Entrepreneurial Teams' Social Capital and Funding Acquisition

by

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Declaration

I declare that this PhD thesis entitled 'Entrepreneurial teams' social capital and funding acquisition' has been composed by myself under the guidance and supervision of Professor Nicos Nicolaou and Dr Noni Symeonidou. This thesis has not been submitted for any degree to any other university, and is submitted only to the University of Warwick for the degree of Doctor of Philosophy.

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Abstract

Much research suggests that financial capital links to the likelihood of success in fledging firms. Scholars have argued that entrepreneurs are expected to benefit from their network relationships while seeking funding. However, prior research has presented conflicting results thus far in terms of addressing the association between entrepreneurs' network structure and their funding acquisition outcomes. I conjecture that the inconclusive debates are due to the paucity of attention at the team-level perspective, where focusing on individual entrepreneurs who may be part of a team could introduce bias in terms of our understanding of the social capital perspective in entrepreneurship. This thesis thus aims to ascertain the impact of entrepreneurial teams' external social network structure on the outcome of receiving financial capital support through the integration of the structural hole and upper echelons perspectives. I first argue that an entrepreneurial team as an ego arching over many non-redundant ties (i.e. brokering many structural holes) will enjoy superior external funding injection into the start-up. Further, I contend that the brokerage advantage of a team's structural network is not homogenous, and will be altered by the new venture team's demographies. To address these arguments, I assemble a unique longitudinal dataset through drawing data from the Crunchbase database and the U.S. Patent and Trademark Office. Based on a sample of 3,083 U.S. start-ups founded between 2009 and 2013, I find that the entrepreneurial team's external network nonredundancy significantly provides a positive impact for new ventures in terms of obtaining funding, as well as the funding amount. Furthermore, I identify team tenure and heterogeneity of education as important contingency factors that negatively and significantly shape the relationship between network nonredundancy and the fundraising outcomes. In contrast, I do not find that industry experience, founding experience, or gender diversity can significantly moderate the network nonredundancy and funding acquisition relationship. This thesis also discusses the theoretical contributions, implications for practice, and future research directions.

Chapter 1

Introduction

For over three decades, network access has been recognised as an important conduit for gathering the broad range of resources necessary to progress new ventures (e.g. Aldrich & Zimmer 1986; Birley 1985; Butler, Garg, & Stephens 2019; Hoang & Antoncic 2003; Semrau & Werner 2014; Stuart & Sorenson 2007). Particularly, financial resource has been documented as a key element for entrepreneurs to successfully launch the new venture and for the ongoing operation of the enterprise. (e.g. Carter, Gartner, & Reynolds 1996; Shane & Stuart 2002; Hanlon & Saunders 2007). Nascent entrepreneurs normally do not have sufficient financial resource and may rely heavily on financial support from family members (Shane & Stuart 2002; Greve & Salaff 2003). Accordingly, the ability to acquire external funding via the founders' social capital contributes significantly towards the early-stage venture's performance (Shane & Stuart 2002). Financial capital also plays significant roles for late-stage venture development. For example, technology-based ventures may be particularly prone to suffering from financial constraint due to the considerable R&D expense involved in the product development process (Hsu 2007). Thus, leveraging further venture capital investment from outside investors is vital for fledging firms' expansion and scaling, once start-ups progress towards the later growth stages (Hsu 2006). Consequently, it is expected that the entrepreneurs' network represents an important instrument for securing external financial resource when establishing new ventures, thus indicating that effectively leveraging their external network contacts might be one of the most important tasks for entrepreneurs.

Albeit the network perspective is flourishing in the entrepreneurship field, the existing literature pays greater attention to examining the effect of the solo entrepreneur's social networks (e.g. tie strength, network size and structural holes) on new venture performance (e.g. Batjargal 2003, 2005, 2007, 2010; Batjargal, Webb, Tsui, Arregle, Hitt, & Miller 2019; Brüderl & Preisendörfer 1998; Hansen 1995; Hirai, Watanabe, & Inuzuka 2013; Stam & Elfring 2008; Patel & Terjesen 2011). Nevertheless, there are relative few studies that explore the relationship between the entrepreneurs' network and financial resources (e.g. Shane & Stuart 2002; Shane & Cable 2002; Florin, Lubatkin, & Schulze 2003; Batjargal & Liu 2004; Semrau & Werner 2014). In addition, these studies primarily focus on investigating the impact of the entrepreneur–investor's direct dyad tie on the investment decision, namely, whether the prior relationship increases the likelihood of receiving financial support (e.g. Shane & Stuart 2002; Shane & Cable 2002; Batjargal & Liu 2004; Semrau & Werner 2014). Moreover, these studies thus far have produced conflicting results, where some show positive findings (e.g. Shane & Stuart 2002; Shane & Cable 2002), present an inverted-U relationship (e.g. Semrau & Werner 2014), or show no significant connection (e.g. Batjargal & Liu 2004). Moreover, an unanswered question remains regarding the impact of the entrepreneurs' network structure on their financial capital acquisition.

Providing insight into this gap is important not only from the social capital perspective, but also in terms of the entrepreneurial practice, since some types of new ventures (e.g. high-tech start-ups) might continually require the supply of external financial capital to ensure their survival. As prior studies underscore the importance of having a prior relationship with investors to receiving additional financial support from outside (e.g. Shane & Stuart 2002), I contend that we should not neglect the entrepreneurs' external network effects in this context. Managing an effective network structure might provide entrepreneurs with an alternative perspective in terms of attracting funding, rather than solely relying on the maintaining of specific relationships with investors, since the entrepreneur–investor tie could dissolve over time if the new venture does not achieve the desired outcomes (Shafi, Mohammadi, & Johan 2020). Therefore, achieving a better understanding of the structural network's impact might offer further theoretical and practical implications in assisting entrepreneurs to secure their financial resources.

With respect to studying the role of entrepreneurs' structural social capital, the majority of the studies in this area primarily focus on the individual entrepreneur's supporting networks (as shown above), and rarely consider the team as the unit for analysis (Hansen, Podolny, & Pfeffer 2001; Nicolaou & Birley 2003; Vissa & Chacar 2009). However, considering the lens of the team-level network perspective would be important for two simple rationales. First, studies that only focus on the solo entrepreneur or founder's network may not capture the full spectrum of the accessible contacts (Vissa & Chacar 2009), since most start-ups are now team-based (Bolzani, Fini, Napolitano, & Toschi 2019; Lazar, Miron-Spektor, Agarwal, Erez, Goldfarb, & Chen 2020). Second, the collective working mode differs from working alone, and hence the strategic decision-making process in terms of how to leverage the benefit from network relationships would be more complicated when considering the group effect (e.g. Paruchuri & Awate 2017; Reagans & Zuckerman 2001; Reagans, Zuckerman, & McEvily 2004). Accordingly, I contend that neglecting the team-level effects might affect the manner in which we apply the social capital perspective under the entrepreneurship context, since "Scholars in the entrepreneurship field are, however, recognizing that focusing on a single entrepreneur who may be part of a team can produce biases in our understanding of entrepreneurship" (Lockett, Ucbasaran, & Butler 2006, p.119).

In this thesis, two goals are thereby established. First, I intend to explore and extend the current understanding of the impact of the entrepreneurial team's social network effect on acquiring external financial capital, specifically by focusing on exploring the effect of the entrepreneurial team's external network structure on a new venture's likelihood of securing funding/funding amounts based on an integrative consideration of two foundational theories: structural holes theory (Burt 1992) and upper echelons theory (Hambrick 2007, 2016; Hambrick & Mason 1984).

Furthermore, I draw upon previous research indicating that the network effects on venture performance are not uniform, and may be altered by distinct contingent factors (Vissa & Chacar 2009). Therefore, this thesis also aims to reveal certain parts of the 'black box' through examining the potential moderating effect that can vary the value of the entrepreneurial team's external network in terms of the fundraising capability. In this study, the entrepreneurial team's demographic characteristics (i.e. the team tenure, heterogeneity of education, gender diversity, industry experience, and prior founding experience) are considered as representing important contingent factors for moderating the relationship between their external networks and funding acquisition. As the findings from the team network literature (e.g. Reagans et al. 2004; Reagans & Zuckerman 2001) suggest, internal team dynamics such as organisational tenure heterogeneity and internal team network density may influence the team performance in terms of completing tasks. Combined with the upper echelons theory claims that top managers' characteristics will influence the strategy and performance of the firm, it is expected that the top management team’s demographic characteristics will also significantly present the internal team dynamics (Foo, Sin, & Yiong 2006) and impact the decision-making process. For example, top managers’ demographic variables such as educational background and previous experience can reflect an individual’s values, cognitive style, and risk propensity (e.g. Wiersema & Bantel 1992), where these represent important factors that influence the team’s strategy for accessing heterogeneous information and resources via external networks, and then impact the organisational performance.

Besides, a longitudinal research design is applied in this study while considering the temporal effect in order to provide empirical evidence in support of the two above-mentioned goals. Tracking entrepreneurial teams’ network structure and other characteristics over time can significantly help in capturing the dynamics of each feature, since the entrepreneurial team’s formation and network development are not static (Lazar et al. 2020). For example, the entrepreneurial team’s composition might change when receiving venture capital funds due to the potential ownership change of the initial founding team (Hellmann, Schure, Tergiman, & Vo 2019). The start-up team thereby may be expanded to fill all the managerial positions, or even be fully replaced by professional top managers (Ewens & Marx 2018; Hellmann et al. 2019; Wasserman 2003). Intuitively, the team member adjustment would also alter the ‘collective team’s social networks’, as well as other start-up characteristics such as the culture and vision. Thus, if this study were to adopt a cross-sectional research design, it would not be possible to capture such potential dynamics for further empirical analysis. Moreover, such design enables the employment of more econometric techniques to mitigate certain empirical concerns such as endogeneity and reverse causality (i.e. a superior network effect leading to greater start-up performance or, conversely, greater start-up performance shaping the entrepreneurs' superior network). Therefore, it is expected that such longitudinal research design would introduce advantages in several aspects to help disentangle the inconclusive debate in terms of the network effects on either financial capital acquisition or new venture performance.

I make three theoretical contributions. First, I contribute to the entrepreneurial team and entrepreneurial finance literature by filling a research gap in terms of identifying how the external network structure of the entrepreneurial teams influences the external funding acquisition outcomes. Second, this study contributes to the social networks and entrepreneurship literature through linking the structural hole theory and upper echelons perspective, with the findings suggesting that the team demographics would alter the effectiveness of the entrepreneurial team's external networks' usage in terms of influencing start-ups' funding outcomes. Third, this study adds new insight to the team networks literature by examining the team network effect under the entrepreneurship context, where this field has been dominated by research investigating the impact of R&D teams' network on team performance within an organisation. Likewise, the team networks' development dynamic is highlighted by applying the longitudinal research design in reflecting the team network evolution over time, through consideration of the change in the concurrent team composition (i.e. member entry and exit). The results also provide a number of practical implications for leveraging the advantage of social networks and building efficient entrepreneurial teams in order to effectively obtain funding.

1.1 Research questions

In response to the research gaps highlighted above, this thesis proposes two research questions:

In response to the research gaps highlighted in the introduction section, I thereby specifically propose to investigate the following two research questions:

1. What is the impact of an entrepreneurial team's external network structure on the likelihood of receiving funding and the amount of funding received?

2. How do team demographics alter (strengthen or weaken) the impact of an entrepreneurial team's network structure on the likelihood of receiving funding and the amount of funding received?

These two research questions focus on two important rationales that would affect our usage in terms of the social network and entrepreneurship theories. First, the team-level network structure is distinct when compared with a single person's network, and hence disregarding it might introduce bias to our understanding of the social network impact under the entrepreneurship context. Second, the team-level network effect is not always uniform, and hence the effectiveness is highly likely to vary via the internal team dynamics. Overall, I aim to respond to these two research questions in order to bring new theoretical insights and practical implications in the social network and entrepreneurship field.

1.2 Structure of the thesis

This thesis consists of six chapters. After the introduction, Chapter 2 introduces the theoretical framework of the study and synthesises the literature across the social network and entrepreneurship field in order to summarise the existing findings in detail, and identify potential gaps in relevant research streams.

Chapter 3 presents the hypotheses development, along with a proposed test model.

Chapter 4 delineates the methodology in detail, first by depicting how the unique longitudinal dataset is constructed for hypotheses testing, followed by the introduction of the statistical analysis models. Important endogeneity concern is also addressed, as well as potential solutions to alleviate this issue.

Chapter 5 reports the results of the main analysis and the other five robustness tests. The association between the entrepreneurial network structure and funding acquisition is explored, as well as those significant contingencies that moderate the network–funding relationship.

Chapter 6 discusses the contribution of the thesis based on the empirical evidence presented in Chapter 5, along with the practical implications applied to entrepreneurs (or teams) in building an effective team to leverage external networks in order to seek superior venture outcomes. Then, the limitation and future research directions are presented.

Finally, Chapter 7 draws the thesis to a close with concluding remarks.

Chapter 2

Theoretical background and literature review

This chapter introduces the theoretical background of the thesis and reviews the relevant literature in five primary sections. In sections 2.1–2.3, I commence the chapter by depicting the theoretical foundation of this thesis, which is built upon two important theories, namely, structural hole theory and upper echelons theory. Besides, the broad social network theory is also introduced in order to provide a comprehensive picture of how scholars have applied the network perspective in the general management and entrepreneurship research.

In particular, I localise the position of the synthesised literature into a further four sub-sections that discuss the connections between social networks, organisational performance, and entrepreneurship in section 2.2. Due to the paucity of team-level social network research to date, thus greater attention is required in order to more fully comprehend the role that social networks play when predicting financial capital acquisition.

Section 2.3 presents the upper echelons theory, and then in section 2.4, the overarching integration of the theoretical framework of this thesis is presented. I first describe the entrepreneurial team phenomenon and justify its value for consideration as a research stream or level of analysis in the entrepreneurship field. In addition, the interaction of social capital and human capital in the network-based research is discussed, since those studies represent important ground for further investigation of the key moderating factors in terms of the relationship between social networks and new venture performance. Furthermore, on the basis of the recent theoretical framework developed by Lazar et al. (2020), I underscore that the entrepreneurial team formation is a dynamic process in order to accentuate the importance of a longitudinal research design while conducting research in this field.

Finally, in the end of section 2.4, I portray several topologies in order to illustrate the insightful concepts to be explored in this research. Overall, on the basis of the discussion in this chapter, I further develop the hypotheses as well as the proposed test model in Chapter 3.

2.1 Social networks theory

2.1.1 Overview

The concept of the network or so-called ‘network approach’ is widely employed in a number of research fields including sociology, anthropology, social psychology, statistics, physics, biology, and computer science. The key network notion is to examine the interactions between any units (also referred to as ‘actors’), while such applications can be traced back to the early twentieth century.

There are three major origins of the network concept channelling into the social sciences that can help us to define the idea of social networks. Following the time series, the first source of the network concept is derived from a ten-year series (in the 1920s) of anthropological examination of fieldworkers in the United States (U.S.)-based Western Electric Company developed by a team from Harvard Business School, while Kilduff and Tsai (2003, p.14) claimed that “social network analysis had its roots in organisational settings”. Then, Lewin (1951) and Heider (1958) embraced the concept to inspect social interaction from field theory in physics during the 1920s and 1930s. This source is considered to represent the inception of "network research on cognition and interpersonal influence" (*ibid*, p.13). The final major source originated from a mathematical approach developed to provide quantitative evidence for Lewin's (1951) work through graph theory by Harary, Norman, and Cartwright in 1965. This led the study of social networks to shift from "description to analysis" (*ibid*, p.13). Thus, social networks intrinsically represent interdisciplinary theory, which has emerged from a range of different disciplines.

Essentially, the transfer of the general network perspective into the social sciences determines that those actors involved in a social network can be either individuals or organisations. The relationship between social actors can function through different types of structure (i.e. the pattern of network ties) depending on the network characteristics. In addition, a string of social network analysis methods was developed to enable analysis of the network structure that produces patterns to unpack theories (Wasserman & Faust 1994).

2.1.2 Theoretical foundations of social networks

As a broad domain, an explanation of social networks theory could be considered a challenge. Kilduff and Tsai (2003, p.37) asserted that the theoretical foundations of social networks can generally be grouped into three divisions, viz. (1) imported theories, (2) indigenous social network theories, and (3) exportation theories. Such decomposition of an entire social network's theoretical perspective might present an opportunity to enhance our understanding of the insight of social networks. However, not all arrays of social network theories have close links to this study. Accordingly, here I will simply outline how such relevant social networks' theoretical foundations are linked to organisations and the entrepreneurship context on the basis of the first two categories.

Imported theories

As this section title suggests, social networks theory borrows concepts from other theories, and primarily from mathematics and social psychology.

First, the social network analysis concept has emerged from graph theory. The actors and ties can be illustrated as points and lines, while arrows can be included to represent direct graphs in highlighting the degree of reciprocation (Harary et al. 1965). Furthermore, Krackhardt (1994) applied graph theory and noted that an informal organisation can be inspected through four graph-theoretic perspectives, namely, the degree of connectedness, graph hierarchy, graph efficiency, and least upper boundedness. Degree of connectedness describes the extent of "resource-sharing" and "collaboration" in the organisation (Powell, Koput, & Smith-Doerr 1996, p.143). The graph hierarchy describes a top-down single-direction hierarchical relationship, whereas the graph efficiency is concerned with whether redundant links exist between actors in the organisation. Similarly, a hierarchy structure represents perfect graph efficiency. Moreover, a pair of actors can both influence a third actor (e.g. where one person has two managers), implying a violation of the least-upper-boundedness notion.

The other aspect of imported theories is concerned with borrowing balance theory and social comparison theory from social psychology. The territory of balance theory primarily focuses on the cognitive consistency and the interpersonal relationship regarding tendencies to divide organisations into distinct cliques (Heider 1958; Davis 1963). With regards to social comparison theory, it states that people have a tendency to interact with others who are identified as similar to themselves in order to self-evaluate their abilities or opinions (Goethals & Darley 1987).

Indigenous social network theories

To discuss the primitive social network theories, it may be pertinent to divide them into two streams: first, the concept of the strength of weak ties and structural holes concerns how diverse knowledge and resource flow can be explained by the actor's position and the advantage of weak ties; second, structural role theory focuses on the impact of particular actors on other actors' behaviour in the networks.

- The strength of weak tie theory; structural holes theory

The strength of weak tie theory was developed by Granovetter (1973, 1983) to explain how actors' ties beyond the confines of closed social structures can access the flow of heterogeneous knowledge and resource. Actors within the closed social structures can also benefit from the weak tie; for example, approximately 80% of the previously unemployed who lived in Boston's countryside finally found employment positions through the unfamiliar contacts in their own social networks (Granovetter 1974). Furthermore, in the first version of weak tie theory, the strength of ties is found in the amount of time, reciprocity, intimacy, and emotional intensity (Granovetter 1973). Subsequently, Granovetter (1983) conducted a revision of the theory and claimed that strong ties illustrate the relationships between friends, whereas weak ties represent the relationships between acquaintances. Basically, his claims are based on the emotion domain and are dependent on balance theory. Hence, a network constituted of strong ties between actors can be referred to as a clique. Then, the function of weak ties is to serve as bridges between different cliques. To extend the concept into the examination of the organisation, different organisational departments can be considered as different cliques comprising of the strong ties of the team members. Without the weak tie, each department would be seen in isolation and any information contained inside the organisation would be fragmented and unable to flow. In contrast, departments can be linked via weak ties and reduce any existent conflict between cliques (Nelson 1989). In addition, Kilduff and Tsai (2003, p.14) underscored that “not all weak ties will be bridges” if the pressures between the actors have already approached the point of equilibrium.

Structural holes theory accentuated the importance of the position of an actor located or embedded within a network or social structure (Burt 1992). Individuals who can occupy the broker’s position in bridging different groups (or clusters) are believed to have the ability to obtain more nonredundant information. On the other hand, if individually connected actors are not separated and connected with a more diverse group of other actors, then the individuals’ position is not unique and overlap information will be acquired from their contacts. The implication of this theory can be extended to the entrepreneurial network, whereby entrepreneurs will be more likely to remain in the broker’s position (Burt 2004, 2019). Once the entrepreneurs’ network spans many non-redundant contacts, it is believed that entrepreneurs can have greater potential for success through obtaining a wide range of resources (Vissa & Chacar 2009), discovering the most prolific opportunities, “communicating the value of their proposal to diverse audiences”, and being “better able to bounce back from reversals” (Burt 2019, p.26).

- Structural role theory

With regards to the structural role theory, it encompasses three concepts, viz. structural cohesion, structural equivalence, and role equivalence (Kilduff and Tsai 2003, p.37). Actors who maintain strong relationships and are bound together in a clique or within a social structure can be considered to represent the phenomenon of structural cohesion. The concept of structural equivalence means that the role of two actors in the same social structure can be deemed to be alike (e.g. Lorrain & White 1971), whereas role equivalence signifies that they perform as similar characters in different networks (e.g. Krackhardt & Porter 1986).

