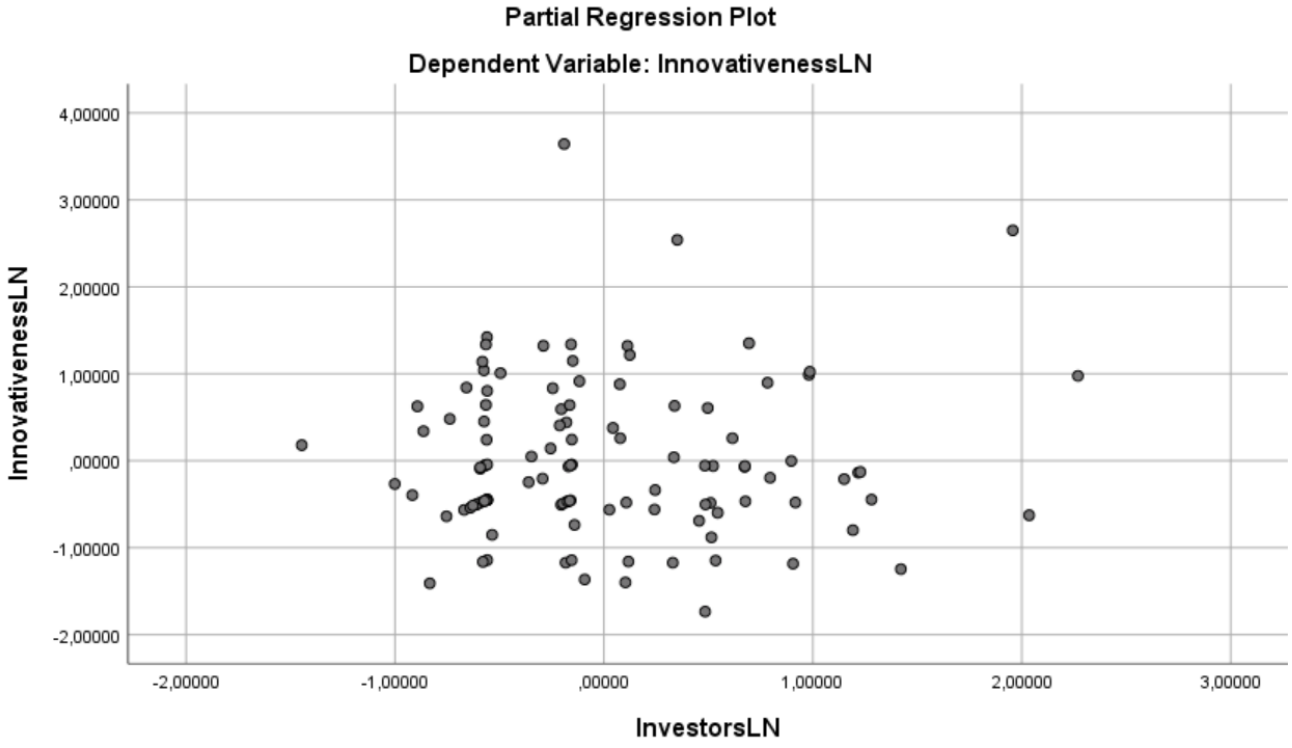

Figure B2: *Partial regression plot Investors LN & Innovativeness LN sample India*