Summary

In sum, the broad social networks theory can indeed be applied and extended in different subject areas and interdisciplinary research. Nevertheless, since the main interest of this study is examining the effect of the entrepreneurial team's network structure on the start-up's funding acquisition, the lens of focus will be trained on applying the structural hole theory in order to develop the hypotheses in Chapter 3.

2.2 Social networks and entrepreneurship

2.2.1 Social networks and their impact on entrepreneurial performance

Research in the past 30 years has shown that entrepreneurs' network relationships play a significant role in new venture success (e.g. Birley 1985; Aldrich & Zimmer 1986; Hoang & Antoncic 2003; Stuart & Sorenson 2007; Vissa & Chacar 2009; Semrau & Werner 2014; Butler et al. 2019). Network studies on entrepreneurial success can be simply grouped into two domains, which either focus on the relational or the structural features of the entrepreneurs' egocentric network (Hoang & Antoncic 2003; Semrau & Werner 2014). Relational features typically consider tie strength and the quality of the relationship effects on start-ups' performance, while structural characteristics primarily target the network position that the ego occupies within the network, and the external network size of the ego. Following this theoretical framework, I further divide the level of analysis into the individual (i.e. solo entrepreneur) and team level (i.e. entrepreneurial team) in order to represent the prior findings[1] of the literature in Table 2.1. As shown in the table, the impact of social networks on new venture performance remains inconclusive to date. In sections 2.2.2 and 2.2.3 below, relevant qualitative and quantitative studies are discussed regarding social networks and new venture performance that extend from the single founder to the team level.

2.2.2 Solo entrepreneur's social networks and entrepreneurial performance

The majority of previous studies focused on the individual level to investigate the association between social networks and entrepreneurial performance, as illustrated in Table 2.1. However, the effect of such relationships is inconclusive at present. In the following paragraphs, the literature regarding relational network effects (i.e. tie strength and the quality of the relationship) is first discussed, followed by those studies that explore structural networks (i.e. network size/network position).

Empirical studies of the influence of relational network characteristics on new venture performance are primarily built on the power of weak ties theory, as described above (Granovetter 1973, 1983). Julien, Andriambeloson, and Ramangalahy's (2004, p.251) qualitative study again claimed that weak tie networks can make a "complementary contribution to technological innovation" in small and medium-sized enterprises. However, this does not imply that weak ties are always beneficial at different entrepreneurial stages. Elfring and Hulsink (2003) focused the lens on innovation in order to examine the power of strong and weak ties under the

[1] Table 2.1 presents the quantitative findings of the literature on interpersonal or teams' social network effects on entrepreneurial performance, where studies regarding the inter-firm network (e.g. inter-firm collaboration) effects are not included.

entrepreneurial processes. Their results revealed that weak ties are powerful at the opportunity discovery stages, and have a positive effect on the pursuit of radical innovation. In contrast, at the new venture growth stages, strong ties are more beneficial when the entrepreneurial activities are focused on incremental innovation for new product development. The reason for this is that strong ties can exchange tacit knowledge, and have greater trust levels than weak ties when viewing opportunities at the new venture growth stage. In addition, Elfring and Hulsink's (2003) research noted that crucial information can be secured through the medium of strong ties. Jack's (2005) ethnographic study also reported similar results to Elfring and Hulsink (2003), whereby strong ties are important in terms of providing knowledge and information for new venture business activities. Thus, we can simply conclude that both strong and weak ties can positively impact organisational performance under specific contexts. Nevertheless, besides the in-depth qualitative studies, we still require quantitative research for testing the generalisability of the relationship between social networks and start-ups' performance.

In quantitative relational network studies, the measures of social networks are typically constructed as strong ties, weak ties, and the frequency of interaction between entrepreneurs and their contacts (or the so-called 'relationship quality'). The debate on whether strong or weak ties have impacts on new venture performance has not yet been resolved. Brüderl and Preisendörfer (1998) found that the benefit provided from strong ties is more crucial than weak ties, as obtaining support from strong ties is positively associated with both venture survival and sales growth, while receiving support from weak ties only offers a positive impact on sales growth but is insignificant for improving the likelihood of venture survival. In contrast, Batjargal (2003) uncovered no significant effect of strong ties on revenue and profit margin, while weak ties presented a negative impact. Moreover, both strong and weak ties were found to positively enhance new ventures' sales and profitability in Davidsson and Honig's (2003) study. To explain such inconsistent results, we might revisit Granovetter's (1973) theory, which claims that business connections are relatively weaker ties compared to the relationship between individuals and friends/family members. However, business ties can become strong ties in certain contexts (Semrau & Werner 2014). For example, when start-ups deal with venture capitalists for providing continued and structural financial support through different entrepreneurial stages, the initial weak tie between the new venture and venture capitalists can transform into a strong tie in the later financing stages (Steier & Greenwood 1995). Research regarding the relationship quality then found an inverted-U relationship between tie quality and venture performance, indicating that the impact of social network ties is not always positive (Watson 2007). Thus, perhaps this type of phenomenon is the reason that the relationship between relational social networks and venture performance presents distinct findings in the literature.

Except for the tie strength and quality of relationship measures, network size has traditionally been considered as an important characteristic for venture success. Larger network size was generally thought to enable entrepreneurs' access to greater resources, and thus offer a positive effect for starting a new business (Hansen 1995; Baum, Calabrese, & Silverman 2000; Raz & Gloor 2007; Semrau & Hopp 2016; Batjargal et al. 2019). However, there are also findings suggesting that no significant relationship (Reese & Aldrich 1995; Johannisson 1996; Batjargal 2003, 2005).

Along with the network size, network position is another stream of network studies on entrepreneurial success (Hoang & Antoncic 2003). Research investigating the network position and organisational performance is primarily based on Coleman's (1988) social capital theory that emphasises the advantage of dense network structures, and Burt's (1992) structural hole theory that indicates the importance of occupying the broker position when obtaining diverse resource and information. Under the entrepreneurship context, the majority of the studies are based on the later theory in terms of exploring the network position effect on entrepreneurial performance (Semrau & Werner 2014). Hansen (1995) found the average number of ties between the entrepreneur's network contacts to be positively significant in terms of the succeeding new venture's growth. In Renzulli, Aldrich, and Moody's (2000) study, they found that the likelihood of achieving venture success increased for entrepreneurs with highly heterogeneity networks. Similarly, another positive effect on sales growth through bridging ties to start-ups outside their industry was found by Stam and Elfring (2008), while Batjargal (2007) also reported the positive effect of structural holes on venture performance. Furthermore, study on university spin-off's external network nonredundancy on "sales volume, employment, and competitive capabilities" concluded with a significantly positive relationship (Hirai et al. 2013, p.1120). In contrast, Batjargal (2010) found that the presence of structural holes in entrepreneurs' external networks has a negative impact on a new venture's profit growth. Nevertheless, a number of studies found no significant relationship between network positions and new venture performance (Batjargal 2003, 2005, 2007; Patel & Terjesen 2011). Overall, studies regarding the sole entrepreneur's network position and new venture performance again present an unclear picture to date, with a possible explanation for such inconclusive results being that the findings have emerged from the distinct operationalisation of network characteristics (Burt 2000). Likewise, another potential explanation for the conflicting findings could stem from the level of network analysis, since focusing on the founder's contacts may not collect the full accessible network outside the new venture (Vissa & Chacar 2009). Moreover, as the existing literature in this domain involves a cross-sectional-based research design, and thus might suffer from reverse causality, this could also be one of the reasons why researchers have reported conflicting findings. Finally, distinct performance measures and particular context setting might also influence the consistency of the findings.

2.2.3 Entrepreneurial teams' social networks and new venture performance

Considering the entrepreneurial team as a unit, it appears that there is no reason not to embed it into a network structure. Particularly, most start-ups nowadays are founded by a team, as mentioned above. Thus, rather than focusing on the lone entrepreneur, it is worth placing the lens of focus on entrepreneurial teams, since it was found that "teams do better than solo founders" (Aldrich & Kim 2007, p.249).

The top management team's external network range and external tie strength were found to be positively associated with sales growth and stock returns in established firms, respectively (Collins & Clark 2003). Furthermore, Collins and Clark (2003) found no significant relationship between the top management team's external network size and performance measures. Nevertheless, can we expect similar results to present under the entrepreneurial context? In fact, whether the entrepreneurial team's social networks benefit, hinder, or have no impact on a new venture's performance is again inconclusive in the literature.

Investigating the university spin-off phenomenon, Nicolaou and Birley (2003) found an increasing tendency towards exodus when the academic teams' exoinstitutional business discussion network has a high level of nonredundancy, along with strong ties. In addition, Vissa and Chacar (2009, p.1181) found that "more structural holes in the entrepreneurial team's external network is associated with superior venture performance".

According to the above discussion, we similarly cannot acquire a clear picture while examining the team-level network position effect on entrepreneurial performance, since the number of available studies is still limited.

2.2.4 Entrepreneurs/Entrepreneurial teams' social networks and financial capital attainment

There are relatively few studies that explore the association between social networks (either relational or structural) and the financial resources. Table 2.2 lists the current contribution from the literature regarding this research domain.

Similar to those studies exploring the link between social networks and new venture performance (as shown in Table 2.1), most focus on the individual level network analysis. Shane and Cable (2002) found entrepreneurs having direct or indirect ties to investors prior to them formally launching a new venture increases the likelihood of receiving the seed-stage investment, while Semrau and Werner's (2014) research displays a non-linear association (i.e. an inverted-U relationship) between network ties and receiving the financial support or not. Furthermore, Batjargal and Liu (2004) found that entrepreneur teams' prior relation with venture capitalists does not have a significant effect on investment decisions. Yet, they found that entrepreneurial teams who have prior strong ties connecting with venture capitalists have an increased likelihood of receiving investment when the prior strong ties interact with start-ups' growth potential and those start-ups having competitive products/technology in the market. Moreover, Florin et al.'s (2003) research reported that a larger external team network is positively associated with financial capital, but has no effect on sales growth.

Besides, as far as I am aware there are no studies documenting the direct effect of network position on receiving financial resources. Perhaps researchers have traditionally believed that building a strong relationship with investors is a more effective means of obtaining the external financial support, and hence pay greater attention to studying the entrepreneur–investor tie effect. However, I argue that examining the effect of the entrepreneurial team's network structure on funding acquisition is also crucial to theory extension and entrepreneurial practice. My hunch is that the prior entrepreneur–investor dyads may not always continue, since the start-ups cannot always meet the initial investors' expectations and obtain continuous financial support. The most recent study (Shafi et al. 2020) provides evidence on this view and claims that the investment tie could 'go awry' due to its double-edged sword property. Having investors to support the nascent period on the one hand can demonstrate a 'track record' in attracting future funding, yet this can also sour the reputation for the investors' syndication networks once the start-up cannot meet the initial investors' expectations. Nevertheless, stable external funding provision might be more important for start-ups, especially for high-tech new ventures, where financial constraints will lead to the failure to develop intellectual property and commercial products (Hsu 2007). Thus, effectively leveraging the network structure might be another means of securing the long-term financial resources. Nevertheless, there remains no clear picture regarding the impact of entrepreneurs' external network patterns on ventures' funding outcomes to date.

The other rationale that supports the study of the network structure–financial resource attainment gap is from the prosperous research documentation on the network position–new venture performance association. In fact, unlike established firms, start-ups may not have revenues in their very nascent stages, and hence remaining focused on identifying important factors for obtaining financial resources should hold the same priority level as exploring the contingency factor of new venture performance. Foo et al. (2006, p.390) support this argument, since they highlight that “For a nascent venture, measures of performance such as sales, profits, and positive cash flows may not yet be relevant as the team is unlikely to have any substantial sales figures when the primary focus is to establish the venture”.

Overall, raising external funding is not only important for start-ups to continue to grow, but also for their survival in the highly competitive world of business. Therefore, it is believed that understanding the exact impact of entrepreneurs’ external network structure on financial resource acquisition will offer new insight for both social capital and entrepreneurship theories.

Table 2.1 Findings for social networks and entrepreneurial performance

Level	IV / DV	Relational (Tie strength/relationship quality)	Structural (network size)	Structural (network position)
Solo entrepreneur	Entrepreneurial performance	Hansen (1995) *venture growth (+)* Johannisson (1996) *venture success (not significant)* Brüderl & Preisendörfer (1998) *venture survival and growth (+) strong ties* Lee & Tsang (2001) *growth (+)* Batjargal (2003) *revenue and profit margin (+) IV: weak ties* *(not significant) IV: strong ties* Davidsson & Honig (2003) *sales and profitability (+) strong/weak ties* Watson (2007) *venture survival and growth (inverted-U)* Patel & Terjesen (2011) *monthly income (+)*	Reese & Aldrich (1995) *venture survival (not significant)* Hansen (1995) *venture growth (+)* Johannisson (1996) *venture success (not significant)* Baum et al. (2000) *revenues (+)* Batjargal (2003) *revenue and profit margin (not significant)* Batjargal (2005) *revenue growth (not significant)* Raz & Gloor (2007) *venture survival (+)* Semrau & Hopp (2016) *start-up activities that nascent entrepreneurs had completed (+)*	Hansen (1995) *venture growth (+)* Renzulli et al. (2000) *Network heterogeneity on venture success (+)* Batjargal (2003) *network heterophily on revenue and profit margin (not significant)* Batjargal (2005) *network diversity (external contacts) on revenue growth (not significant)* Batjargal (2007) *structural holes on venture survival (not significant)* Stam & Elfring (2008) *bridging ties on sales growth (+)* Batjargal (2010) *structural holes on profit growth* (-) Patel & Terjesen (2011) *network range on monthly income (not significant)*

			Batjargal et al. (2019) *revenue growth (+)*	Hirai et al. (2013) *nonredundancy on sales volume, employment, and competitive capabilities (+)*
Entrepreneurial team	Entrepreneurial performance	Gap	Florin et al. (2003) *sales growth (not significant)* *return on sales (+)*	Nicolaou & Birley (2003) *nonredundancy on academic exodus (+)* Vissa & Chacar (2009) *network constraint on revenue growth (+)*

Table 2.2 Findings for social networks and financial resource acquisition

Level	IV / DV	Relational (Tie strength/relationship quality)	Structural (network size)	Structural (network position)
Solo entrepreneur	Financial resource acquisition	Shane & Cable (2002) *Seed-stage investment decision (+) direct ties; indirect ties* Semrau & Werner (2014) *financial capital support (inverted-U)*	Semrau & Werner (2014) *financial capital support (inverted-U)*	Gap
Entrepreneurial team	Financial resource acquisition	Shane & Stuart (2002) *Receiving venture capital funding (+)* *IV: prior relations (direct/indirect ties) to venture capitalists or angel investors (dummy variable)* Batjargal & Liu (2004) *investment decision (not significant)* *IV: prior relations (strong ties) between entrepreneurs and venture capitalists*	Florin et al. (2003) *financial capital (+)*	Gap

2.3 Upper echelons theory

The provenance of upper echelons theory can be attributed to the concept of bounded rationality, which was developed by three Carnegie School theorists' research on organisational behaviour (i.e. Simon 1945; March & Simon 1958; Cyert & March 1963). The bounded rationality concept asserts that perfect rationality is not feasible when an individual makes decisions in practice, as individuals might suffer from cognitive limitations under different environmental conditions. Applying this perspective to business organisations, top managers may strain every sinew to achieve the 'full' rationality in making an optimum decision to result in enhanced firm performance. However, finite information and previous experience will limit managers to partial rationality, and thus being 'bounded rational' while processing the decision-making. Following such foundations and after synthesising the previous literature on top executives, Hambrick and Mason (1984) proposed the 'upper echelons theory' by claiming that top managers' background characteristics will partially predict the executing strategy and performance of firms.

Revisiting the theoretical concept in detail, top executives will rely upon their personal cognition and experience to interpret the situation (e.g. opportunities and threats) they encounter in order to make a strategic choice under the conditions of bounded rationality. The decision-making outcome will then shape the organisational performance, such as profitability and growth (Hambrick & Mason 1984; Carpenter, Geletkancz, & Sanders 2004; Hambrick 2016). For instance, if there are more top managers with financial background in the composition of a top management team, perhaps we can expect that the firm will have a greater reliance on merger and acquisition events to boost the firm's growth or increase liquidity (Munyon, Summers, & Ferris 2011). On the other hand, top executives in high-tech firms that hail from an engineering background may tend to invest more in research and development (R&D) projects to develop innovative and competitive products, rather than focusing on marketing or financial events to improve the organisational performance.

Another core of upper echelons theory is to emphasise that "strategic decisions typically involve multiple executives, not only the chief executive officer (CEO), and therefore organization outcomes are best thought of as the result of group decision processes, rather than individual action" (Hambrick 2016, p.2). Furthermore, Pfeffer's (1985) organisational demography concept provides similar insight, whereby measuring individuals' demographic factors at the collective level is vital to understand the organisation.

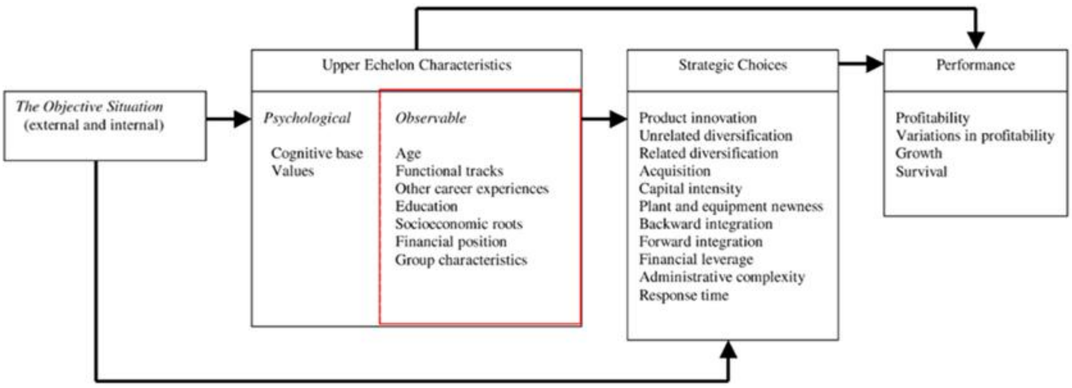

Figure 2.1 An upper echelons' perspective of organisations (Hambrick & Mason 1984, cited in Carpenter et al. 2004, p.751)

Besides, Hambrick and Mason's upper echelons theory not only contributes to theory building, but also methodology (Carpenter et al. 2004). As shown in Figure 2.1, the top managers' characteristics are applied as the proxies since personal cognitive values are difficult to measure. For example, *age*, *functional tracks*, *other career experiences*, *education background*, *socioeconomic roots*, *financial position*, and *group heterogeneity* are alternative observable measures to determine the cognitive values (Hambrick & Mason 1984). Similarly, *product innovation*, *diversification*, *acquisition*, and *financial leverage* are several observable measures for representing the strategic choice (*ibid*, p.198). Researchers then could leverage these observable proxies to predict whether there are relationships between the top management team characteristics and the strategic choices or organisational performance.

Based on the upper echelons theoretical foundations, scholars have applied a broad range of top management team characteristics with distinct measures in studying the effect on organisational outcomes. For example, Bantel and Jackson (1989) hypothesised and found that both the average education level and functional background heterogeneity of top managers in banks are positively associated with firms' innovation performance, where their sample included 199 U.S.-based banks. In Wiersema and Bantel's (1992) study, top management team members' age heterogeneity, team tenure heterogeneity, and educational heterogeneity were applied in predicting the effect on the company's strategic change (measured by the percentage change in diversification strategy). Similarly, except for the above-mentioned team characteristics measure, Hambrick, Cho, and Chen (1996) applied the top management team's functional heterogeneity in examining its impact on competitive actions and performance, respectively. The results revealed that team heterogeneity is a "double-edged sword" (*ibid*, p.659) that is negatively associated with competitive moves, while being positively associated with the firm's performance in terms of the growth in market share and profits. Moreover, under the entrepreneurship context, scholars not only examined the role of traditional top management team demography measures, but also investigated whether the team's prior industry experience or founding experience influence start-ups' performance (e.g. Delmar & Shane 2006; Shah & Smith 2010). More recently, in a study of the top management team's gender diversity effect in a sample of 3,392 private Danish firms, Lyngsie and Foss (2017) found that more females in the top management team (over a threshold) is positively associated to engagement with entrepreneurial activity in established firms.

Overall, upper echelons theory provides a significant framework for researchers studying top management team-related research, indicating that top managers' demographic characteristics are important predictors in influencing firms' strategic decision-making processes and the organisational performance. However, there are two important issues existing in the relevant upper echelons research domain. First, due to the inconsistent measures of individuals' characteristics, the results across the literature are antithetical (Nielsen 2010). Secondly, the majority of the research did not consider the temporal effect causing the phenomenon of top management team change. Cross-sectional studies would thus suffer from the limitation in capturing the dynamic team demographic effects, and thus consideration of a longitudinal design is suggested (Beckman & Burton 2010).