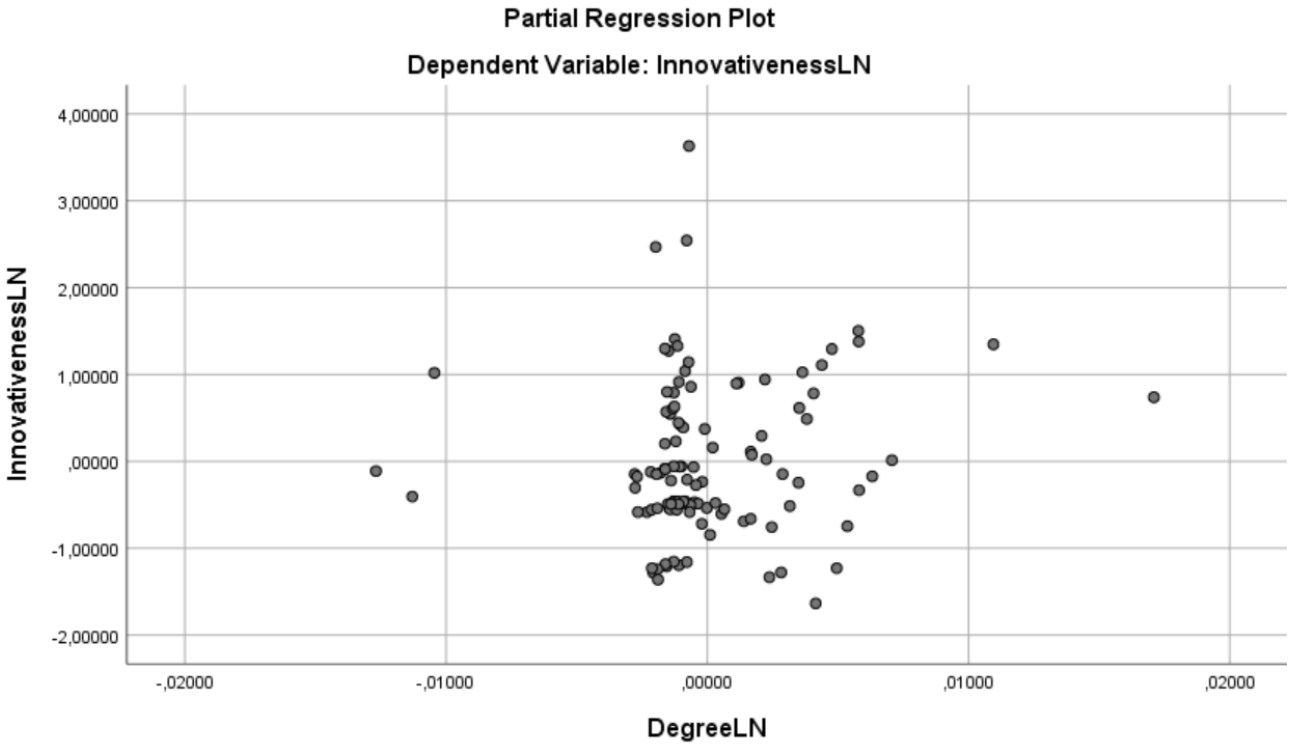

Figure B3: *Partial regression plot Degree LN & Innovativeness LN sample India*

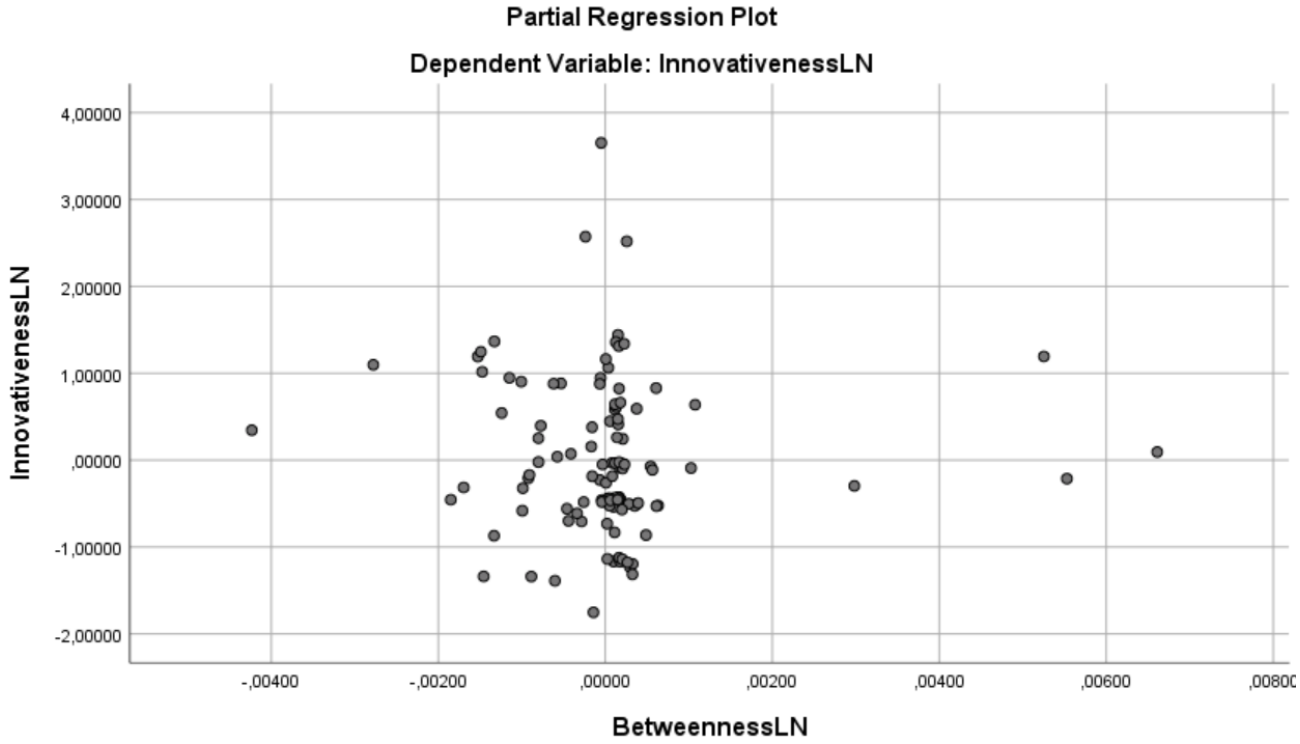

Figure B4: *Partial regression plot Betweenness LN & Innovativeness LN sample India*

Table B5: *Model Summary including Durbin-Watson test sample India*

Model Summary[d]

Model	R	R Square	Adjusted R square	Std. Error of the Estimate	R Square Change	df1	df2	Sig. F Change	Durbin-Watson
1	.080a	.006	-.002	.89878516	.006	1	112	.398	
2	.198b	.039	.022	.88776151	.033	1	111	.054	
3	.201c	.040	.014	.89125823	.001	1	110	.718	2.067

a. Predictors: (Constant), Investors LN
b. Predictors: (Constant), Investors LN, Degree LN
c. Predictors: (Constant), Investors LN, Degree LN, Betweenness LN
d. Dependent Variable: Innovativeness LN

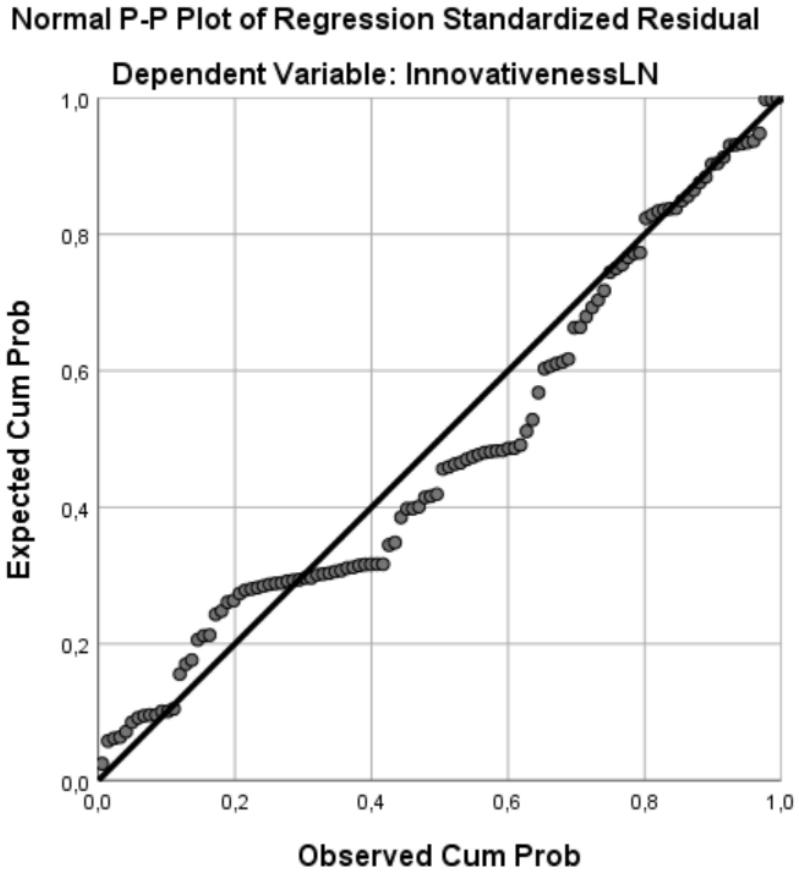

Figure B5: *Normal p-p plot sample India*

Table B6: *Coefficients sample India*

Coefficients[a]