2.4 The overarching theoretical framework: integration of the social network theory and the upper echelons theory

Since the team-level network structure effect has been highlighted as an important research gap in the social network and entrepreneurship field, I thereby intend to build an overarching theoretical framework in this section to address the integration of the social network theory and the upper echelons perspective to link to the hypotheses development in Chapter 3.

Hence, the entrepreneurial team phenomenon and definition is introduced first in section 2.4.1, followed by a review of the studies that consider the interaction of entrepreneurs' social capital and human capital with new venture performance in section 2.4.2. Then, the importance of the temporal effect and dynamic nature for entrepreneurial team formation and its team-level social network development is accentuated in section 2.4.3. Finally, several topologies will be drawn upon in illustrating and summarising the core concepts to be explored and discussed in this thesis.

2.4.1 The entrepreneurial team

Whether being an individual entrepreneur or co-founding with other partners can both lead to successful business outcomes is a continuing debate in the entrepreneurship field. Rather than focusing on resolving this argument or joining the conversation, I intend to apply basic statistics, logic, and the time effect of entrepreneurial team formation to present and explain why the team-based venture phenomenon should receive greater attention.

We may encounter interviews on television or social media where a particular individual shares his or her successful and inspirational start-up story. Such stereotypes could lead us to overlook the important contributions to a new venture's success made by those behind the key individual, since entrepreneurial movements are myriad and complex. In fact, multiple entrepreneurial pioneers are more commonplace as they can effectively accomplish the development of a new venture, with Gartner, Shaver, Gatewood, and Katz (1994, p.6) underscoring that “The locus of entrepreneurial activity often resides not in one person, but in many”.

Since the late 1970s, academic studies have started to pay greater attention to the team-based phenomenon, as a vast number of new ventures have been founded and operated by two or more individuals, namely, a team (e.g. Timmons 1975; Cooper, Woo, & Dunkelberg 1989; Kamm, Shuman, Seeger, & Nurick 1990; Gartner et al. 1994; Klotz, Hmieleski, Bradley, & Busenitz 2014; DeSantola & Gulati 2017; Bolzani, Fini, Napolitano, & Toschi 2019; de Mol, Cardon, de Jong, Khapova, & Elfring 2020; Lazar et al. 2020).

This team-based venture phenomenon can be observed not only in high-tech but also in low-tech industries, even though high-tech start-ups have tended to attract the majority of scholars’ attention. Moreover, in Beckman’s (2006) research on the impact of the founding team’s composition on developing firm ambidexterity and firm behaviour, her analysis found that 90% of new ventures in the medical, manufacturing, and telecom sectors were established by joint effort. On the other hand, around two-thirds of team-based start-ups belonged to professional services, retail, and tourism (which can be categorised into low-tech industries) in Delmar and Shane’s (2006) research that studied the relationship between the founding team’s industry/start-up experience and venture failure/level of sales. Similarly, within the university spin-out context, Chiesa and Piccaluga (1999) reported that only 10% of spin-off firms are operated by an individual. Overall, even though the creation of a new business by an individual or a team should be determined by the specific context of entrepreneurship, since many different factors can influence a start-up’s development, the above-mentioned statistics show that multiple founders or top entrepreneurial management teams appear to represent the main stream in the founding world.

In addition, to capture the complete picture of the entrepreneurial team phenomenon, we should not neglect the ‘time effect’, as the dynamic change of the entrepreneurial team’s composition over time is normal and will have a significant impact in terms of a new venture’s development. In the most recent study, Lazar et al. (2020) organised the previous literature and claimed that a new venture team’s formation process involves different features in three distinct phases (i.e. Formation → Founding → Evolution and Growth) over time. In the developmental stage of the formation phase, it can be discriminated within two approaches. The first type comprising a start-up team concerns a solo entrepreneur who comes up with a business idea and then seeks potential co-founders to externalise it (Timmons 1975; Kamm et al. 1990). The other approach concerns multiple people that have reached an agreement to create a business and then produce the entrepreneurial plan collectively (Timmons 1975; Kamm et al. 1990; Forbes, Borchert, Zellmer-Bruhn, & Sapienza 2006). Lazar et al. (2020, p.50) also depicted a steady status of the entrepreneurial team (i.e. no change in team composition) under the “founding phase”, while the team will evolve during the final “evolution and growth phase”. Following the same line of thought, I collect the team characteristics’ variables longitudinally in order to reflect the real new venture team’s development roadmap and the phenomenon. The following sub-section now presents a review of the scholarly definitions of the entrepreneurial team.

Defining the composition of entrepreneurial teams

‘Entrepreneurial teams’, ‘new venture teams’, and ‘start-up teams’ are the most widely employed terminology in the entrepreneurship literature to describe a group of people who choose to collectively start or manage a new business. However, the criteria for identifying who comprise the entrepreneurial team differ across the literature (e.g. Schjoedt, Monsen, Pearson, Barnett, & Chrisman 2013; Klotz et al. 2014; Ben-Hafaïedh 2017; Lazar et al. 2020). These varying definitions of the composition of the entrepreneurial team may stem from the background characteristics, since researchers tend to have a distinct research focus under diverse entrepreneurial contexts. Moreover, when considering the timing effect, this induces a complex entrepreneurial team formation process. Therefore, disparate dimensions for defining the composition of an entrepreneurial team can be found (Kamm et al. 1990; Klotz et al. 2014; Lazar et al. 2020). Accordingly, I believe that providing a clear boundary for the framing of an entrepreneurial team is essential, in order to facilitate further statistical analysis and theoretical discussion in this thesis.

There are three primary identifications in defining entrepreneurial teams, namely, by examining whether the member’s title is “founder”, “owner”, or “top manager” (Ben-Hafaïedh 2017, p.13). Considering the time or entrepreneurial stage effect while studying the pre-founding phase, it can be expected that the ‘founder’ and ‘owner’, or ‘founder’ only, will be counted in defining the team. Accordingly, ‘top managers’ might not normally be considered as team members in a start-up’s nascent period. For example, Kamm et al. (1990, p.7) suggested that the founder and owner are the members of the entrepreneurial team, when they asserted that “we define an entrepreneurial team as two or more individuals who jointly establish a business in which they have an equity (financial) interest". In Hsu's (2007) study investigating the association between new venture teams' founding experience and venture capital funding/venture capital valuations, he counted 'founders' only as the entrepreneurial team members. Then, other research (e.g. Watson, Ponthieu, & Critelli 1995; Ensley, Pearson, & Amason 2002; Ucbasaran, Lockett, Wright, & Westhead 2003) that focused on exploring the entire entrepreneurial process or the venture growth stage applied another condition for framing the team, that is, by including the top managers. In addition, Klotz et al. (2014) argued the entrepreneurial team composition should focus solely on individuals in the executive position, namely, the top managers. Moreover, they claimed that entrepreneurial teams only include those who conduct "strategic decision making and [the] ongoing operations of a new venture" (*ibid*, p.227), which suggests that the entrepreneurial team is the new venture's top management team.

In fact, in the early stage of the venture, founders typically carry out several functional roles, since there are an insufficient number of team members. Hence, we may encounter titles such as 'founder & CEO' or 'co-founder & CTO' when examining a high-tech start-up. In different industries (or say, low-tech industries), a similar presentation of the title still exists, and may only lack the executives in managing technology. Of course, we may not see a clear functional title for the founders of some low-tech start-ups but overall, founders in all industries are invariably involved in different kinds of executive tasks, and hence should be considered as a condition when identifying the entrepreneurial team. Thus, on the basis of Klotz et al.'s (2014) definition, this thesis not only considers the top managers, but also includes the founders as a criterion for defining the entrepreneurial team.

2.4.2 The interaction of entrepreneurs' social capital and human capital with new venture performance

It is widely recognised (e.g. Davidsson & Honig 2003) that entrepreneurs' social capital and human capital can both benefit a new venture's performance. Social capital constructs typically refer to the tie strength, network size, or network position in presenting network structure; while human capital is mainly regarded as people's experience, knowledge, and skills in identifying the difference among individual workers. Aside from exploring the social capital and human capital effect on new venture performance, respectively, scholars have also debated how entrepreneurs' social capital and human capital interact in terms of the impact on new venture performance (Florin et al. 2003; Batjargal 2007; Klyver & Schenkel 2013; Semrau & Hopp 2016; Hernández-Carrión, Camarero-Izquierdo, & Gutiérrez-Cillán 2017). In general, studies in this domain remain scarce and provide inconclusive findings.

As per studies regarding entrepreneurs' social networks and new venture performance, the majority of research applies the solo entrepreneur as the unit in studying social capital and human capital's interaction. Batjargal (2007) found that entrepreneurs who have employment or academic experience in North America and Europe (i.e. developed countries) can strengthen the leverage of information and resource from their structural holes, which promotes venture survival. However, he did not determine a significant effect from testing industry experience and start-up experience as the moderators on the relationship between entrepreneurs' structural holes and venture survival. In contrast, a negative moderating effect of prior founding experience was reported by Klyver and Schenkel (2013). With these two aforementioned studies suggesting opposing directions in terms of the interaction effect of experience, subsequent studies attempted to decompose entrepreneurs' social capital into different network measures in order to examine the interaction with human capital and new venture performance. For example, Semrau and Hopp (2016) divided the entrepreneurs' network size into two types: receiving financial support and obtaining information support. Then, they found that the interaction effect of industry experience enhances the effect of financial networks in terms of the percentage of completed entrepreneurial activities, while the same interaction hinders the relationship between information networks and the percentage of completed entrepreneurial activities. Semrau and Hopp (2016) also examined the interaction effect of prior founding experience and reported the same results as the interaction effect of industry experience and the two types of entrepreneurs' network size. However, Hernández-Carrión et al. (2017) obtained different results, with their interaction tests of industry experience and professional network size presenting a positive moderating effect on the venture performance. Thus, it is clear that there is a lack of consensus in this area that requires further attention from scholars.

In addition, we may also wish to examine whether the interaction effect of social capital and human capital at the team level will result in similar or distinct findings when compared with the effect of testing on a single entrepreneur. For example, Florin et al. (2003) found that while entrepreneurial teams' network size (sum up the number of alliances, personal network size, and number of underwriters) and human capital (integrate start-up and industry experience, and directorships in venture capital firms) interaction can have a positive impact on the return on sales, there is a negative influence on receiving financial capital. Overall, the interaction effect of team-level social capital and human capital seems to show similarly inconclusive results to those seen when placing the lens of focus on solo entrepreneurs. However, it could be argued that Florin et al.'s (2003) study blends the firm's collaboration ties and top management team members' personal networks together, and thus the presented social capital is not a 'pure' team-based measure. Likewise, combining different experience measures together as human capital could also overlook the fine-grained interaction effect of particular human capital constructs (e.g. the interaction of entrepreneurial teams' social capital and industry experience, and the interaction of teams' social capital and start-up experience). Accordingly, perhaps the above argument could be the explanation for the contradictory interaction effects on the performance measures in this study.

In sum, studying the interaction of social capital and human capital under a team-level entrepreneurship context is still limited, while the findings of the interactions of solo entrepreneur's social capital and human capital are also inconclusive. Thus, according to the most recent study in this research stream, Semrau and Hopp (2016, p.421) "believe that further research should also address the interplay between the social and human capital among founding teams". Their concluding remarks thus indicate an important research gap for researchers to further investigate in this research territory.

2.4.3 Entrepreneurial team formation and team-level social network development: the temporal effect and dynamic nature

Network evolution and network dynamics during the entrepreneurial stages

The extent of the network dynamics is concerned with monitoring the 'change' of network characteristics through distinct entrepreneurial periods over time. For several decades, the stages approach has been the most popular instrument utilised in viewing venture creation and formation (Levie & Lichtenstein 2010). In the following paragraphs, several stage models of new venture creation will be introduced, while a further argument of a dynamic states model is presented to assist in understanding the network dynamics from another perspective.

From a longitudinal perspective, Larson and Starr's (1993) three stages model is recognised as a beneficial starting point for the conceptualisation of the building blocks of the network development processes of emerging ventures (Hoang & Antoncic 2003). Larson and Starr (1993, p.6) claimed that "network relationships are transformed from simple, often single-dimensional dyadic exchanges into a dense set of multidimensional and multilayered organizational relationships" over time. In contrast, Hite and Hesterly (2001) argued that the shift of network change should be from path dependency (which they referred to as being identity-based) to intentionally managed (referred to as being more calculative) over time. However, following Hoang and Antoncic's (2003) line of thought, more qualitative works are encouraged for the conceptualised framework, due to the insufficiency of the discussion of the roles of networks from the emergence to the formation period of new ventures.

As an ongoing proposition, Lechner and Dowling (2003) provided a four-stage model as a more detailed approach to addressing issues at distinct moments. They also highlighted that opportunities are derived from an "appropriate network composition" (*ibid*, p.22).

Then Jack, Moult, Anderson, and Dodd (2010) applied a longitudinal case study over a six-year period to demonstrate that the social ties are important for the overall operation of networks, and illustrated how the network structure shifts from being calculative to affective (i.e. built upon social relationships) over time. In addition, Slotte-Kock and Coviello (2010) proposed another theoretical framework to suggest that firstly, the organisation and network co-evolve over time; secondly, to explain how and why the network develops; and finally, to reveal what occurs over time. Their work echoes the previous literature, the further development of Van de Ven and Pool's (1995) underlying four theories (i.e. life cycle, dialectic, teleology, and evolution) in explaining the development and change in organisations, and represents the extension of Larson and Starr's (1993), Hite and Hesterly's (2001), and Hite's (2005) models.

In addition, by tracing and analysing 104 published management articles, Levie and Lichtenstein (2010, p.317) argued that there was "no consensus on basic constructs of the approach, and no empirical confirmation of stages theory". Consequently, a dynamic states approach to entrepreneurship was introduced, with scholars being encouraged to adopt this new perspective. Levie and Lichtenstein's (2010) argument might be valuable to know, but it requires further development since their model is not well accepted by the majority of the scholarship. Indeed, from their argument some scholars have exactly attempted to test stage growth models through inspecting network dynamics; however, the models they have tested are typically different. For example, following Wilken's (1979) three phases (i.e. motivation, planning, and establishment) conception of starting a business, Greve and Salaff (2003) applied the entrepreneurial phase as the independent variable and discussed networks as the dependent variable in order to investigate the shift of entrepreneurs' activities through the distinct venture formation stages. The results revealed that entrepreneurs do employ different networking strategies in distinct phases. Nascent entrepreneurs tend to spend greater time in discussion with family members and intimates during the motivation phase, while they move to expand their network to friends and strangers (i.e. business partners) through the planning phase. Finally, entrepreneurs only select their important social networks to maintain the relationship once the venture is physically established. They provided a breakthrough contribution in the early twenty-first century through confirming that the manner in which entrepreneurs develop the network varies through the different phases of entrepreneurship. Nevertheless, Greve and Salaff's (2003) data only resulted from a 6-month period of venture creation and formation, whereas a lengthier longitudinal study might have led to more robust findings. Also, Greve and Salaff's (2003) study failed to consider the environmental dynamic issue (Jansen, Van Den Bosch, & Volberda 2006).

Similarly, in order to combine network theory and resource-dependence theory, Sullivan and Ford (2014) carried out analysis on new-venture launches and the early venture development stages. Their results illustrated that in order to gather the required resource at the burgeoning stage, nascent entrepreneurs have a tendency to adjust the network size and the tie strength, while in the pursuit of network knowledge heterogeneity is more associated at the development stage. From their analysis, the stages approach is somehow a relatively superior approach to be applied, examining and generating insight of the change in the network development over time.

While it might be more challenging to test the dynamic states model proposed by Levie and Lichtenstein (2010) than the stages of growth models, it is still valuable to understand the implication that it offers. Why did Levie and Lichtenstein (2010) consider the dynamic states model to be more appropriate for explanation of the process of venture creation and formation? They debated that the assumption of the stages growth model is in considering that changes through the process are "linear" and thus rather "predictable" (*ibid*, p.335). Therefore, the model can display a specific number of stages. Notably, they disagreed strongly with another assumption that "organizations grow as if they were organisms" (*ibid*, p.335).

In contrast, the proposed dynamic states model claims that organisations would adjust their business strategy to accommodate the change of environment, and hence the number of dynamic states can be infinite or sometimes "predictable depending on context" (*ibid*, p.335). This also implies that the changes of firms' network structure and business development shift smoothly over time depending on the external environmental churn, rather than transiting within a specific or rigid time. In sum, the characteristics of the stages growth model may be regarded as regulated and predictable, yet the dynamic states model might be more interdependent and flexible in its ability to adapt to environmental change. On the whole, such statements regarding the dynamic perspective for studying organisation emergence are plausible, but require further empirical examination. Moreover, while considering the network development from the entrepreneurial context, this perspective leads us to consider whether network development can be conceptualised as a process.

Other aspects of the entrepreneurial team formation and social network development during the entrepreneurial process

As the perspective by Hoang and Antoncic (2003, p.175) suggested, "process-oriented network research focuses on the development and evolution of networks over the venture formation process". In such an orientation, the network is viewed as the dependent variable. From this concept, the notion of observing the network development processes might have some overlap, as per the discussion of the network evolution models in the network dynamics section above. However, outside such a framework, a number of perspectives from the management literature remain that can still be discussed in this section. Overall, the purpose of this section is to offer a further extension of network dynamics in enhancing greater understanding of the perspective.

Early entrepreneurial process-oriented research found that entrepreneurs access resource via their own strong network ties (i.e. family members and friends) during the new venture creation process (Birley 1985; Zimmer & Aldrich 1987). However, this is still insufficient for us to comprehend the role of the social network through the entrepreneurial process.

There are a number of other facets available to inspect the relationship between the entrepreneurial processes and entrepreneurial network development. First, the entrepreneur's age, working experience, and education level positively influence his or her social network development (Cooper, Folta, & Woo 1991). Moreover, developing and implementing a business plan can support entrepreneurs in gaining further contacts than those who do not have such a plan in place (Smeltzer, Van Hook, & Hutt 1991). Furthermore, there are also some studies that are related to entrepreneurial processes but that do not directly examine the impact on network development from entrepreneurial processes. Block and MacMilan (1985) claimed that there are several milestones that a successful organisation will achieve over time; for example, product testing, first finance, market testing, bellwether sale, and so on. Similarly, Bhave (1994) developed a three-stage entrepreneurial venture creation process model: the opportunity stage, the technology setup and organisation creation stage, and the exchange stage (*ibid*, p.223). At each stage, entrepreneurs undertake a range of activities in order to develop the new venture. It is indicated that entrepreneurs have to initially conduct some precursory trial-and-error activities that will allow them to define the opportunity, and thus lead to the commitment of physical venture creation. Later on, entrepreneurs should overcome the challenges of establishing the product production technology and facilities, and then can proceed to the exchange stage and becoming part of the demand–supply chains. Moreover, in 1996 Carter et al. explored start-up activities, and finally presented a clear list and sequence of those initial activities (or precursor activities) that nascent entrepreneurs conducted in order to create a new business. To enumerate, the initial activities include requesting funding, seeking facilities, applying for patent(s), preparing the plan, forming a legal entity, recruiting employees, and so forth. Moreover, they considered that positive cash flow and the Federal Insurance Contributions Act (FICA) are regarded as start-up indicators in the U.S.

Nevertheless, the entrepreneurial process literature discussed above essentially does not consider any change in the founding team members during the venture development process, as those studies still focus their lens on the single entrepreneur, or even neglect the multiple founders' effect altogether, with no consideration of the impact of any change in the founding team members over time. In fact, entrepreneurial team member adjustment is quite common nowadays, with external investors often involved in the ownership allocation (Wasserman 2003; Beckman 2006; Ewens & Marx 2018; Hellmann et al. 2019). Particularly, experienced top managers might replace the nascent founders or other team members in order to operate the start-up in the later funding stages, as well as to assist the new venture's progression to IPO (Hellmann et al. 2019). Accordingly, we can expect that an entrepreneurial team's network will vary through this addition and loss of members. Furthermore, considering the upper echelons perspective (Hambrick & Mason 1984; Hambrick 2007, 2016), different entrepreneurial team members would have distinct cognition on risk-taking and strategic planning, and thereby it is expected that the interpersonal network development would be assorted during the entrepreneurial stages. Therefore, the social network development of the entrepreneurial team during the start-up journey is complicated since it involves people, entrepreneurial activities, and time.

In sum, the above-mentioned qualitative and quantitative (i.e. applying social network measures as the dependent variable) literature suggests that network development is a dynamic and evolving process. Moreover, the team dynamic is another underlying dimension causing the evolution of network development. Accordingly, studying the network effects on new venture performance might necessitate the tracking of the network effects longitudinally in order to capture the 'change' and classify the effect causality, and to thus present a clearer picture of the role that social networks play during the entrepreneurial process.

2.4.4 The structural topology of entrepreneurial team formation and external network dynamics: the general concept

In this section, I illustrate the overarching framework via the structural topology in representing the theoretical concepts discussed in this chapter.