Model		Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Toler.	VIF
1	(Constant)	1.139	.187		6.099	.000		
	Investors LN	.102	.120	.080	.848	.398	1.000	1.000
2	(Constant)	1.091	1.86		5.861	.000		
	Investors LN	.046	.122	.036	.376	.708	.945	1.059
	Degree LN	21.388	10.974	.187	1.949	.054	.945	1.059
3	(Constant)	1.089	.187		5.826	.000		
	Investors LN	.043	.123	.034	.348	.729	.940	1.064
	Degree LN	29.016	23.802	.253	1.219	.225	.202	4.941
	Betweenness LN	-24.438	67.590	-.074	-.362	.718	.207	4.821

a. Dependent variable: Innovativeness LN

Table B7: *ANOVA sample India*

ANOVA[a]

Model		Sum of squares	df	Mean square	F	Sig.
1	Regression	.581	1	.581	.719	.398[b]
	Residual	90.475	112	.808		
	Total	91.056	113			
2	Regression	3.575	2	1.787	2.268	.108[c]
	Residual	87.481	111	.788		
	Total	91.056	113			
3	Regression	3.679	3	1.226	1.544	.207[d]
	Residual	87.378	110	.794		
	Total	91.056	113			

a. Dependent variable: Innovativeness LN
b. Predictors: (Constant), Investors LN
c. Predictors: (Constant), Investors LN, Degree LN,
d. Predictors: (Constant), Investors LN, Degree LN, Betweenness LN

Table B8: *Correlation matrix sample India*

	1	2	3
1. InvestorsLN	1.000		
2. DegreeLN	-.171	1.000	
3. BetweennessLN	.070	-.886	1.000

Appendix C – SPSS output sample Japan

Also for the sample representing Japan, a square root, exponentiation, log(x+1) and inverse transformation were applied. Again, the abnormality of the control variable 'number of investors' and of the dependent variable 'innovativeness' was fixed most with either an inverse or a log(x+1) transformation. For the independent variables 'degree centrality average' and 'betweenness centrality average', the square root transformation solved the skewness and kurtosis the most. As was described previously, it is not allowed to apply different transformations to the variables that are included in the analysis (Field, 2009). Similar to the sample representing India, the inverse transformation led to an increase of the skewness and kurtosis for both the 'degree centrality average' and 'betweenness centrality average'. Meaning the inverse transformation must be cast aside. The log(x+1) transformation was superior to the square root transformation regarding meeting the assumptions for a multiple regression analysis. Hence, a log(x+1) transformation was also used for this sample. The results from applying each type of transformation are displayed in Tables C1-C4 on the next page. As was described in Appendix B, the different variables are abbreviated in all tables and figures.

Table C1: *Transformation 'Degree centrality average' sample Japan*

	Degree orig.	**Degree SQRT**	**Degree M2**	**Degree LN**	**Degree INV**
Skewness	1.846	.267	7.041	1.817	6.911
Kurtosis	6.427	-.187	70.542	6.203	52.144

Table C2: *Transformation 'Betweenness centrality average' sample Japan*

	Betweenness orig.	**Betweenness SQRT**	**Betweenness M2**	**Betweenness LN**	**Betweenness INV**
Skewness	5.391	1.247	12.363	5.365	16.476
Kurtosis	43.403	4.066	172.853	43.038	277.062

Table C3: *Transformation 'Number of investors' sample Japan*

	Investors orig.	**Investors SQRT**	**Investors M2**	**Investors LN**	**Investors INV**
Skewness	2.548	.868	9.450	.253	.955
Kurtosis	12.496	1.059	119.813	-.766	-.639

Table C4: *Transformation 'Innovativeness' sample Japan*

	Innovativeness orig.	**Innovativeness SQRT**	**Innovativeness M2**	**Innovativeness LN**	**Innovativeness INV**
Skewness	13.089	4.003	17.347	.872	.938
Kurtosis	201.808	30.126	302.205	.630	-.558