2.4.4.1 The single entrepreneur's brokerage network structure

Figure 2.2 illustrates the term 'network structure' discussed in this thesis. The left-side of the figure refers to a single entrepreneur as an ego who occupies a broker position in representing the higher level of network nonredundancy in his/her network structure. In contrast, the right-side of the figure presents a relatively dense structure due to a connection between two contacts of the focal entrepreneur, and hence shows a lower level of network nonredundancy.

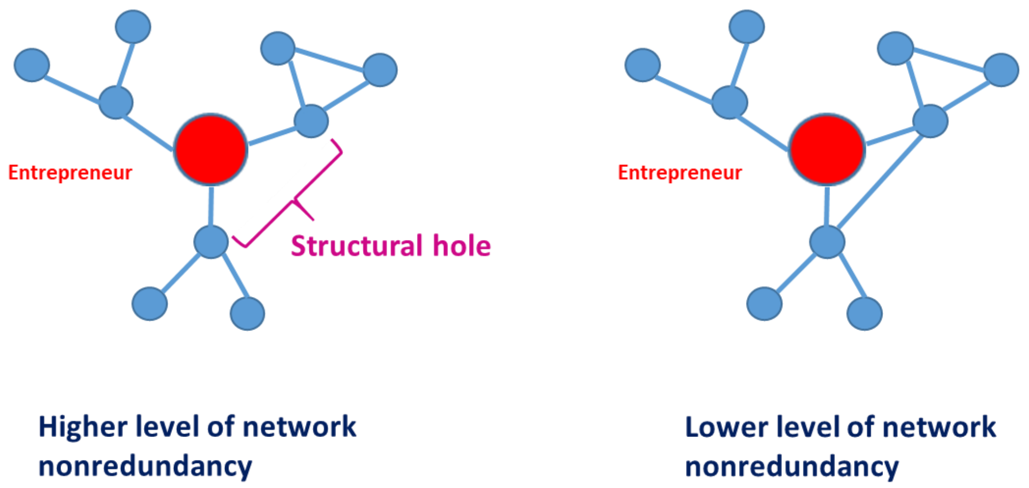

Figure 2.2 Single entrepreneur’s brokerage network structure

2.4.4.2 Entrepreneurial teams’ external network structure

Having reviewed the single entrepreneur’s brokerage network structure, we now explore how it may change if the network structure is at the team-level (see Figure 2.3). The explanation for the team-level network structure is addressed in section 3.2.

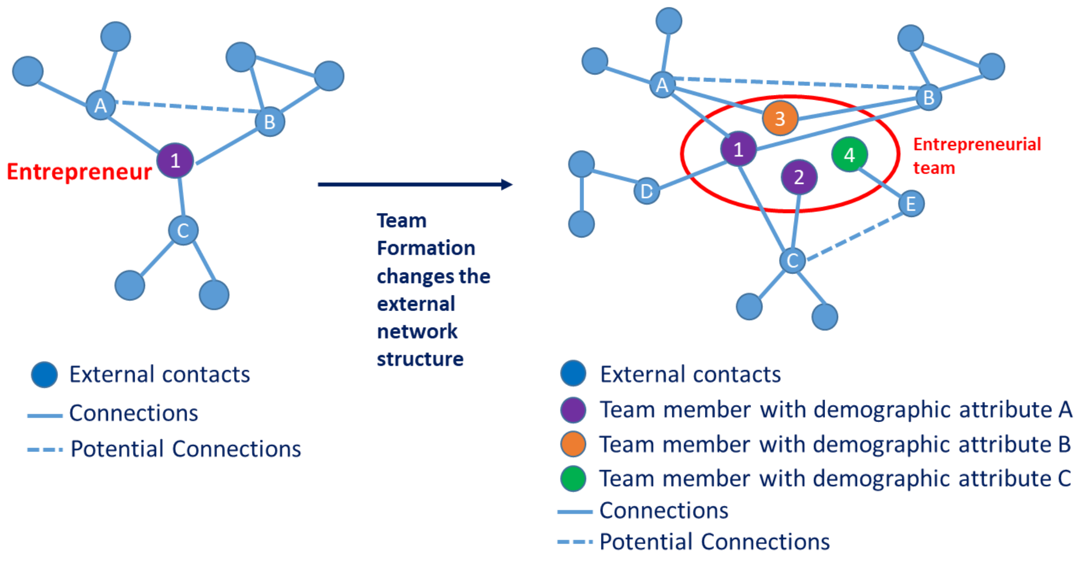

Figure 2.3 Team-level network structure

2.4.4.3 Evolution of entrepreneurs/entrepreneurial teams' external network

The nature of network development has been highlighted as a dynamic process in section 2.4.3 above. In Figures 2.4–2.6 below, I illustrate three different basic scenarios regarding the network development in a two time-point frame by extending Vissa and Bhagavatula's (2012) individual network churn concept.

Scenario 1: A solo founder initiates an idea for a new venture, and then continues to operate the start-up independently until the next founding stage

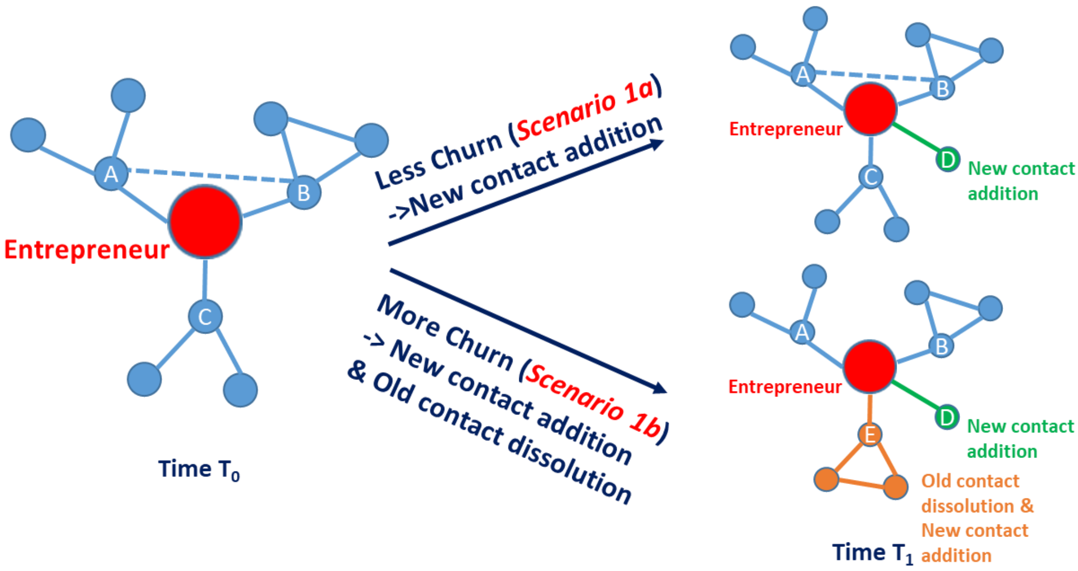

Figure 2.4 Single entrepreneur's network churn over time

Scenario 2: A single founder launches a new venture, and then searches for additional team members or cofounders to join the entrepreneurial journey

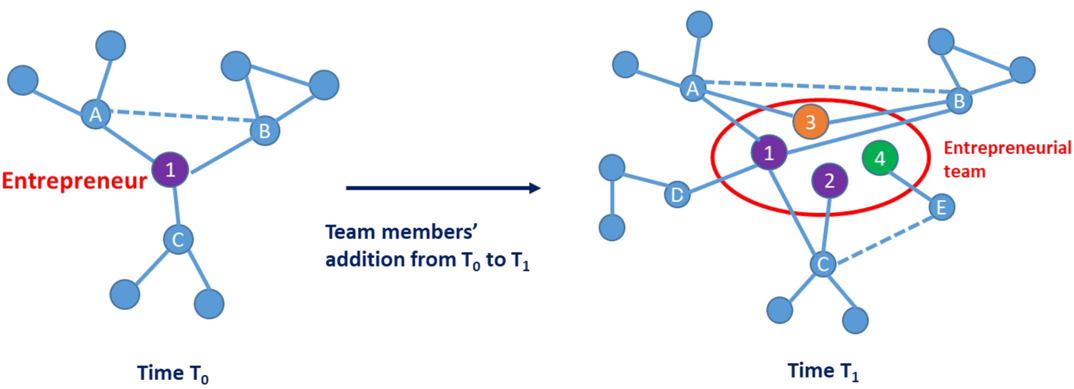

Figure 2.5 Entrepreneurial team formation and network development over time

Scenario 3: Multiple founders start a new business together, and then collectively progress the new venture into the following stage -> team member addition (Scenario 3a) or reduction (Scenario 3b) at a subsequent time T1

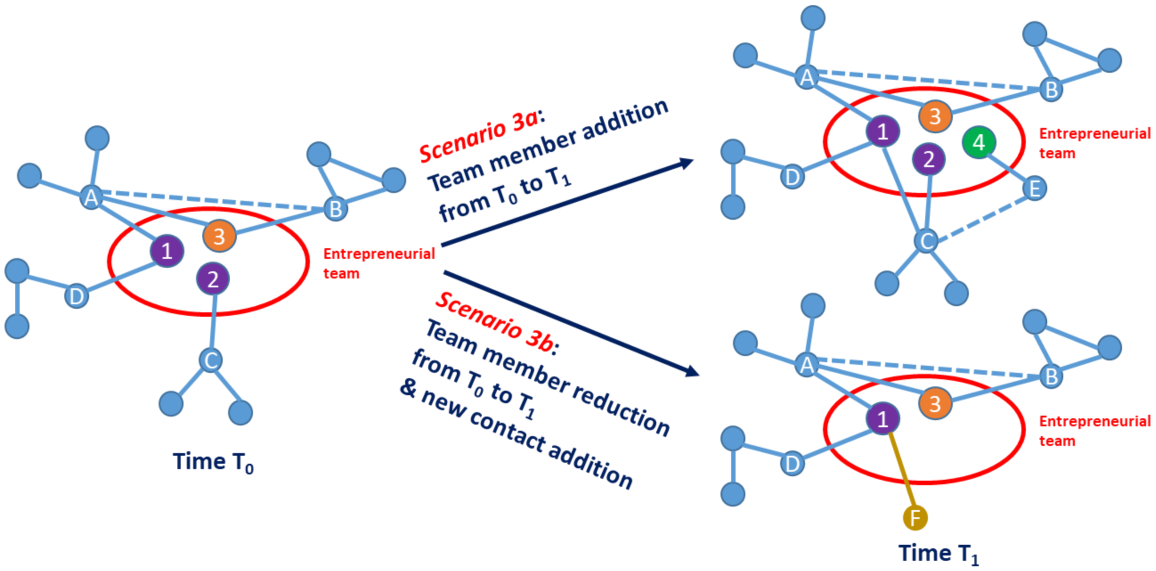

Figure 2.6 Founding teams' network development over time

2.4.4.4 Taking into account the different types of team formation/size reduction and team network evolution over a long-term entrepreneurial process (more than two temporal points)

In section 2.4.4.3, Figures 2.4–2.6 depict the basic scenarios of network dynamics over time. However, these might not present the relative real events of team formation and network dynamics while considering a long-term frame of the entrepreneurial process. Thus, in Figure 2.7 I add a further clarification for the network development and team formation phenomenon.

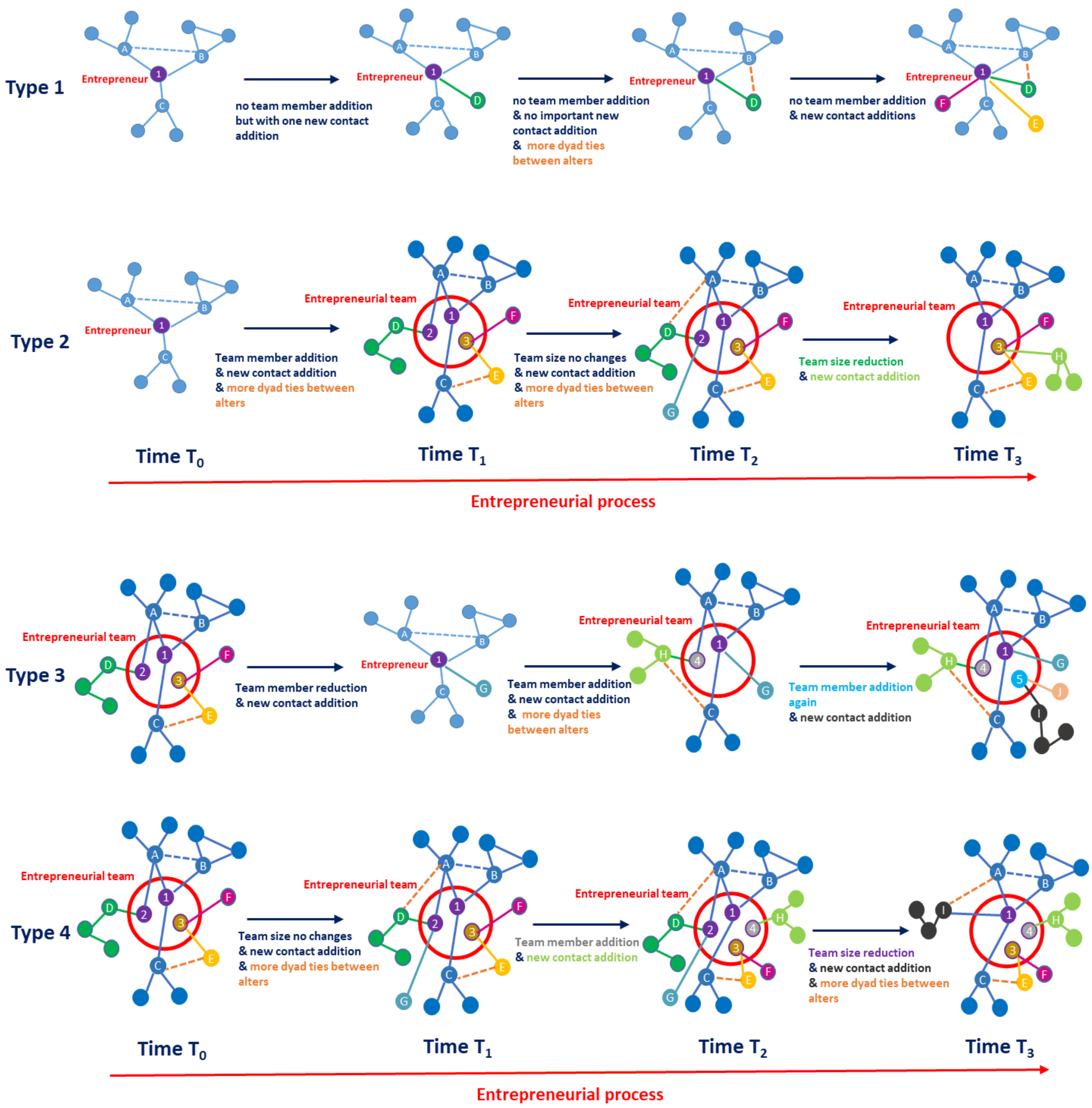

Figure 2.7 Team formation and network dynamic topology: the general concept

As shown in Figure 2.7, I argue there might be four types of team size dynamics and network development during the entrepreneurial process, described as follows:

Type 1: A sole founder initiated an idea for a new venture, and then continued to operate the start-up independently through all stages of its entrepreneurial journey.

Type 2: Start-up was founded by one founder, but then expanded its team in the subsequent years.

Type 3: Start-up was founded by multiple founders, but might only have one team member in one or more of the following years (e.g. some members leave due to conflict).

Type 4: Start-up was founded by multiple founders and continued as 'team-based' throughout its journey.

In sum, this section uses the topology method to highlight the distinction of the team-level network structure, as well as to emphasise the importance of considering the temporal effect of network development and the team formation process. Accordingly, a longitudinal research design is necessary, as described above, in order to comprehensively capture the dynamics of team network development.

Chapter 3

Hypotheses development

3.1 Entrepreneurial teams' external social networks and new venture fundraising outcomes

Granovetter's (1973, 1983) strength of weak tie theory and Burt's (1992) structural holes theory are the two major pillars to explain the importance of the role of social networks under the entrepreneurial context. The strength of weak tie theory portrays how the ego can capture variant and dissimilar knowledge and information via a weak tie between the person and his or her acquaintance (i.e. a tenuous relationship). The ego and the acquaintance both tend to have their own networks that are connected with strong ties (i.e. the ego and the acquaintance belong to disparate groups, respectively). The weak ties between the ego and his or her acquaintances wrap groups together, and thus act as conduits for the flow of heterogeneous information across social structures. Burt (1992) argued that the value of weak tie theory is not related to the strength, but rather concerns the bridging function it provides in linking network structures. Hence, structural holes theory underscores that individuals who can occupy the broker's position in bridging different groups (or clusters) are believed to gain greater advantage since they can obtain diverse resource, advice, or information from nonredundant ties, with such heterogeneous knowledge and resource advantageous for strategic decision-making and thus leading greater success. Besides, the structural hole can be said to be addressing a "non-redundancy relationship between two contacts" (Batjargal 2007, p.610), and thus scholars also applied the 'network nonredundancy' as another means of representing the number of structural holes (e.g. McEvily & Zaheer 1999; Nicolaou & Birley 2003; Hirai et al. 2013).

Empirically, previous network research under the entrepreneurship context primarily employed an individual (i.e. CEO or founder) as the unit to examine the effect of the network structure on new venture performance (e.g. Hansen 1995; Stam & Elfring 2008; Hirai et al. 2013). However, as asserted by Vissa and Chacar (2009, p.1180), consideration of applying the entrepreneurial team as a unit when examining the network structure effect "provides a more complete picture of the knowledge and informational resources accessible to the new venture". Indeed, following the upper echelons perspective, making a strategic decision is a group discussion process as opposed to an individual task conducted by the CEO (Hambrick 2016). Thus, once the entrepreneurial team has a high-level of network nonredundancy (i.e. a large number of structural holes in their ego-centric network), it is expected that the team will enjoy extensive access to novel information and knowledge, thus making more effective strategic decisions and inducing exceptional venture performance.

Although the interest of this thesis is in exploring the network structure effect on financial capital in order to fill an identified gap in the literature, the line of thought would be similar when we focus on examining the impact of external ties on organisational performance measures. Following this line of thought, a mechanism is claimed for predicting the relationship between an entrepreneurial team's network nonredundancy and their fundraising outcomes. A higher degree of nonredundancy will offer heterogeneous knowledge/information/resource to the entrepreneurial team, thus facilitating their ability to deliver remarkable strategic choices; for example, identifying opportunities more accurately and hence developing innovative products to bring to market, or hiring talented employees to enhance their human capital. The greater the entrepreneurial activities in comparison to other start-up competitors, the highly the likelihood that the focal entrepreneurial team can attract investors' attention for making investment decisions.

In sum, with the inference of the fitness to apply structural holes theory at the team level, the first formal prediction of this thesis is as follows:

Hypothesis 1: The external network nonredundancy of the entrepreneurial team is positively associated with the funding amount.

3.2 The interaction between social networks and the entrepreneurial team's demography

In this thesis, I propose that the impact of the entrepreneurial team's external network structure on external funding acquisition may vary depending on the entrepreneurial team's demography. The first rationale is that the internal team dynamics would influence the team performance via accessing the team's external ties in completing tasks (Reagans & Zuckerman 2001; Reagans et al. 2004). On the other hand, the upper echelons theory claims that top managers' characteristics can reflect each individual's values, cognitive style, and risk propensity for the strategic choice, and consequently influence the organisational performance. Following this line of thought, it is expected that the top management team's demographic characteristics would also significantly present the internal team dynamics (Foo et al. 2006), impacting the decision-making process and ultimately the organisational outcomes. According to Klotz et al.'s (2014) definition, the entrepreneurial team can be referred as the new venture's top management team. Then, combined with the abovementioned first rationale and the upper echelons perspective, the entrepreneurial team's demography is expected to reflect the internal team dynamics, and thereby affect the usage of their external network contacts.

Figure 2.1 shows that top managers' cognitive values can be the proxy of several observable characteristics such as *education*, *other career experiences*, or *group characteristics.* Under the entrepreneurial context, I therefore contend that *heterogeneity of education* (i.e. *education*), *prior founding experience* (i.e. *other career experiences*), *industry experience* (i.e. *other career experiences*), *team tenure* (i.e. *group characteristics*), and *gender diversity* (i.e. *group characteristics*) correspond to those substituted characteristics proposed in the upper echelons perspective. Accordingly, constructing the overarching framework in addressing these five demographic attributes of entrepreneurial team members (i.e. *heterogeneity of education*, *prior founding experience, industry experience, team tenure,* and *gender diversity*) might act as important moderators in altering the effectiveness of leveraging their external network structure on acquiring financial capital from outside investors.

Overall, such a concept is visualised in Figure 3.1, where team members with distinguishing attributes are represented with different symbols inside the circle, which represents the ego. In reality, they may all have different personal characteristics, or some of them may present similar or identical features. Outside the circle, the team's 'external' networks are displayed. These network contacts (i.e. A, B, C, D, E) may or may not know each other. The dash line indicates the indirect ties that exist among these contacts, which are referred to as 'actual ties'. If all contacts are connected by dash lines, then the total number of these indirect ties is termed ‘potential ties’. This definition is utilised to measure the team-level nonredundancy (For more details, see Chapter 4).

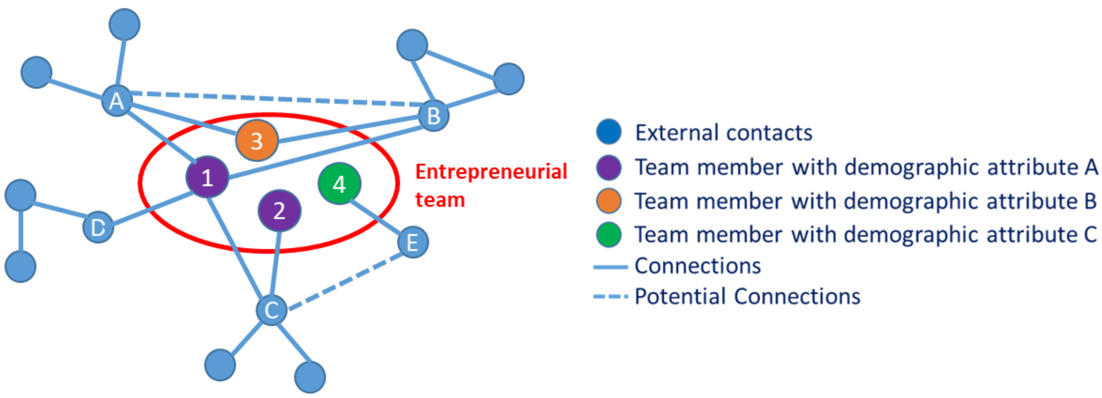

Figure 3.1 Team-level network structure along with the team member demographic dynamic.

3.2.1 The moderating effect of the entrepreneurial team’s tenure

Team tenure, which refers to the duration that team members work together, represents one of the key demography variables that will influence the entrepreneurial team’s network effect in terms of the outcome of fundraising. Researchers have recognised that team tenure is an important component in developing team effectiveness (e.g. Finkelstein & Hambrick 1990; Marks, Mathieu, & Zaccaro 2001) and in the resulting team performance (e.g. Katz 1982). Accordingly, team tenure was applied as the main independent variable in top management team research for predicting firm performance (e.g. Wiersema & Bantel 1992; Wiersema & Bird 1993), as a control variable in the majority of team research (e.g. Bernerth & Aguinis 2016), and even as a moderator (Carboni & Ehrlich 2013) in highlighting its importance regarding group performance. Thus, team tenure is expected to impact how entrepreneurial teams leverage external networks for securing funding via a number of mechanisms.

First, longer team tenure leads to deeper mutual trust among the top management team members (Michel & Hambrick 1992), since interpersonal psychological safety improves over time (McGrath 1984; Koopmann, Lanaj, Wang, Zhou, & Shi 2016). Therefore, greater team tenure results in a higher level of team cohesion (Roberts & O'Reilly 1979; Ebadi & Utterback 1984; O'Reilly, Caldwell, & Barnett 1989) and reduced communication cost (Smith, Smith, Olian, Sims, O'Bannon, & Scully 1994). Entrepreneurial teams enjoying long tenure will thus be expected to gather potential resource more effectively across their external nonredundancy networks. Furthermore, through building upon the deeper trust, the longer tenure teams will have greater confidence in accessing information and resource from specific individual member's networks (Vissa & Chacar 2009). In contrast, start-up teams with a relatively shorter tenure might spend more time seeking an optimal collective working mode, thus leading to the less efficient use of their external nonredundancy networks.

Similarly, there is enhanced chemistry in longer tenure teams. Well-established entrepreneurial teams reduce the potential for conflict and can focus on accessing heterogeneous information among their contacts, that is, longer tenure team members are well coordinated and are highly likely to achieve a "strategic consensus" to "clarify the venture's needs and what resources are required to be brought into the venture" (Vissa & Chacar 2009, p.1182). Such characteristic enables entrepreneurial teams to concentrate on searching for particular information and resources, which can help to attract funding. Hence, it is proposed:

Hypothesis 2a: The impact of nonredundancy on the funding amount will be more positive for start-ups with longer duration of team tenure.

The moderating effect of team tenure, however, can be a double-edged sword. For example, longer team tenure may induce inverse fundraising performance results in start-up teams in terms of leveraging the nonredundant information for accessing resources.

It was found that longer team tenure can lead to enhanced stability within the team (Katz 1982), stronger team cohesion with reduced conflict (Katz 1982; Vissa & Chacar 2009), and a higher degree of shared vision, along with more effective communication (Tsai & Ghoshal 1998). Nevertheless, effective communication also means that team members will engage in less conversation while accessing information from the group's external networks, due to the belief that they can foresee others' perspectives or attitudes on strategic directions. Hence, external heterogeneous information might be reduced with the lower level of overall group communication (Pelz & Andrews 1966), as long tenure team members' behaviour patterns become less dynamic. Therefore, important nonredundant information for awarding funding may be partially neglected or omitted when the entrepreneurial team has greater tenure.

Alternatively, stronger team cohesion and high-level shared vision would also reduce the motivation to search for new information and innovative strategies for venture development (Staw 1977; Barr, Stimpert, & Huff 1992). This scenario tends to manifest when teams do not wish to rupture the chemistry that develops within team collaboration, and hence additional nonredundant information may not be captured once the team has become accustomed to operating within a routine working mode (Beckman 2006).

Following such a line of thought, it is anticipated that when the duration of team tenure is long, this may reduce the entrpreneurial team's potential to interpret nonredundant information in terms of forming a suitable strategy to stimulate investors' interest. Hence, this thesis formalises:

Hypothesis 2b: The impact of nonredundancy on the funding amount will be less positive for start-ups with longer duration of team tenure.

3.2.2 The moderating effect of the entrepreneurial team's heterogeneity of educational background

The heterogeneity of educational background should be considered as another important moderator that will strengthen the association between network nonredundancy and financial capital acquisition. The increased heterogeneity of education background within a team links to a broad range of diverse knowledge (Wiersema & Bantel 1992), and is thereby expected to enhance a team's strategic decision-making ability and improve the ability to complete the required task (Bell, Villado, Lukasik, Belau, & Briggs 2011). Entrepreneurial teams with greater diversity in terms of the educational background would thereby be expected to have improved performance when completing the tasks of arriving at and implementing strategic decisions, while leveraging the external network's nonredundant information and resources more effectively, and thus enhancing the likelihood of receiving funding.

As highlighted above, teams with greater heterogeneity of education can refer to a broad body of diversified knowledge, thereby suggesting an enhanced ability to interpret information, and leading to improved strategic decision-making results (Wiersema & Bantel 1992). Holland (1973) accentuated that personalities and cognitive styles are correlated to the choice of the field of study, while the individuals' perspectives and opinions will be developed over the duration of the programme of study. Further, Hambrick and Mason (1984) noted that the formal educational background of individuals will induce distinctive value and cognitive preferences. For example, it can be imagined and expected that individuals who studied history would have a somewhat different perspective to interpreting a business phenomenon when compared to those who studied engineering or business. Empirically, for instance, Hitt and Tyler (1991) found that top management teams with qualifications in diverse academic subjects would get benefit during their strategic decision-making process. Thus, in this vein, more educationally diverse entrepreneurial teams are also expected to perform better in making strategic decisions when compared to less educational heterogeneity in start-up teams.

Research based on the informational diversity–cognitive resource perspective (e.g. Williams & O'Reilly 1998) also found that educational diversity positively influences the team performance, since the various educational backgrounds offer diverse task-relevant knowledge for team members in terms of completing the required tasks (Pelled 1996; Bell et al. 2011). Furthermore, teams with diverse knowledge have enhanced creativity (Milliken, Bartel, & Kurtzberg 2003) and innovative ability (Bantel & Jackson 1989), which are other important 'nutritional' facets for teams when dealing with particular tasks. Therefore, following this line of thought, greater educational diversity in the start-up team is expected to lead to better task arrangement and completion when exploring nonredundant information from their external networks, and the more efficient use of their networks is expected to result in increased fundraising outcomes.

In sum, and on the basis of the discussion above, it is believed that with greater heterogeneity of the entrepreneurial team members' education background, their ability will be enhanced by such a heterogeneous knowledgebase in terms of effectively leveraging nonredundant information and the improved interpretation of nonredundant information for making strategic decisions and achieving venture fundraising success. Thus, this thesis proposes:

Hypothesis 3a: The impact of nonredundancy on the funding amount will be more positive for start-ups with greater heterogeneity of education.

The prior research also provides a number of theoretical explanations, whereby educational diversity could be detrimental for the network nonredundancy and fundraising performance relationship, since increased diversity may reduce the team cohesion, erode the strategic consensus, and augment the communication cost, while leading to inferior strategic decision performance in leveraging nonredundant resources and information (Milliken & Martins 1996).

More educationally diverse teams may become less cohesive since a potential affective conflict may occur among team members (Pelled 1996), which could lead to negative team performance on decision-making (Murray 1989). Indeed, individuals from different education backgrounds tend to utilise their respective terminologies in communication, which can cause misunderstanding in certain conditions and lead to interpersonal friction (Neuliep 2000). Moreover, according to Byrne's (1971) attraction paradigm, team members will have greater mutual trust when they hail from similar backgrounds or have relevant characteristics. Accordingly, he argued that homogenous teams should perform in a superior manner to their heterogeneous counterparts. Similarly, Vissa and Chacar (2009, p.1182) claimed that in such scenario, teams with high levels of conflict or low team cohesion would less efficiently employ shared "task-relevant resources obtained from the external network". These arguments thus imply that teams with high educational diversity could suffer such low cooperation issues that negatively impact on the strategic decision-making of applying nonredundant information and resource via their external networks.

In terms of the communication cost, team with high educational heterogeneity might experience greater debate when decision-making than teams with low educational diversity (Murray 1989). Team members from their respective educational backgrounds would utilise different terminologies in depicting their thoughts and proposals, and hence the communication cost might increase since teams would have to devote additional time to both understanding each other and achieving the integration of consensus on strategic decision-making (O'Reilly et al. 1989; Wagner, Pfeffer, & O'Reilly 1984; Wiersema & Bantel 1992). Under such scenario, the top management team's educational heterogeneity would diminish the efficiency of the collective action and hinder the firm's overall performance (Murray 1989). Accordingly, if more educationally diverse teams suffer from reduced communication efficiency and less effective attainment of strategic consensus, it is expected that they might use nonredundant resources and information less efficiently (Vissa & Chacar 2009), and ultimately perform worse in terms of obtaining funding. Conversely, less educationally diverse teams can avoid such inter-team dynamics and achieve increased funding.

In sum, the above-mentioned argument suggests that the team's educational heterogeneity may negatively impact the team's ability to benefit from their external networks for obtaining funding. Thus, this thesis proposes:

Hypothesis 3b: The impact of nonredundancy on the funding amount will be less positive for start-ups with greater heterogeneity of education.

3.2.3 The moderating effect of the entrepreneurial team's industry experience

Entrepreneurial teams' industry experience should strengthen the relationship between network nonredundancy and fundraising. First, start-up teams with a higher proportion of team members possessing the same industry experience can reduce the group communication cost. Individuals from the same or similar backgrounds employ a common language, which enables barriers to be overcome during communication (Neuliep 2000). Essentially, founding team members who previously worked in the same industry can easily discuss the business development strategy via the industry nomenclature without the need for further explanation and illustration. Furthermore, team members hailing from a shared background can enjoy improved team cohesion compared to those from more diverse backgrounds (Harris & Sherblom 2018). Accordingly, a team with more effective communication and higher cohesion is expected to more productively exploit nonredundant information and resources from its external networks. Teams lacking industry experience, on the other hand, would need to devote more time to understanding the professional terms applied in the industry and to integrating their approaches to work, hence limiting the more efficient use of resources via their networks.

Second, entrepreneurial teams with greater industry experience have enhanced understanding of the market, where their higher level of tacit knowledge facilitates the process of investigating entrepreneurial opportunities and resources more accurately and smoothly through external nonredundant networks (Shane 2000; Corbett 2005; Baron & Ensley 2006; Parker 2006). In the nascent period of launching a new venture, teams with greater industry experience have an increased ability to transform heterogeneous information into a well-developed business plan to demonstrate their understanding of the market (Johnson 1986; Delmar & Shane 2006), and hence might convince potential investors more easily in terms of making funding decisions. Further, teams with more industry experience are expected to more effectively respond to the customers' needs through developing improved products more quickly, which also means they could acquire the necessary resources spanning the structural holes within their network structure more rapidly. This advantage benefits start-ups by increasing the likelihood of securing the next several rounds of funding for further expansion and growth.

Third, those founding teams with enhanced industry experience can facilitate the process of acquiring the required resources more effectively because they can exploit their existing social ties within industry (Delmar & Shane 2006), and hence they can quickly identify key contacts in order to explore the nonredundant resources and information through their networks. Particularly in high-tech and manufacturing industries, the transfer of industry connections helps those start-up teams with greater industry experience establish a supply chain more quickly than those teams with less industry experience. This benefit also increases the likelihood of a team with industry experience being awarded funding, since investors will have greater confidence in receiving a return on their investment due to the start-up being well prepared for occupying a position within the industry ecosystem.

On the other hand, industry experience could hinder entrepreneurial teams' ability to make decisions while leveraging their external nonredundant information and resources. This argument is grounded in the debate of whether the experience of decision-making is always beneficial, as scholars discuss it from the cognitive bias perspective, such as overconfidence (Cassar & Craig 2009). Scholars have found that decision-makers suffering from cognitive bias (i.e. overconfidence) might fail to make better decisions (e.g. Oskamp 1982; Mahajan 1992; Camerer & Lovallo 1999; Shepherd, Zacharakis, & Baron 2003). Under such scenario, experienced industry teams might extrapolate event outcomes only from their experiences in the industry. Such subjective industry experience may induce incomplete knowledge for teams that leads to worse decisions being made while leveraging the heterogeneous information from their external networks. Nevertheless, despite the plausibility of the prior viewpoints, it is believed that the overconfidence effect should not be that strong for the entrepreneurial teams. According to Weber and Zulehner (2010, p.358), "Start-ups are small, dynamic, and risky enterprises, which are particularly sensitive to business decisions". Therefore, entrepreneurial team members will be deliberative and avoid being 'overconfident' while making strategic decisions, due to their awareness that every single decision is vital for a start-up's success.

In sum, the above arguments suggest a positive influence of industry experience on the association between network nonredundancy and the fundraising outcomes. Thus, this thesis proposes:

Hypothesis 4: The impact of nonredundancy on the funding amount will be more positive for start-ups with a higher proportion of team members having industry experience.

3.2.4 The moderating effect of the entrepreneurial team's prior founding experience

The entrepreneurial team's prior founding experience is also one of the key team characteristics that will influence the manner in which start-up teams acquire external nonredundant information and resources to generate funding. Greater start-up experience within the entrepreneurial teams means higher levels of tacit knowledge in terms of managing a new company, and thus will induce a positive impact on funding obtained through the nonredundant external networks.

The literature in the organisational learning field asserts that managers or employees can learn from experience (e.g. Boh, Slaughter, & Espinosa 2007; Argote & Miron-Spektor 2011), which can be traced to the educational theory of 'learning by doing' advocated by the American philosopher John Dewey. Indeed, with incremental levels of experience, managers improve their ability to deal with managerial duties due to the benefits of gaining tacit knowledge (Holcomb, Holmes, & Connelly 2009; Shamsie & Mannor 2013; Mannor, Shamsie, & Conlon 2016). Further, the learning by doing concept can be applied under the entrepreneurship context.

Individuals can learn how to create a successful new ventures through their previous founding experience (Jovanovic 1982; Delmar & Shane 2006). Compared to novice entrepreneurs, serial entrepreneurs possess greater tacit knowledge acquired from their prior entrepreneurial activities, and hence can search for more pertinent information and make more effective strategic decisions (Duchesneau & Gartner 1990; Mosey & Wright 2007). Prior founding experience also equips entrepreneurs with the relevant knowledge for managing the different types of resources required for their start-ups. For instance, Mosey and Wright's (2007) qualitative study found that serial entrepreneurs have better skills than novice entrepreneurs in connecting with external business contacts for accessing financial support. Moreover, entrepreneurial team with prior founding experience are better in terms of developing new products since they understand how to exploit R&D resources to their maximum potential (Westhead, Ucbasaran, & Wright 2005; Zhao, Libaers, & Song 2015). Furthermore, Dencker and Gruber (2015) found that experienced founders not only interpret nonredundant information more effectively, but also perform better in exploiting higher-risk opportunities. Thus, following this line of thought, it is expected that entrepreneurial teams with greater start-up experience can have superior performance to those founding teams with less experience, in terms of leveraging nonredundant information for developing ventures and seeking funding.

Scholars also highlighted that team members with prior founding experience will influence the team composition, as novice entrepreneurs tend to rely on and hire convenient acquaintances, while experienced entrepreneurs have a tendency to recruit more experienced team members (Leung 2004; Cope 2005). This is because habitual entrepreneurs enjoy previously constructed networks and can thus assemble skilful and task-oriented teams (Politis 2005). More professional team composition enables the entrepreneurial team to comprise higher levels of heterogeneous knowledge when analysing divergent sources of information, and thus enhances the potential for more effective decision-making when seeking funding.

In similarity to the industry experience, the entrepreneurial teams' prior founding experience could also curtail the impact of network nonredundancy on attracting funding. As shown in previous studies regarding decision-making, accumulating experience does not always result in better decisions being made (e.g. Einhorn 1974; Shepherd et al. 2003; Mannor et al. 2016), since experienced decision-makers may become overconfident, and thus could overestimate their skill-sets while being responsible for the strategic decision (Oskamp 1982; Mahajan 1992). Accordingly, experienced entrepreneurs suffering from such overconfidence may have a tenacious mindset and not consider the broader situation when capturing variant information and resources via their networks. However, in similarity with the discussion above in section 3.2.3, even the above-mentioned argument is possible, since start-up team members will indeed avoid adopting arrogance during the strategic decision-making process. In particular, serial entrepreneurs might make more comprehensive considerations when they are making decisions, since many of them may have already experienced prior founding failure. Thus, it is supposed that the overconfidence concern should not be that strong within experienced entrepreneurial teams.

In sum, serial entrepreneurs understand how to utilise their resource more effectively than novices, and hence once the former obtain more nonredundant information, it is expected that they will develop better leverage for such opportunities. Linking such a perspective to the team level, it is also expected that a start-up team with a higher proportion of members with founding experience could embrace these advantages to better leverage their nonredundant networks and enhance the likelihood of being awarded a higher funding amount. Thus, this thesis proposes:

Hypothesis 5: The impact of nonredundancy on the funding amount will be more positive for start-ups with a higher proportion of team members having prior founding experience.

3.2.5 The moderating effect of the entrepreneurial team's gender diversity

Gender diversity suggests that the female proportion of the entrepreneurial teams could also be an important moderator in intensifying the relationship between network nonredundancy and fundraising. Bringing females into the entrepreneurial team is likely to enhance the team's knowledge diversity and offer a distinct cognitive frame, since female top managers' experience and perceptions could be quite different compared to their male counterparts (Post & Byron 2015). As Daily, Certo, and Dalton (1999, p.96) suggested, involving women in the top management team is an effective means of "capitalizing on the full range of intellectual capital available to the firm". Diverse knowledge is expected to improve teams' ability to identify and interpret pertinent information and resources for effective strategic decision-making. Accordingly, entrepreneurial teams with a higher proportion of female top managers would be expected to enjoy enhanced capability in terms of leveraging the external nonredundant information in order to influence the decision-making process for securing funding.

Similarly, female top managers could introduce new insight and understanding from the market based on their unique life experience (e.g. Campbell & Mínguez-Vera 2008). For example, since women are accustomed to considering household purchases and expenditure (Phipps & Burton 1998), female managers may have a deeper understanding of consumer behaviour (e.g. Campbell & Mínguez-Vera 2008). Moreover, female managers could offer important suggestions while developing products related to female consumers (Daily et al. 1999). These characteristics thereby not only enable female top managers to bring more varied information into the team for strategic decision-making purposes, but also improve the quality of the decision-making process due to their distinct insight (Loyd, Wang, Phillips, & Lount 2013). Thus, it is expected that a greater number of females within an entrepreneurial team could raise the quality of the strategic decision-making process through the team's application of external nonredundant information in seeking funding. In contrast, reduced gender diversity or purely male start-up teams may have relatively limited knowledge and understanding of the marketplace, and hence might perform worse when leveraging external nonredundant resources in making strategic decisions for attracting funding.