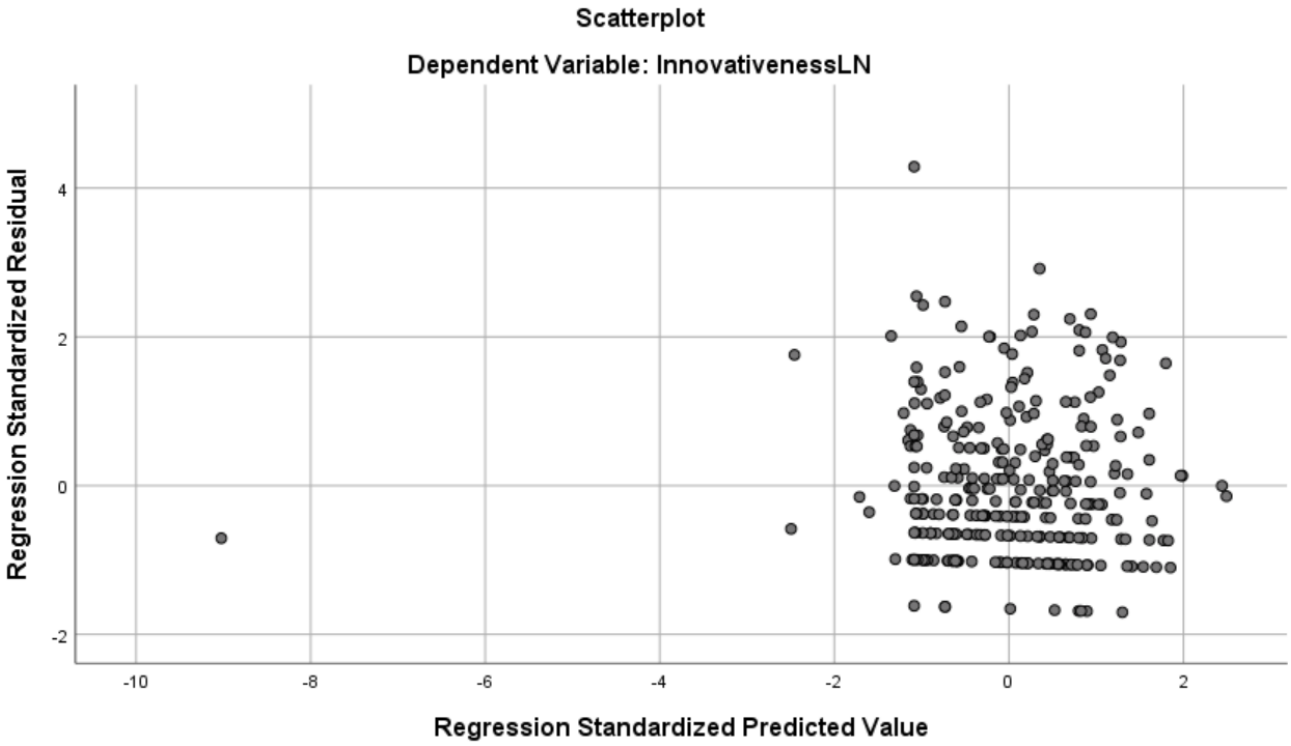

Figure C1: *Scatterplot sample Japan*

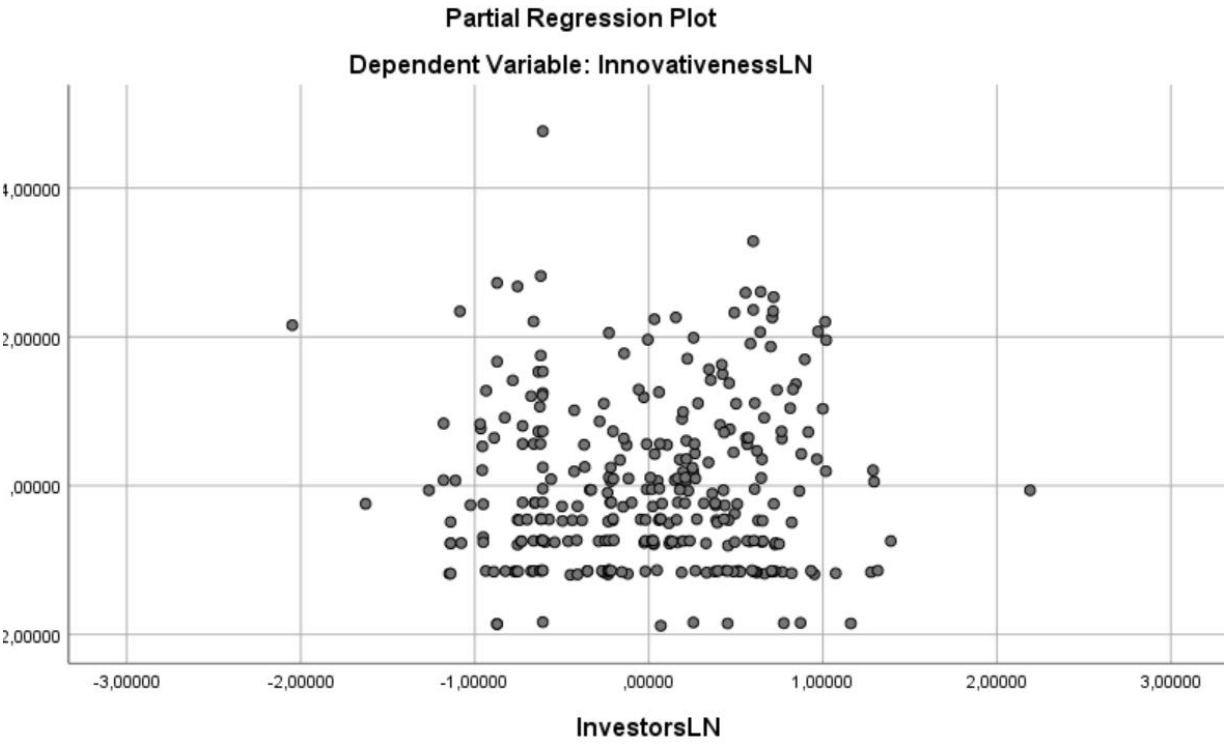

Figure C2: *Partial regression plot Investors LN & Innovativeness LN sample Japan*