Despite diversity appearing to benefit team performance, it may induce communication issues within the team (Wiersema & Bantel 1992). However, this might not be a concern when the diversity stems from the inclusion of additional female members, since research has demonstrated that women have superior communication skills and cooperation intention than men within a team (e.g. Book 2000; Scott & Brown 2006). In particular, Pearce and Zahra (1991) studied four types of boards (i.e. participative, proactive, statutory, and caretaker boards) in their investigation of which board style can lead to improved financial performance. They found that the participative board has superior financial performance for firms, while including a higher number of female top managers compared to the other three types. As the name suggests, 'participative' implies considerable discussions, debate, or even disagreement amongst the board members. Accordingly, we can infer that the inclusion of female top managers or directors could result in enhanced communication, leading to greater strategic consensus in achieving exceptional team performance. Following this line of thought, it is expected that more gender-diverse entrepreneurial teams will communicate more effectively than less gender-diverse teams when utilising external nonredundant resources and information, thus engendering superior decision-making for raising external funding.

In sum, including females in the entrepreneurial team offers start-ups the ability to interpret distinct market insights and benefit from enhanced communication among team members. Accordingly, it is expected that start-up teams having female top managers would better leverage the heterogeneous information and resources from the team's external networks than those teams exclusively populated by men. Thus, the arguments above would suggest that female representation in entrepreneurial teams offers a positive impact on the relationship between entrepreneurial teams' network nonredundancy and fundraising. Thus, this thesis proposes:

Hypothesis 6: The impact of nonredundancy on the funding amount will be more positive for start-ups with greater gender diversity in the entrepreneurial team.

Overall, Figure 3.2 visually summarises the proposed hypotheses.

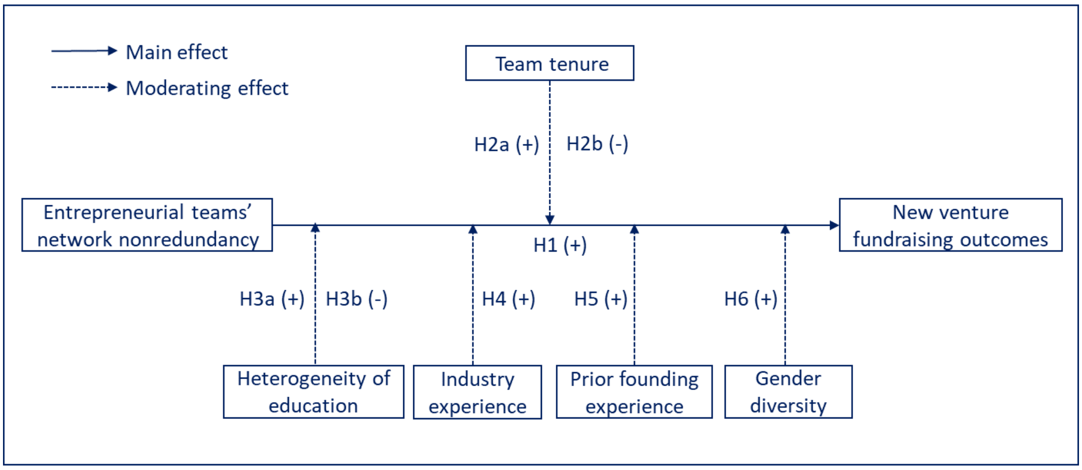

Figure 3.2 Proposed model.

Chapter 4

Method

4.1 Data and sample

To test the hypotheses, a unique longitudinal dataset was constructed that scraped and cleaned start-ups' relevant data drawn from Crunchbase (https://www.crunchbase.com/).[2] Crunchbase is a platform that provides up-to-date business information for private and public firms, especially in terms of providing granular-level information for tracking start-ups and investments over time (Alexy, Block, Sandner, & Ter Wal 2012; Ter Wal, Alexy, Block, & Sandner 2016; Butler et al. 2019). Crunchbase's data on start-ups primarily records information regarding the headquarter location, industry categories, financial information (e.g. funding series history and funding amount), and the exiting events (i.e. whether closed, acquired, or gone public). Moreover, Crunchbase provides personal background information about the founder(s), board members, and key employees (current and past), such as prior working experience (i.e. employment history), and the education level and academic specialisation. To test how the nonredundancy of the external network of entrepreneurial teams affects the funding amounts received, these start-ups' and individuals' data are utilised to construct the network nonredundancy variable and the team demography measures. Particularly, the employment history (e.g. the Chief

[2] Professional computer scientists/web developers assisted in facilitating the data collection and variables' construction for the unique longitudinal dataset. First, we scraped the raw data from Crunchbase. Then, we developed the code for computing the network nonredundancy and other variables. After the coding and computing process were complete, we examined the accuracy of the results.

Technology Officer in company X from 2009 to 2012) facilitates the defining of dyad relationships by matching the period of employment history and longitudinally creating team demography measures on a yearly basis. Sections 4.2–4.5 present the details of how these variables are constructed. In addition, Crunchbase offers information indicating different types of investors such as business angels, venture capitalists, and investment banks. Therefore, conducting alternative operationalisation of the funding variable for the robustness tests is ideal in order to examine the consistency of the main analysis results.

To test the hypotheses properly, several control variables are added in the testing models. For example, patents and trademarks are two important signals for investors in terms of evaluating the quality of start-ups (Block, DeVries, Schumann, & Sandner 2014; Ter Wal et al. 2016). The majority of the controls can be extracted and cleaned from the Crunchbase data that I scraped. Nevertheless, regarding the number of patents and trademarks of start-ups, these were collected longitudinally from the U.S. Patent and Trademark Office (USPTO), since Crunchbase does not record such information. Belonging to the U.S. Department of Commerce, and as its name suggests, the USPTO's primary service involves the issuing of patents and trademark registrations, and is thus an optimum source for obtaining accurate and relevant patent and trademark data for U.S. start-ups.

I collected the Crunchbase data in March 2019, where there were data from 104,374 U.S. companies stored in the database. As the focus is on new ventures and aims to control for part of the impact from the dynamic external environment resulting from the financial crisis in 2008, I first select companies founded after 2008 from the population of 104,374 U.S. companies. In addition, it is aimed to include those start-ups that were in operation for a reasonable period of time, in order to allow for longitudinal monitoring (by year). Hence, I establish a criterion whereby only those start-ups established for at least six years during the post-financial crisis period are included. Consequently, a list of 24,686 start-ups founded between the 1st of January 2009 and the 31st of December 2013 is created based on the above-mentioned conditions. Thus, if the start-up continues operating until the end of 2018, then the firm age spans from 6 to 10 years under this setting. For example, if a start-up was founded in 2009 and continued operating until 2018, then its data are collected yearly from 2009 to 2018, and thus 10 observations are constructed for this new venture in the dataset. Furthermore, start-ups that exit (either closed or acquired by another firm) are also included in this dataset for analysis. In these cases, the firm age spans much less than 6 to 10 years (e.g. 2 to 3 years). For instance, if a start-up was founded in 2009 and closed in 2012, then its data are collected yearly from 2009 until 2012. Similarly, if a new venture was founded in 2012 and acquired in 2014, then its yearly data are collected from 2012 to 2014, generating 3 observations in total. Moreover, for those start-ups that quickly went public through IPO (e.g. less than 5 years from founding to IPO), I continue to track them after their IPO year, since the majority of these firms continue receiving post-IPO funding[3] and the firm age remains less than 10 years, which still can be considered as a new venture. (Note:

[3] Some investment firms may provide funding or invest in post-IPO firms. For example, Kala Pharmaceuticals raised a total of $380.2M in funding over 9 rounds. Their first post-IPO fundraising (post-IPO equity) was $110M on Oct 3, 2018, from Athyrium Capital Management, LP (an investment firm); and their latest post-IPO (debt round) funding of $125M was raised on May 12, 2021, from Oxford Finance LLC (also an investment firm) (https://www.crunchbase.com/organization/kala-pharmaceuticals/company_financials).

Table 4.5 presents the number of start-ups under different statuses (i.e. either operating, closed, or acquired) in the analysis.)

Table 4.1 presents how this unique longitudinal dataset is constructed, namely, the data structure for applying the relevant panel models' analysis in Stata (Note: due to the limitations of space, only some of the variables are included in the table). The first column records the start-up ID and the second column displays the tracking years from the year of founding. From the third column and beyond, each column stores the value of each dependent and independent variable, which correspond to the company ID and year. For example, company ID 7278 was founded in 2010, and thus I begin to track it from this year. In the first row, we can see the entrepreneurial team size in column TS is 3, while the measured network nonredundancy in column NR is 156.06. Then, the second row records company ID 7278's data of variables in 2011. As shown below, it has a new team member addition, and thus the team size increases to 4, and the network nonredundancy is 153.78. Another example shown here is company ID 7280, which represents the existence of missing values in the sample. Due to the lack of data, this firm will not be included in the final sample of firms for analysis. In sum, each row represents the values of the variables in the specific year of a start-up from the sample. The benefit of this longitudinal design is that we can capture the team dynamic (e.g. the team members might change year on year, and thus the team size and external networks may differ over time) and obtain the entrepreneurial team's network nonredundancy, as well as other team demography variables over time. There are also certain limitations, which will be discussed in the limitation section. Nevertheless, it is believed that this design overall provides significant advantages in terms of testing the hypotheses and obtaining reliable results.

Table 4.1 Example of the dataset structure

company	year	poten_tie	actual_tie	TNS	TS	NR	IE	TT	PFE
7278	2010	124645	63185	545	3	156.0642	1	1	1
7278	2011	125190	64819	546	4	153.7839	.75	1.75	.75
7278	2012	125190	65777	546	4	152.0293	.75	2.75	.75
7278	2013	125190	66781	546	4	150.1905	.75	3.75	.75
7278	2014	125190	67451	546	3	148.9634	1	5	1
7278	2015	125190	68184	546	3	147.6209	1	6	1
7278	2016	125190	69271	546	3	145.63	1	7	1
7278	2017	125736	69374	547	3	146.1737	1	8	1
7278	2018	125736	69715	547	3	145.5503	1	9	1
7279	2010	56115	45585	365	3	57.10959	1	1	.333333
7279	2011	56703	45693	389	4	76.53728	1	1.75	.25
7279	2012	1128	121	64	3	29.60938	1	2.666667	.333333
7279	2013	7283	2437	159	4	63.67295	1	2.25	.5
7279	2014	7283	2438	159	4	63.66667	1	3.25	.5
7279	2015	7283	2438	159	4	63.66667	1	4.25	.5
7279	2016	7237	2453	158	3	62.97468	1	4.666667	.666667
7280	2010	.	.	.	.	.	.	.	.
7280	2011	.	.	.	.	.	.	.	.
7280	2012	.	.	.	.	.	.	.	.
7280	2013	.	.	.	.	.	.	.	.
7280	2014	.	.	.	.	.	.	.	.
7280	2015	.	.	.	.	.	.	.	.
7280	2016	.	.	.	.	.	.	.	.
7280	2017	.	.	.	.	.	.	.	.
7281	2010	.	.	.	.	.	.	.	.

Overall, I scraped and cleaned data on these 24,686 companies from Crunchbase in March 2019, along with a total of 91,114 relevant individuals' background information (i.e. the current team members, past team members, and board members of these start-ups), to further construct the longitudinal dataset. The initial organised dataset thus includes 24,686 companies with 174,366 firm-year observations (i.e. an unbalanced panel spanning the 2009–2018 period). Besides, these sample firms are classified into 43 industry category groups[4] by Crunchbase, where their headquarters are located in 2,172 cities from 51 U.S. states. However, the initial organised dataset contains missing values across variables. Accordingly, the

[4] Start-ups are classified via the Crunchbase labels for industry (https://support.crunchbase.com/hc/en-us/articles/360043146954-What-Industries-are-included-in-Crunchbase-).

final dataset for the main statistical modelling and analysis includes only 12,247 observations within 3,083 firms (corresponding to 41 industry category groups and located in 405 U.S. cities in 47 U.S. states). Table 4.2 presents the industry category group that the start-ups are classified into, revealing that the majority are located in the advertising industry, which accounts for 10.27% of the sample. However, we can see that the start-ups are distributed quite evenly across most industries, since the proportion of the sample located within each industry is approximately 1–3%. Table 4.3 presents the geographical distribution of the start-ups at the state level, indicating that most new ventures are located in the State of California (CA), which accounts for 45.7% of the sample. Moreover, the second-most popular state for establishing new ventures is the State of New York (NY), which accounts for 15.08% of the sample. Table 4.4 presents the geographical distribution at the city level, specifying that most start-ups are located in San Francisco, which accounts for 18.49% of the sample. Furthermore, the second and third most popular cities for launching a new business are New York (13.74%) and Boston (3.27%), respectively. Such basic statistics reveal the real-world phenomenon since most reports (e.g. Egan, Dayton, & Carranza 2017) found that the majority of investments flow into the states of California and New York, and particularly in the San Francisco Bay area and New York City, respectively. In addition, Table 4.5 presents the start-up status in the final organised dataset. A total of 1,966 firms continued operating from their founded date until the close of 2018 (including 62 firms which proceeded to IPO within this period), while 313 firms closed earlier and 804 start-ups were acquired before the end of 2018.

Consequently, I categorise different types of start-ups based on the team size dynamics, where Table 4.6 shows the details. All types of firms will be included in the main analysis first, and a further robustness check will remove the Type 1 firms to examine whether the results are consistent with the main analysis.

Table 4.2 Industry distribution of the sample

Industry category	Frequency	% of sample
Advertising	1,258	10.27
Commerce and shopping	1,134	9.26
Data and analytics	1,068	8.72
Apps	1,028	8.39
Financial services	741	6.05
Information technology	727	5.94
Biotechnology	545	4.45
Artificial intelligence	531	4.34
Internet services	523	4.27
Health care	515	4.21
Hardware	471	3.85
Consumer electronics	469	3.83
Education	459	3.75
Content and publishing	450	3.67
Clothing and apparel	280	2.29
Community and lifestyle	279	2.28
Media and entertainment	189	1.54
Energy	185	1.51
Gaming	149	1.22
Mobile	147	1.2
Software	125	1.02
Administrative services	120	0.98
Food and beverage	107	0.87
Events	100	0.82
Professional services	101	0.82
Design	91	0.74
Government and military	79	0.65
Real estate	80	0.65
Agriculture and farming	64	0.52
Consumer goods	53	0.43
Manufacturing	43	0.35
Sales and marketing	27	0.22
Transportation	19	0.16

Travel and tourism	20	0.16
Privacy and security	16	0.13
Science and engineering	15	0.12
Sports	11	0.09
Payments	8	0.07
Platforms	8	0.07
Natural resources	7	0.06
Navigation and mapping	5	0.04
Total	12,247	100

Table 4.3 Geographical distribution of the sample (U.S. states)

U.S. States	Frequency	% of sample
CA	5,597	45.7
NY	1,847	15.08
MA	799	6.52
TX	604	4.93
WA	403	3.29
IL	389	3.18
CO	251	2.05
FL	244	1.99
PA	194	1.58
GA	166	1.36
VA	158	1.29
NC	131	1.07
DC	112	0.91
TN	109	0.89
MI	102	0.83
OH	102	0.83
UT	102	0.83
AZ	95	0.78
MO	82	0.67
MD	79	0.65
MN	69	0.56
OR	55	0.45
CT	50	0.41
NV	50	0.41
NJ	49	0.4
IN	42	0.34

KS	40	0.33
AR	37	0.3
NM	36	0.29
WI	31	0.25
NH	28	0.23
NE	24	0.2
IA	23	0.19
ME	20	0.16
MT	20	0.16
RI	15	0.12
AL	13	0.11
KY	13	0.11
MS	14	0.11
ID	11	0.09
LA	9	0.07
HI	7	0.06
VT	7	0.06
WV	6	0.05
OK	5	0.04
SC	5	0.04
DE	2	0.02
Total	12,247	100

Table 4.4 Geographical distribution of the sample (U.S. cities)

U.S. Cities	Frequency	% of sample
San Francisco	2,264	18.49
New York	1,683	13.74
Boston	400	3.27
Austin	397	3.24
Mountain View	361	2.95
Chicago	349	2.85
Los Angeles	302	2.47
Seattle	280	2.29
Palo Alto	272	2.22
Santa Monica	245	2

San Mateo	236	1.93
Redwood City	225	1.84
San Diego	162	1.32
Cambridge	159	1.3
Atlanta	151	1.23
Santa Clara	131	1.07
San Jose	129	1.05
Boulder	112	0.91
Washington	112	0.91
Denver	109	0.89
Irvine	87	0.71
Dallas	86	0.7
Philadelphia	84	0.69
Brooklyn	83	0.68
Oakland	77	0.63
Sunnyvale	77	0.63
Culver City	76	0.62
Nashville	66	0.54
Menlo Park	65	0.53
Portland	59	0.48
Minneapolis	55	0.45
Waltham	53	0.43
Ann Arbor	51	0.42
Bellevue	48	0.39
Raleigh	48	0.39
Berkeley	47	0.38
Burlingame	45	0.37
Las Vegas	44	0.36
Pittsburgh	42	0.34
Los Altos	41	0.33
Miami	41	0.33
Reston	39	0.32
Santa Barbara	39	0.32

Scottsdale	39	0.32
Salt Lake City	37	0.3
Arlington	35	0.29
Campbell	34	0.28
St Louis	34	0.28
West Hollywood	34	0.28
Foster City	33	0.27
Albuquerque	31	0.25
Cincinnati	31	0.25
San Antonio	31	0.25
Tampa	31	0.25
Charlotte	29	0.24
Durham	30	0.24
Houston	27	0.22
Indianapolis	27	0.22
Kirkland	27	0.22
Newton	26	0.21
Redmond	24	0.2
La Jolla	23	0.19
Bethesda	22	0.18
Los Gatos	22	0.18
Woburn	22	0.18
American Fork	21	0.17
Columbus	21	0.17
Baltimore	20	0.16
Newark	20	0.16
Orlando	20	0.16
Pasadena	20	0.16
El Segundo	18	0.15
Kansas City	18	0.15
Mclean	18	0.15
Sherman Oaks	18	0.15
Aliso Viejo	17	0.14

Phoenix	17	0.14
Venice	17	0.14
Emeryville	16	0.13
Pleasanton	16	0.13
Richardson	16	0.13
Ventura	16	0.13
California City	15	0.12
Chattanooga	15	0.12
Costa Mesa	15	0.12
Detroit	15	0.12
Fort Lauderdale	15	0.12
Fremont	15	0.12
Providence	15	0.12
San Bruno	15	0.12
Beverly Hills	13	0.11
Chandler	13	0.11
Clearwater	14	0.11
Cleveland	13	0.11
Cupertino	14	0.11
Hayward	14	0.11
Little Rock	14	0.11
Manchester	13	0.11
Marina Del Rey	13	0.11
Morrisville	14	0.11
Omaha	13	0.11
Roseville	14	0.11
St. Petersburg	13	0.11
Delray Beach	12	0.1
Lucerne Valley	12	0.1
Sarasota	12	0.1
Wakefield	12	0.1
Altadena	11	0.09
Burlington	11	0.09

Lincoln	11	0.09
Madison	11	0.09
Newport Beach	11	0.09
Tempe	11	0.09
Wa Keeney	11	0.09
Brentwood	10	0.08
Carlsbad	10	0.08
Fountain Valley	10	0.08
Mill Valley	10	0.08
Missoula	10	0.08
Orem	10	0.08
Peoria	10	0.08
San Juan Capistrano	10	0.08
Addison	8	0.07
Alameda	9	0.07
Alpharetta	8	0.07
Ambler	9	0.07
Bentonville	9	0.07
Berwyn	8	0.07
Blacksburg	8	0.07
Broomfield	8	0.07
Charlottesville	8	0.07
Chesterfield	9	0.07
College Station	9	0.07
Concord	8	0.07
Fairfax	8	0.07
Franklin	9	0.07
Gaithersburg	8	0.07
Goleta	8	0.07
Granville	8	0.07
Gwynedd	8	0.07
Irving	8	0.07
Jamaica Plain	8	0.07

Joplin	9	0.07
Michigan City	9	0.07
Millbrae	8	0.07
New City	8	0.07
New Orleans	9	0.07
Oak Park	9	0.07
Olathe	8	0.07
Oxford	8	0.07
Palm Beach Gardens	8	0.07
Plymouth	9	0.07
Rockville	8	0.07
San Carlos	9	0.07
San Ramon	8	0.07
Santa Cruz	9	0.07
South San Francisco	8	0.07
Spokane	9	0.07
Toronto	8	0.07
Torrance	8	0.07
Wayne	9	0.07
West Palm Beach	8	0.07
Worcester	9	0.07
Auburndale	7	0.06
Belmont	7	0.06
Birmingham	7	0.06
Boca Raton	7	0.06
Cape Canaveral	7	0.06
Chalfont	7	0.06
Champaign	7	0.06
Clifton	7	0.06
Fayetteville	7	0.06
Framingham	7	0.06
Greenwich	7	0.06
Groton	7	0.06

Harvey	7	0.06
Herndon	7	0.06
Honolulu	7	0.06
Lake Forest	7	0.06
Lewisville	7	0.06
Melbourne	7	0.06
Miami Beach	7	0.06
Monterey	7	0.06
Needham	7	0.06
Northville	7	0.06
Nyack	7	0.06
Orinda	7	0.06
Park City	7	0.06
Pembroke	7	0.06
Portsmouth	7	0.06
Purchase	7	0.06
Rochester	7	0.06
Rogers	7	0.06
Rye	7	0.06
Sacramento	7	0.06
San Pablo	7	0.06
Stony Brook	7	0.06
Tennessee	7	0.06
Wellesley	7	0.06
Woodland Hills	7	0.06
Woodstock	7	0.06
Youngstown	7	0.06
Bainbridge Island	6	0.05
Bozeman	6	0.05
Buffalo	6	0.05
Carrboro	6	0.05
Cedar Rapids	6	0.05
Chevy Chase	6	0.05

Columbia	6	0.05
Coralville	6	0.05
Covington	6	0.05
Douglasville	6	0.05
Drexel Hill	6	0.05
Fishers	6	0.05
Fraser	6	0.05
Fullerton	6	0.05
Hoover	6	0.05
Leawood	6	0.05
Martinsburg	6	0.05
Mechanicsville	6	0.05
Milwaukee	6	0.05
Moffett Field	6	0.05
Netherlands	6	0.05
New Smyrna Beach	6	0.05
Ocala	6	0.05
Provo	6	0.05
Reno	6	0.05
Richmond	6	0.05
Ridgeland	6	0.05
Saint Louis	6	0.05
San Clemente	6	0.05
Scranton	6	0.05
Sonoma	6	0.05
St. Helena	6	0.05
Stoneham	6	0.05
Tenafly	6	0.05
Ada	5	0.04
Ames	5	0.04
Auburn	5	0.04
Bend	5	0.04
Boise	5	0.04

Centennial	5	0.04
Chelsea	5	0.04
Coral Gables	5	0.04
Georgetown	5	0.04
Hoboken	5	0.04
Hudson	5	0.04
Ithaca	5	0.04
Lake Oswego	5	0.04
Lanham	5	0.04
Lindon	5	0.04
Louisville	5	0.04
Middleton	5	0.04
Morristown	5	0.04
Neshkoro	5	0.04
Norwalk	5	0.04
Old Greenwich	5	0.04
Orono	5	0.04
Overland Park	5	0.04
Redwood Shores	5	0.04
Santa Fe	5	0.04
Shelton	5	0.04
Troy	5	0.04
Tucson	5	0.04
Union City	5	0.04
Valencia	5	0.04
Vienna	5	0.04
Virginia Beach	5	0.04
Watertown	5	0.04
White Plains	5	0.04
Wilmington	5	0.04
Anaheim	4	0.03
Bedford	4	0.03
Bradenton	4	0.03

Brookville	4	0.03
Burbank	4	0.03
Carbondale	4	0.03
Chatham	4	0.03
Cheshire	4	0.03
Columbia Falls	4	0.03
Des Moines	4	0.03
Dulles	4	0.03
Eden Prairie	4	0.03
Farmington	4	0.03
Fitchburg	4	0.03
Fort Myers	4	0.03
France	4	0.03
Glendale	4	0.03
Independence	4	0.03
King Of Prussia	4	0.03
Lehi	4	0.03
Lexington	4	0.03
Littleton	4	0.03
Manhasset	4	0.03
Marlborough	4	0.03
Mc Lean	4	0.03
Memphis	4	0.03
Mission	4	0.03
Montvale	4	0.03
New Haven	4	0.03
Pleasant Grove	4	0.03
Somerville	4	0.03
Southfield	4	0.03
Stamford	4	0.03
Syracuse	4	0.03
Tarzana	4	0.03
The Woodlands	4	0.03

Tulsa	4	0.03
Woodside	4	0.03
Xenia	4	0.03
Akron	3	0.02
Amherst	3	0.02
Annapolis	2	0.02
Ashburn	2	0.02
Aurora	3	0.02
Aventura	3	0.02
Belvedere Tiburon	2	0.02
Billerica	2	0.02
Branford	2	0.02
Brea	3	0.02
Brighton	2	0.02
Brookline	3	0.02
Camarillo	2	0.02
Canada	3	0.02
Cedar Park	2	0.02
Chelmsford	3	0.02
Colleyville	3	0.02
Cuyahoga Falls	3	0.02
Dania	2	0.02
Danville	2	0.02
Downingtown	2	0.02
Doylestown	2	0.02
Dublin	2	0.02
Edison	3	0.02
Elmhurst	3	0.02
Englewood	3	0.02
Fort Collins	2	0.02
Gainesville	3	0.02
Germantown	3	0.02
Grand Rapids	3	0.02

Greenville	3	0.02
Harrisonburg	3	0.02
Hermosa Beach	2	0.02
Holmdel	3	0.02
Houghton	2	0.02
Hyattsville	3	0.02
Issaquah	3	0.02
Jacksonville	3	0.02
Jersey City	2	0.02
Johnston	2	0.02
Lebanon	3	0.02
Mercer Island	3	0.02
Minnesota City	2	0.02
Montclair	3	0.02
Morgan Hill	3	0.02
Mount Pleasant	3	0.02
New Windsor	2	0.02
Oakmont	3	0.02
Ogden	3	0.02
Plantation	2	0.02
Playa Vista	2	0.02
Prairie Village	2	0.02
Puyallup	3	0.02
Quincy	3	0.02
Rexburg	2	0.02
Rocklin	3	0.02
San Rafael	3	0.02
Sandy	3	0.02
Scotts Valley	3	0.02
Sudbury	2	0.02
Utah	3	0.02
Walnut	3	0.02
Wayzata	3	0.02

Westborough	2	0.02
Westlake Village	2	0.02
Wichita	3	0.02
Wilton	3	0.02
Winter Haven	3	0.02
Wrightsville Beach	2	0.02
Bloomington	1	0.01
Cardiff By The Sea	1	0.01
East Palo Alto	1	0.01
Everett	1	0.01
Florida	1	0.01
Frisco	1	0.01
Garner	1	0.01
Irvin	1	0.01
Kaysville	1	0.01
Larkspur	1	0.01
Livermore	1	0.01
Long Island City	1	0.01
New Castle	1	0.01
Oklahoma City	1	0.01
Peachtree City	1	0.01
Port Washington	1	0.01
Princeton	1	0.01
Saratoga	1	0.01
Saugus	1	0.01
Sausalito	1	0.01
South Jordan	1	0.01
Stanford	1	0.01
Stockholm	1	0.01
Weston	1	0.01
Weymouth	1	0.01
Whippany	1	0.01
Total	12,247	100

Table 4.5 Start-up status in final organised dataset for analysis

Types	Number of start-ups	(Proportion)
Operating	1966 (62 IPO)	64%
Closed	313	10%
Acquired	804	26%
Total	3083	100%

Table 4.6 Start-up types in final organised dataset for analysis

Types of team change dynamics	Number of start-ups	(Proportion)	Number of closed firms	Number of acquired firms
Type 1	1444 (35 IPO)	47%	158	338
Type 2	549 (11 IPO)	18%	25	125
Type 3	247 (5 IPO)	8%	35	50
Type 4	843 (11 IPO)	27%	95	291
Total	3083 (62 IPO)	100%	313 (10%)	804 (26%)

Type 1: A sole founder initiates an idea for a new venture, and then continues to operate the start-up independently through all stages of its entrepreneurial journey.

Type 2: Start-up was founded by one founder, but then expanded its team in the subsequent years.

Type 3: Start-up was founded by multiple founders, but might only have one team member in one or more of the following years (e.g. some members leave due to conflict).

Type 4: Start-up was founded by multiple founders and continued as 'team-based' throughout its journey.

4.2 Dependent variables

New venture performance can be assessed by a range of indicators such as the revenue growth (Vissa & Chacar 2009), or the sales volume (Hirai et al. 2013). However, such measures could lead to potential bias, because they may not be suitable for evaluating start-ups' performance since the majority of start-ups may not have revenue or sales volume in their nascent period (Carter et al. 1996; Foo et al. 2006). On the contrary, funding is a fundamental resource necessary for start-ups across all the development stages, even those already within the IPO process. Since the network is the conduit for accessing resource (Adler & Kwon 2002), using the amount of funds or whether receiving funding can represent an improved and direct performance measure choice to produce an estimated relationship with greater validity. In addition, in recent research, receiving funding was applied as the performance measure to define start-ups' success (e.g. Ter Wal et al. 2016; Jin, Wu, & Hitt 2017). Thus, in the main model, the funding amount (on an annual basis) is employed as the dependent variable in order to capture the direct effect of the network structure on start-ups' fundraising performance. Furthermore, the other three alternative operationalisations of the dependent variable are applied for the robustness checks, namely, *whether start-ups receive funding or not* (on an annual basis), *whether start-ups receive second and later rounds of funding or not* (on an annual basis), and *whether start-ups receive venture capital funds or not* (on an annual basis). Consistent results are obtained while employing these three different dependent variables.

Funding amount (log)

The interest of this thesis is analysing the effect of entrepreneurial teams' external network structure on the start-ups' fundraising outcomes, and hence I define the main outcome measure as the funding amount.

Prior to targeting the IPO, start-ups are typically funded multiple times by venture capitalists or independent investors. Receiving each round of funding until achieving the IPO assists start-ups in overcoming the challenges that inevitably arise at each stage, and ultimately leads to early success. Furthermore, post-IPO start-ups may also raise funds from investment firms via post-IPO equity or post-IPO debt.

For the longitudinal design, I sum up the total amount of funds on a yearly basis (between the study period from 2009 to 2018). For example, company X receives two rounds of funding in 2009, which comprise (USD) $10,000 and $35,000, respectively. Then, let us sum up the total amount of funds for company X awarded in 2009, which is $45,000. If company X received only one round of funding in 2010 of $40,000, then the funding amount received in this year is $40,000, with no further summation applied. Similarly, if company X did not receive funding in later years (e.g. 2011), then the funding amount recorded is $0 for the corresponding year. Overall, in the above example company X received $45,000 in 2009, $40,000 in 2010, and $0 in 2011, and is thus recorded as such in the dataset.

Consequently, since this measure ranges widely and statistically presents a positively skewed distribution, I take a natural logarithmic transformation to ensure that this measure is approximately normally distributed. Moreover, where the dependent variable takes the value of 0, I add the value of 1 and then take the log, due to the log 0 being undefined (i.e. not a real number). Also, the funding amount (log) is a time varying variable tracking start-ups' fundraising outcomes longitudinally.

Receiving funding or not

I employ the second outcome measure as whether start-ups receive funding or not (a binary variable: code yes as "1", no as "0") within each year (start-ups can be funded several times in a single year, or have a vacant year) for one of the robustness tests. Note that the funding in each round could come from different sources such as angel groups, venture capital, micro venture capital funds, and investment banks. Regardless of the start-up's funding sources, I code "1" for the year when the start-up receives the funding.

Receiving venture capital funds or not

Business angels (individual angel investor or angel groups) and venture capital firms are two of the most common sources of funding for start-ups. Business angels typically invest in start-ups located within the nascent stage, ordinarily in angel and seed rounds, while venture capitalists tend to provide funding to start-ups across all the new venture creation stages, normally from seed to series A, B, C and later rounds (Crunchbase 2020). Thus, *whether receives venture capital funds or not* should represent a better alternative operationalisation of the dependent variable than *whether receives business angel funding or not* for application in the robustness tests, since this thesis tracks start-ups longitudinally. Selecting the investor type of business angels as the dependent variable is expected to produce a result inconsistent with the main model, since the fundraising performance is limited to the early year observations. This dependent variable is a binary variable (i.e. 0 or 1) to describe not receiving (code as “0”) and receiving funding from venture capital (code as “1”).

4.3 Independent variables

Network nonredundancy (log)

Nonredundancy is another means of representing the number of structural holes. Scholars define the single person’s network nonredundancy as: nonredundancy = (potential ties - actual ties)/number of advisors (Aldrich, Rosen, & Woodward 1987; McEvily & Zaheer 1999). The potential ties are defined as the maximum number of indirect ties that exist among contacts (i.e. N*(N - 1)/2, where N is the total number of contacts that the person has listed in a network structure (i.e. the network size). For example, if we assume that an individual has a total of 5 contacts in his or her external network, and there are also 2 actual ties between contacts, then the nonredundancy would be (5*(5 - 1)/2 - 2)/5 = 1.6.

A slight difference of measuring the team nonredundancy is that we should add one more step before applying the same formula. A team can be treated as an 'ego', and the N under this context presents the total number of a team's external network size. Each team member may have overlapping contacts in the team's external network structure, and thus we should remove the duplicate ones to get the 'net' number of N. For example, consider a team consisting of 3 members. Team member 1 has three external contacts whose names are Kevin, John, and Nathan, while team member 2's two external contacts are Kevin and Chloe, and team member 3's four external contacts are Ethan, Nathan, Alex, and Bob. The cumulative number of these 3 team members' external contacts is equal to 3 + 2 + 4 = 9. However, while treating these 3 team members as an ego, Kevin and Nathan will be double counted. Then the 'net' number of this team's external contact should be 7. Thus, this team's potential ties will be (7 * (7 - 1))/2 = 21. If there are 3 actual ties among these 7 contacts, this team's network nonredundancy will be (21 - 3)/7 = 2.57.

I extracted the network data from the database (i.e. the teams' potential ties, actual ties, and network size) in order to calculate the team-level nonredundancy measure by following steps 1–6 below.

<u>1. Identify the top management team members</u>

Crunchbase lists people from top managers and middle managers through to lower level employees who do not perform any managerial responsibilities. Those individuals titled Co-Founder, or who are included in the C-suite[5] are defined as the top management team members. To determine the entrepreneurial team members, this thesis follows Klotz et al.'s (2014) definition by identifying entrepreneurial team members as the new venture top management team.

<u>2. Establish each member's network and the team network size</u>

Entrepreneurial team members' important networks for business are drawn from their previous working experience (i.e. the workplace dyad relationship), as particularly in such entrepreneurship contexts, the majority of founders and other team members are not novices in the industry within which they have chosen to create their own team and business. Nanda and Sørensen (2010) found that individuals who have a colleague with a self-employment history will have an increased likelihood of becoming an entrepreneur. Moreover, in Balachandran, Wennberg, and Uman's (2019) research, they found that the cultural diversity of the start-up board is associated with experience of prior cultural diversity in the workplace, since the founder tends to recruit directors from his or her own workplace networks. These two examples suggest that using co-worker dyads to define a network relationship is appropriate and effective under the entrepreneurship context.

Accordingly, I then track each entrepreneurial team member's working history to compile those companies he or she had previously worked for within the same time period. Then, the top managers, board members, and advisors in those companies who also worked in the same time period are listed as the entrepreneurial team member's network. For example, Jack is the CEO of start-up A in 2009, and has

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[5] e.g. Chief Executive Officer [CEO], Chief Financial Officer [CFO], Chief Technology Officer [CTO], Chief Operating Officer [COO], and Chief Marketing Officer [CMO]

worked in company B as the CMO between 2003 and 2006. Jenny also previously worked for company B as the CFO from 2005 to 2007. Since Jack and Jenny both worked for company B in 2005 and 2006, Jenny is thus defined as Jack's network contact. I repeat this dyad relationship definition process for each team member to collect each member's external contacts. After identifying each member's network, I compare the list and delete any overlapping contacts from each member in order to acquire the team network size N.

Team member change will not be an issue since these steps are repeated in each year for each start-up. Accordingly, defining the entrepreneurial team members is always first, followed by capturing their external networks, and then finally obtaining the team network size by removing the overlapping contacts.

<u>3. Calculate team-level potential ties</u>

Once team network size N had been obtained, teams' potential ties can be calculated by the formula $N*(N - 1)/2$.

<u>4. Find the actual ties</u>

Since we now have the network list of the entrepreneurial team, we can track their contacts' employment history, again via Crunchbase. Similarly, as this thesis defines the network of top managers, if these contacts worked in the same companies as top managers, board members, or advisors during the same time period, I assume that these contacts know each other and define that an actual tie exists between them. All contacts on the team network list are scanned to obtain the number of actual ties.

5. Apply the formula to acquire the team network nonredundancy measure

The variables obtained above are plugged into the team-level nonredundancy formula (i.e. (team-level potential ties - actual ties)/number of external contacts) to acquire the nonredundancy measure.

6. Natural logarithmic transformation

Finally, I take the logarithmic transformation (natural log) on the network nonredundancy measure to not only rectify the positive skewed issue, but also for consideration of the underlying economic interpretation. The decision to take a natural log of the independent variable is based on economic grounds, since I consider that the network nonredundancy and fundraising relationship should not be interpreted as an increase of one unit in nonredundancy causing a β unit increase of the funding amount. Instead, it is hypothesised that such a predicted relationship should be interpreted on a percentage basis by assuming that a 1% increase in nonredundancy causes a β% increase in the funding amount. The reason for making such an assumption is the supposition that start-ups have different product development progress and distinct venture sizes, as well as operating their businesses in different industries. For example, high-tech start-ups might receive larger funding amounts than new ventures in relatively low-tech industries. Accordingly, if applying the linear model without taking natural log transformation on the network nonredundancy, then the change in network nonredundancy level may not result in a fair description of the data since the funding amount will range dramatically between start-ups.

4.4 Moderating variables

Entrepreneurial team tenure (Smith et al. 1994)

Team tenure has a long tradition that is empirically linked with organisational performance in the literature (e.g. Finkelstein & Hambrick 1990; Wiersema & Bantel 1992; Zimmerman 2008; Gonzalez-Mulé, Cockburn, McCormick, & Zhao 2020). This thesis measures the entrepreneurial team tenure index by averaging the amount of time that each team member remains in their current team in order to establish the period of time that the entrepreneurial team members have been working together. For example, there is an entrepreneurial team consisting of 3 team members in the start-up's founding year. Therefore, the team tenure will be (1 + 1 + 1)/3 = 1. In the second year, if no team member leaves or is added, the team tenure is (2 + 2 + 2)/3 = 2. If there are two team member additions in the third start-up year, then the team tenure is equal to (3 + 3 + 3 + 1 + 1)/5 = 2.2. In the fourth start-up year, if there is one initial team member who leaves, then the team tenure will be (4 + 4 + 2 + 2)/4 = 3. Overall, a lower number links to a short tenure, while a higher number corresponds to a long tenure.

Heterogeneity of education

I calculate the heterogeneity of education via applying Blau's (1977) heterogeneity index formula of ($1 - \Sigma i^2$), where i represents "the proportion of the group in the ith category" (Smith et al. 1994, p.425).

This thesis relies on past research (e.g. Wiersema & Bantel 1992; Hambrick et al. 1996) to construct the heterogeneity of education measure, which is then modified by proposing five new categories: (1) Science, Technology, Engineering, and Mathematics (STEM), (2) Business and Economics, (3) Liberal Arts, (4) Law, and (5)

Other (i.e. more than two educational backgrounds).[6] Also, I merely use the highest education level to decide their educational background (academic specialisation).

For example, there are 2 members in an entrepreneurial team in the founding year, and their highest education levels are bachelor degree, having studied engineering and law, respectively. Therefore, I first assign them to each proposed category and get the number of people in that specific category. In this case, the number of people in each category from (1) to (5) is 1, 0, 0, 1, and 0. Then, these numbers are divided by the total team members (i.e. 2 in this example) to obtain the *i* index of each category, which is 0.5, 0, 0, 0.5, and 0, respectively. In the next step, these *i* indexes are squared to acquire the individual squared *i* index in each category, which in this case is 0.25, 0, 0, 0.25, and 0, respectively. Then, the sum of these squared *i* indexes is determined: 0.25 + 0 + 0 + 0.25 + 0 = 0.5. Finally, the Blau's formula is applied, namely, using 1 minus the summation of the squared *i* indexes to obtain the heterogeneity of education. Accordingly, the heterogeneity of education in this example is 1 - 0.5 = 0.5, suggesting a balanced educational diversity in this team.

Let us consider another scenario, using the same team as the example. In the next year, two other people join the team. Team members 3 and 4's highest degrees are masters, and thus what they studied at the undergraduate level is ignored. If team member 3 studied chemistry, then he or she will be categorised into category (1). Therefore, along with team member 1 mentioned above, there are now 2 people in category (1). Then, if team member 4 studied management in his or her masters, he or

[6] For example, if an individual's highest degree is at the masters level, and he or she has been awarded two masters degrees in music and information technology, then he or she will be classified into category (5).

she will be assigned to category (2). Accordingly, the number of people in each category from (1) to (5) are 2, 1, 0, 1, and 0 in this scenario. The next step is to divide these numbers by the team size (i.e. 4 in this case) to get the *i* index of each category Therefore, we obtain 0.5, 0.25, 0, 0.25, and 0 as the *i* indexes of categories (1) to (5). Again, the next step is to square each number to obtain the squared *i* index of each category, where we obtain 0.25, 0.0625, 0, 0.0625, and 0 as the squared *i* indexes of categories (1) to (5). After that, we should calculate the summation of the squared *i* indexes: 0.25 + 0.0625 + 0 + 0.0625 + 0 = 0.375. Finally, we apply the Blau's formula to obtain the heterogeneity of education in this scenario, which is 1 - 0.375 = 0.625, thus presenting a high value of educational heterogeneity that indicates this team is quite diverse regarding the educational background.