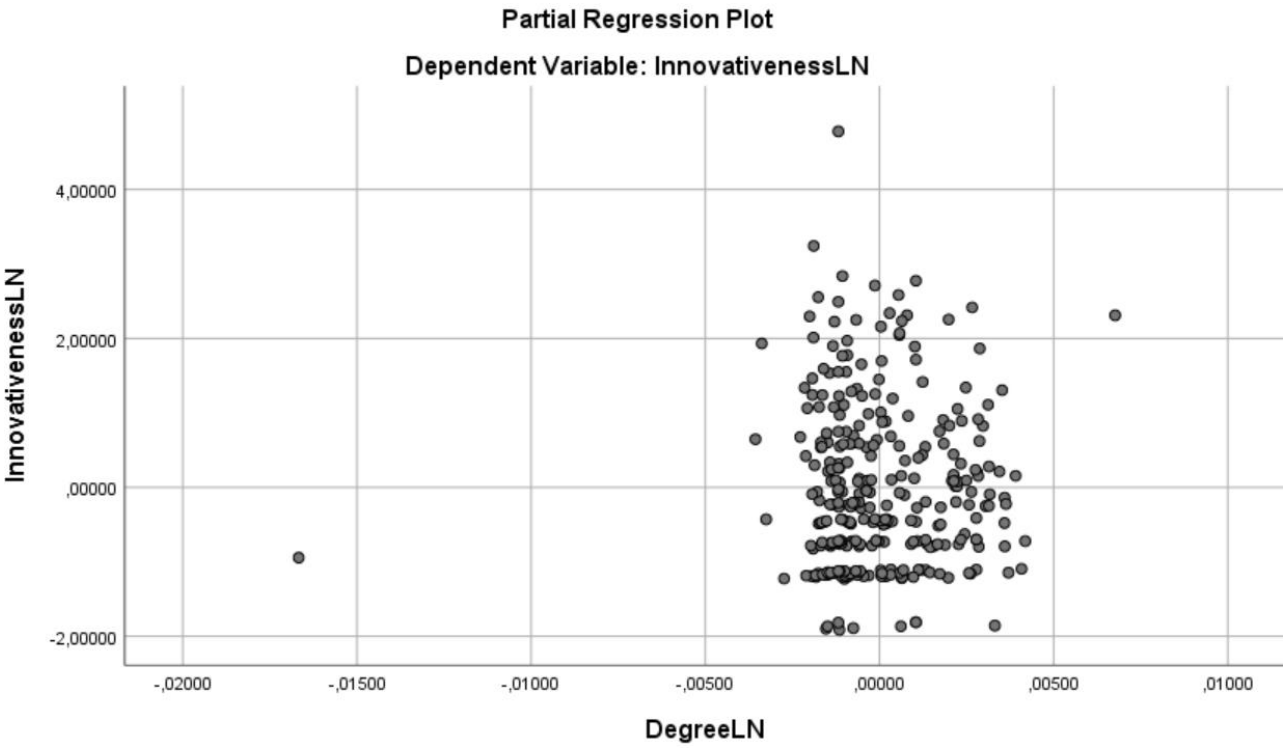

Figure C3: *Partial regression plot Degree LN & Innovativeness LN sample Japan*

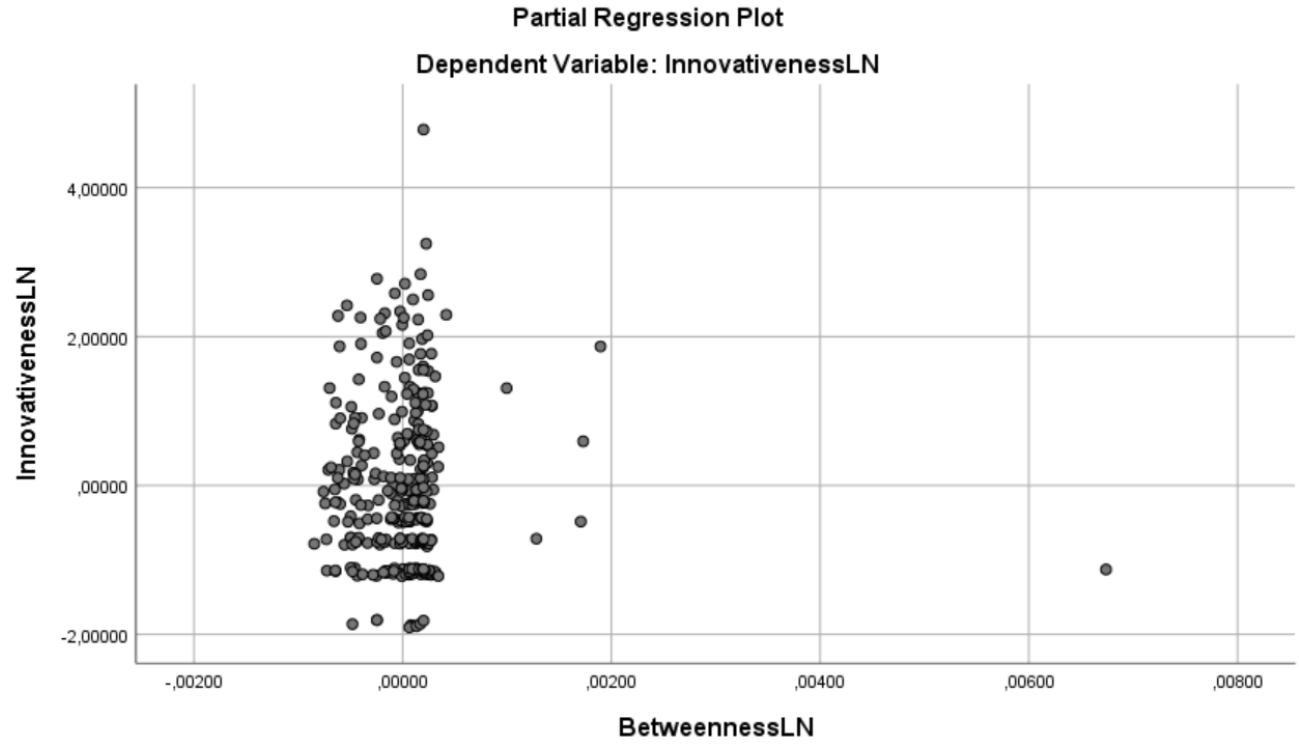

Figure C4: *Partial regression plot Betweenness LN & Innovativeness LN sample Japan*

Table C5: *Model Summary including Durbin-Watson test sample Japan*

Model Summary[d]

Model	R	R Square	Adjusted R square	Std. Error of the Estimate	R Square Change	df1	df2	Sig. F Change	Durbin-Watson
1	.027[a]	.001	-.003	1.11424662	.001	1	303	.645	
2	.028[b]	.001	-.006	1.11604919	.000	1	302	.882	
3	.037[c]	.001	-.009	1.11758957	.001	1	301	.682	2.176

a. Predictors: (Constant), Investors LN
b. Predictors: (Constant), Investors LN, Degree LN
c. Predictors: (Constant), Investors LN, Degree LN, Betweenness LN
d. Dependent Variable: Innovativeness LN

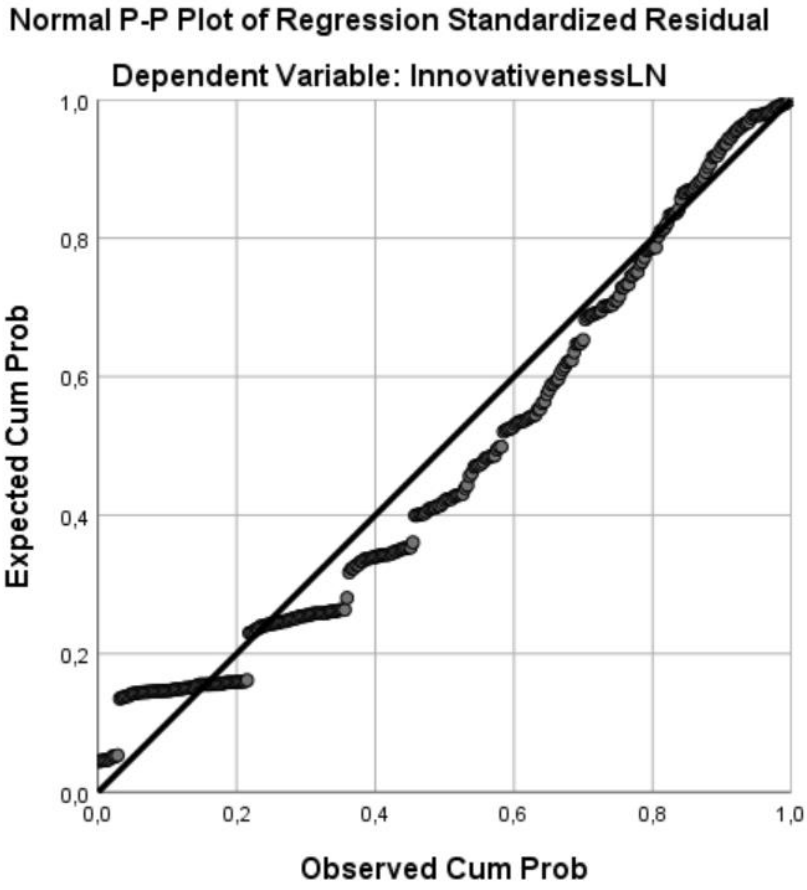

Figure C5: *Normal p-p plot sample Japan*

Table C6: *Coefficients sample Japan*

Coefficients[a]

Model		Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Toler.	VIF
1	(Constant)	1.781	.163		10.940	.000		
	Investors LN	.043	.093	.027	.462	.645	1.000	1.000
2	(Constant)	1.783	.163		10.914	.000		
	Investors LN	.049	.101	.030	.482	.630	.847	1.180
	Degree LN	-2.569	17.316	-.009	-.148	.882	.847	1.180
3	(Constant)	1.776	.164		10.797	.000		
	Investors LN	.044	.102	.027	.437	.663	.838	1.193
	Degree LN	9.206	33.551	.033	.274	.784	.226	4.417
	Betweenness LN	-50.240	122.546	-.048	-.410	.682	.244	4.091

a. Dependent variable: Innovativeness LN

Table C7: *ANOVA sample Japan*

ANOVA[a]

Model		Sum of squares	df	Mean square	F	Sig.
1	Regression	.265	1	.265	.213	.645[b]
	Residual	376.188	303	1.242		
	Total	376.453	304			
2	Regression	.292	2	.146	.117	.889[c]
	Residual	376.161	302	1.246		
	Total	376.453	304			
3	Regression	.502	3	.167	.134	.940[d]
	Residual	375.951	301	1.249		
	Total	376.453	304			

a. Dependent variable: Innovativeness LN
b. Predictors: (Constant), Investors LN
c. Predictors: (Constant), Investors LN, Degree LN,
d. Predictors: (Constant), Investors LN, Degree LN, Betweenness LN

Table C8: *Correlation matrix sample Japan*

	1	2	3
1. InvestorsLN	1.000		
2. DegreeLN	-.290	1.000	
3. BetweennessLN	.104	-.856	1.000