In sum, a higher number refers to greater educational heterogeneity; while in contrast, a lower number presents a higher educational homogeneity in the team.

Industry experience (Hall & Hofer 1993; Matusik, George, & Heeley 2008)

Founders and entrepreneurial team members who have working experience in the same industry may contribute towards positive new venture performance (Delmar & Shane 2006). Furthermore, the industry experience of founders is generally viewed as an assessment criterion for venture capitalists in evaluating start-ups' quality and deciding whether or not to fund them (Hall & Hofer 1993; Matusik et al. 2008). To measure an entrepreneurial team's industry experience, I first define whether each team member has previously worked in the same industry (sector), or say in the same category group (from the Crunchbase data) as their present company, whereby if the person has previously worked in the same industry as their current company, then I enter "1" into the corresponding cell; otherwise, I enter "0". I then calculate the proportion of team members who have previously worked in the same industry as the industry experience variable. For example, there is a team consisting of 5 members, and the first two team members have working experience in the same industry. Therefore, the corresponding cells to calculate the proportion of team members who have industry experience will be 1, 1, 0, 0, and 0, and the final industry experience measure will be calculated as (1 + 1 + 0 + 0 + 0)/5 = 0.4, representing a relative low industry experience team. The range of this variable is from 0 to 1. An entrepreneurial team with industry experience at zero implies that no team members have prior industry experience, while a team with an industry experience variable equal to 1 means that every team member is experienced in the same industry.

Prior founding experience (Hall & Hofer 1993; Matusik et al. 2008; Vanacker & Forbes 2016)

Founders and entrepreneurial team members' start-up experience is also recognised as a key component in influencing a new venture's performance (Delmar & Shane 2006; Mosey & Wright 2007). Moreover, prior founding experience represents an important evaluating item when venture capitalists make an assessment of a start-up (e.g. Hall & Hofer 1993; Matusik et al. 2008). I construct the prior founding experience variable as the proportion of team members who have previously been a founder or co-founder (Vanacker & Forbes 2016). The measuring method for this variable echoes that of the industry experience. Therefore, the range of prior founding experience is also between 0 and 1, where 0 refers to a team with absolutely no founding experience, and 1 indicates a 'fully experienced' serial entrepreneurial team.

Gender diversity (Matusik et al. 2008)

I present the gender diversity variable as the proportion of females in the entrepreneurial team (Lyngsie & Foss 2017). This is tested and controlled for because the founders' gender has been recognised as an important funding decision criterion when venture capitalists evaluate the venture quality (Matusik et al. 2008). Likewise, diverse gender composition in the entrepreneurial team can boost creative thinking in terms of propelling start-up achievement (Hunter, Cushenbery, & Friedrich 2012), while female top management team members tend to provide high-level communication and knowledge sharing in organisations (e.g. Scott & Brown 2006), which supports the argument that gender differences would have an impact on new venture creation (Bird & Brush 2002) and entrepreneurial behaviour in established firms (Lyngsie & Foss 2017). The range of this variable is also from 0 to 1, where 0 and 1 indicate male-only and female-only entrepreneurial teams, respectively.

4.5 Control variables

Team size (Beckman, Burton, & O'Reilly 2007; Hornuf & Schmitt 2017)

The group size is positively associated with the group diversity/heterogeneity (Allison 1978), and thus it usually needs to be controlled for in studies involving diversity. Moreover, the top management team size has also been found to be an important element that influences the organisational performance (e.g. Finkelstein & Haleblian 1993; Jin, Madison, Kraiczy, Kellermanns, Crook, & Xi 2017). Furthermore, it has been claimed that team size could increase the likelihood of receiving follow-up funding (Hornuf & Schmitt 2017), and thus this thesis considers it as another important control variable. I calculate the entrepreneurial team size as the number of people who serve in top management team roles (Beckman et al.

2007). If an individual fulfils several roles, then he or she is only included once in reporting the actual number of team members.

Venture size (Vissa & Chacar 2009)

I define venture size as the number of full-time employees (natural log) on the basis of previous studies (e.g. Beckman et al. 2007; Vissa & Chacar 2009; Batjargal 2010). Large start-ups may indicate that they inherently “have more resources” and “improved access to venture capital networks” (Beckman et al. 2007, p.158), which implies that they may have greater potential to pitch investors’ calibration points in awarding funding.

Early stage or not (1 or 0)

A start-up will not receive the same scale of funding across its development stages as there are different purposes for each funding round (Gompers 1995). Typically, in the very nascent stage (the so-called ‘pre-seed round’), founders rely on themselves, friends or family to provide financial support to launch the business idea into a tangible venture. Once the business begins to take shape, entrepreneurs might seek the first official funding round (i.e. typically seed) from angel investors or venture capitalists in order to support the new venture’s growth. Following the seed round, investment via Series A and Series B rounds offer funding on the basis of the same purpose in terms of reinforcing the new venture. If a start-up received funding from the later Series C or beyond rounds, then this suggests that the new venture is already in a relatively mature stage and such funding is typically utilised for expanding the business and aiming towards achieving an IPO. Thus, the amount of investment in later rounds is commonly greater than the funding invested in the seed or early rounds.

Accordingly, the thesis defines this control variable on the basis of the above-mentioned phenomenon. If the company never received funding, or received a funding round prior to or at the Series B stage, then this is defined as an early stage venture and code “1” from the established year observation until the corresponding company year that the start-up received Series C round funding, before indicating that the start-up received Series C round funding. Otherwise, code “0” from the year that the start-up received the Series C funding round until the later operating year.

Number of patents & number of trademarks (Ter Wal et al. 2016)

Patents and trademarks are two valuable quality signals for investors to evaluate the start-up (Block et al. 2014; Ter Wal et al. 2016), and thus they are imperative to control for while studying a new venture’s funding outcomes. I scraped patent and trademark data from the USPTO[7] and allocated the number of patents and the number of trademarks into the corresponding company-year cell of the dataset, respectively, by matching the company name, company founded year, application/registration date, and assignee. If no data are found, the value is set as “0” (Ter Wal et al. 2016).

Industry

The product roadmap might differ between high-tech and low-tech start-ups, and thus this could influence both the funding amounts and the timing of the funding granted (Vanacker & Forbes 2016). Therefore, I create an industry dummy to control

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[7] USPTO, available at: https://www.uspto.gov/learning-and-resources/electronic-data-products/patent-assignment-dataset

for the industry effect. The industry category groups of the sample and the distribution can be reviewed in Table 4.1.

Location

Start-ups in the same industry tend to locate together in forming a cluster that evolves into an ecosystem (Egan et al. 2017). In addition, investment also tends to cluster into specific areas, for example, the San Francisco Bay area and New York City (*ibid*, p.12). Accordingly, I create a location dummy variable to refer to the U.S. city in which the start-up is located, and to control for the geographical effect influencing the funding opportunities. The geographical distribution of the start-ups can be appraised in Table 4.3 at the state level, and in Table 4.4 at the city level.

Year dummies

I control for the year effects via the year dummies, while running the fixed-effects panel analysis.

4.6 Model and econometric approach

I estimate the fixed-effects panels to certify the effect of entrepreneurial teams' network nonredundancy on the start-ups' fundraising performance. The majority of the firm-level unobserved time-invariant heterogeneity can be controlled by the fixed-effects model. Accordingly, the effect of these firm-level unobserved characteristics can be eliminated and the estimated coefficients of the panel fixed-effects model will be unbiased (Kohler & Kreuter 2009).

The general specification of the individual-effects model is as follows:

$$y_{it} = \beta x_{it} + \alpha_i + \varepsilon_{it} \tag{4.1}$$

where y_{it} is the funding amount (log) received by start-up *i* at year *t*; x_{it} is the measured independent and control variables of start-up *i* at year *t*; β is the estimated coefficients of the independent and control variables; α_i is the unobserved effect of each start-up; and ε_{it} is the error term.

Applying the fixed-effects model, the unobserved characteristics of start-ups (α_i) in equation 4.1 can be removed by subtracting the individual means $\overline{yi}$, where $\overline{yi}$ = β $\overline{xi}$ + $\overline{\varepsilon i}$ (equation 4.2). This transformation process leads to a mean-difference model (also referred to as a within model) that utilises the within estimator to provide the estimate for the fixed-effects model (Cameron & Trivedi 2010). Thus, the specification of the fixed-effects model is as follows:

$$(y_{it} - \overline{yi}) = \beta\,(x_{it} - \overline{xi}) + (\varepsilon_{it} - \overline{\varepsilon i}) \tag{4.3}$$

Moreover, Stata fits the fixed-effects model as below to "provide an intercept estimate" (Cameron & Trivedi 2010, p.257), while providing the same β as equation 4.3:

$$(y_{it} - \overline{yi} + \bar{\bar{y}}) = \alpha + \beta\,(x_{it} - \overline{xi} + \bar{\bar{x}}) + (\varepsilon_{it} - \overline{\varepsilon i} + \bar{\bar{\varepsilon}}) \tag{4.4}$$

where $\bar{\bar{y}}$ is the grand mean of y_{it}; $\bar{\bar{x}}$ is the grand mean of x_{it}; and $\bar{\bar{\varepsilon}}$ is the grand mean of ε_{it}. (Note: for example, $\bar{\bar{y}}$ = (1/N) $\overline{yi}$. The same form for $\bar{\bar{x}}$ & $\bar{\bar{\varepsilon}}$)

In addition, I apply the robust standard error in the model to control for heteroskedasticity and lag all independent variables by 1 year (i.e. t-1). In the equation, the fixed-effects panel model (with the robust standard error) is estimated as the main analysis, specified as follows:

(1) Main effects:

log (funding amounts) = $\alpha_0 + \beta_0$ log(network nonredundancy) + β_1 team size + β_2 team tenure + β_3 heterogeneity of education + β_4 industry experience + β_5 prior founding experience + β_6 gender diversity + β_7 number of patents + β_8 number of trademarks + β_9 venture size + β_{10} early stage + industry category group + location + year + ε

(2) Moderation effects:

log (funding amounts) = $\alpha_0 + \beta_0$ log(network nonredundancy) + β_1 team size + β_2 team tenure + β_3 heterogeneity of education + β_4 industry experience + β_5 prior founding experience + β_6 gender diversity + β_7 number of patents + β_8 number of trademarks + β_9 venture size + β_{10} early stage + β_{11} team tenure*log(network nonredundancy) + β_{12} heterogeneity of education*log(network nonredundancy) + β_{13} industry experience*log(network nonredundancy) + β_{14} prior founding experience*log(network nonredundancy) + β_{15} gender diversity*log(network nonredundancy) + industry category group + location + year + ε

Furthermore, I conduct the Hausman test to check whether the fixed-effects or random-effects should be the preferred model (Hausman 1978; Greene 2008). The null hypothesis is that the random-effects estimator is consistent and efficient in terms of the true population parameters (Hausman 1978; Glen n.d.). The result (see Appendix 1) suggests that we should reject the null hypothesis and utilise the fixed-effects estimator, because the latter will be consistent (the null of $p<0.05$).

4.7 Endogeneity correction

Endogeneity represents the inherent and salient issues in network studies under the organisational context (Carpenter, Li, & Jiang 2012). The issue occurs when the explanatory variable correlates with the error term (Wooldridge 2010). As Carpenter et al. (2012, p.1350) specified, the cause of endogeneity in network research primarily originates from measurement error and simultaneity. Measurement error is mainly produced by formulating the network structure, namely, the case of not successfully obtaining the real network structure (Carpenter et al. 2012). Simultaneity is induced by the reverse causality. For example, in the case of this study, it may be queried whether a team's network nonredundancy increases or decreases the prospect of being awarded funding, or whether the scenario of funding awarded may help to enlarge or diminish the level of network nonredundancy of the entrepreneurial team. Moreover, the omitted variable bias is another common source of endogeneity.

I employ several strategies (econometric techniques) to reduce and eliminate the endogeneity concern (i.e. measurement error, omitted variable, and simultaneity). First, an upper limit on the number of contacts nominated by the ego is not fixed or set; in contrast, the traditional approach was to allow a maximum of 5 contacts to be nominated via the survey method (e.g. McEvily & Zaheer 1999; Nicolaou & Birley 2003; Vissa & Chacar 2009). Also, the previous workplace dyad is applied to define the network relationship. It is believed that this research design enhances the accuracy of capturing the business network structure. Yet, as I define a business network relationship based on top managers' working history, marginal measurement error could inevitably occur if the working history has some information missing. (This natural limitation will be addressed in detail in the limitation section.) In addition, the omitted variables' issue can be avoided since this thesis applies the fixed-effects panel model, the unobserved αi is controlled, and the estimated coefficient will be consistent.

Finally, to ease the simultaneity issue, all independent variables including the control variables are lagged by 1 year (i.e. The previous year's network nonredundancy is used to predict the amount of funding received in the subsequent year). If the coefficient of variables still shows significance as no lagged independent variables' regression results, then we can consider that less simultaneity concern exists in the study. Nevertheless, this technique cannot fully eliminate the simultaneity issue. Instead, utilising the instrument variable to replace the predictor variable in the model is one of the recognised approaches for correcting the endogenous problem (Wooldridge 2010), and is applicable in the majority of linear and nonlinear regression models. Accordingly, I also run the two-stage least squares (2SLS) instrumental regression with the fixed-effects panel model to alleviate the endogeneity concern. The details and results are discussed and presented in the results chapter that follows.

Chapter 5
Results

Table 5.1 presents the descriptive statistics and variable correlations. All correlation coefficients are lower than 0.55, which suggests that multicollinearity is not a concern in the model. The variance inflation factor (VIF) is also computed to provide further evidence and rule out any multicollinearity issue (mean VIF = 1.19, which is <10) (see Appendix 2).

Standardisation (or the so-called z-standardisation) on the predictor variable and moderator variables is carried out prior to calculating the interaction terms in order to reduce the multicollinearity concern. A number of scholars (e.g. Jaccard, Turrisi, & Wan 1990; Aiken & West 1991) recommend mean-centring (i.e. subtracting the variable's mean value from its original value) before testing the interaction effect (i.e. the moderating effect). However, in terms of capturing and plotting the interaction effect there is no difference between the two methods, and "the choice is more a matter of personal preference. Both methods will produce identical findings, and there are some minor advantages to each" (Dawson 2014, p.12).

Table 5.1 Descriptive statistics and correlations

Variable	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12
1. Funding amount (log)	4.95	7.24	0.00	22.91	1.00											
2. Network nonredundancy (raw) +	36.64	79.45	0.00	1047.51	0.13*	1.00										
3. Team size+	1.66	0.95	1.00	10.00	0.05*	0.28*	1.00									
4. Team tenure+	2.96	1.71	1.00	9.00	- 0.17*	-0.10*	0.03*	1.00								
5. Heterogeneity of education+	0.08	0.18	0.00	0.75	0.06*	0.21*	0.51*	0.004	1.00							
6. Founding experience+	0.28	0.40	0.00	1.00	- 0.01	0.06*	-0.07*	-0.001	-0.003	1.00						
7. Industry experience+	0.58	0.44	0.00	1.00	0.03*	0.40*	-0.10*	-0.07*	0.02	0.23*	1.00					
8. Gender diversity+	0.10	0.26	0.00	1.00	- 0.004	0.003	0.03*	0.01	-0.003	-0.08*	-0.04*	1.00				
9. Number of patents+	0.65	8.12	0.00	636.00	0.02*	0.07*	0.04*	-0.001	0.03*	-0.001	0.02*	-0.01	1.00			
10. Number of trademarks+	0.01	0.10	0.00	4.00	- 0.01	-0.01	0.02	0.03*	0.02*	-0.02*	-0.01	0.003	-0.002	1.00		
11. Venture in early stage or not	0.92	0.27	0.00	1.00	- 0.07*	-0.22*	-0.22*	-0.12*	-0.15*	0.04*	-0.06*	-0.02*	-0.08*	-0.007	1.00	
12. Venture size (raw) +	123.05	783.71	1.00	10001.00	0.20*	0.19*	0.19*	0.01	0.11*	-0.08*	0.06*	-0.06*	0.08*	0.04*	-0.31*	1.00

*: p<0.05; N = 12,247 for all variables.

+ Descriptive statistics reported before standardising the variables, but standardised variables are applied in computing correlations and regression models.

Table 5.2 presents the fixed-effects panel regression estimates. All models are significant, as suggested by the F statistic test. According to the Hausman test (see Appendix 1), as mentioned above in section 4.6, it is suggested that we should apply the fixed-effects model rather than the random-effects model. However, the random-effects model results are still presented in Table 5.3 for reference. Model 1 includes the venture control variables (i.e. the number of patents, number of trademarks, venture size(log), and early stage or not) as the base model. The coefficients for the number of patents and gender are not significant ($p>0.1$), and continue to present their non-significance in the subsequent models until Model 9. Furthermore, the coefficient for early stage is significant ($p<0.001$), with this control maintaining its significance in the remainder of the models.

Model 2 includes the venture controls, team control (team size), and the moderator variables (team tenure, heterogeneity of education, founding experience, industry experience, and gender diversity). The coefficient of team tenure and early stage are significant ($p<0.05$), while the coefficients of the other variables are all insignificant.

Model 3 is the main-effect model that includes the controls, the moderator variables, and the focal independent variables (i.e. network nonredundancy). Hypothesis 1 states that the entrepreneurial team's network nonredundancy is positively associated with the funding amount. The coefficient of network nonredundancy is positive and significant ($\beta = 0.726$; $p<0.05$) and thus Hypothesis 1 is supported. As I take a natural log for both the independent variable (i.e. network nonredundancy) and the outcome variable (i.e. funding amount), the interpretation of the Model 3 estimates is that for every 1% increase in the network nonredundancy, the start-up's funding amount will increase by approximately 0.73%. Furthermore, network nonredundancy continues to be positive and significant ($p<0.05$) in the rest of the models in Table 5.2.

In Model 4, the interaction term of team tenure × nonredundancy (log) is introduced, which presents a negative (β = -0.530) and significant ($p<0.001$) moderation effect on the relationship between network nonredundancy and the funding amount. Thus, Hypothesis 2b is supported and suggests that long team tenure will weaken the entrepreneurial team's network nonredundancy effect on the funding amounts awarded.

Model 5 represents the negative (β = -0.306) and significant ($p<0.01$) moderating effect of the heterogeneity of education, and thus this thesis finds empirical support for Hypothesis 3b, whereby entrepreneurial teams with greater educational diversity will reduce the impact of network nonredundancy on the amount of funding received.

In Model 6, the proposed interaction effect of industry experience on the network nonredundancy and funding amount is tested. The coefficient of the interaction term (industry experience × nonredundancy (log)) is positive (β = 0.050) but not significant. Accordingly, Hypothesis 4 is not supported.

Model 7 allows the examination of the proffered interaction effect of founding experience. Hypothesis 5 proposes a positive moderating effect on the network nonredundancy and funding amounts relationship. However, the coefficient of the founding experience × nonredundancy (log) is positive (β = 0.0001) and insignificant, as well as being very close to zero. Therefore, Hypothesis 5 is not supported.

Model 8 presents another proposed moderating effect, which considers whether the gender diversity will offer a positive influence in terms of enhancing the effect of network nonredundancy on securing funding amounts. The coefficient of the interaction term (gender diversity × nonredundancy (log)) is negative (β = -0.007) and not significant. Hence, the empirical outcome does not support Hypothesis 6.

In Model 9, I finally test the combined significance of all the proposed moderation hypotheses. The coefficient of the team tenure interaction term and the heterogeneity of the education interaction term both remain negative and significant ($p<0.01$), which represents empirical evidence to support Hypotheses 2b and 3b.

Regarding the goodness of fit, Stata (xtreg) reports three types of R^2 (i.e. within, between, and overall), which are presented in the corresponding tables below. The within R^2 presents the amount of variation in the dependent variable within the company unit (i.e. yearly observations), namely, the squared correlation: $[Corr(y_{it} - \overline{yi}, \beta (x_{it} - \overline{xi}))]^2$. The between R^2 provides the amount of variation in the dependent variable between the company units, namely, the squared correlation: $[Corr(\overline{yi}, \beta\, \overline{xi})]^2$. The overall R^2 corresponds to the general equation of the individual effects model (i.e. equation 4.1) and is calculated by the squared correlation: $[Corr (y_{it}, \beta x_{it})]^2$. Since I apply the fixed-effects model, the within R^2 should be the main focus for checking here. As shown in Table 5.2, the within R^2 increases from Model 2, when adding the independent variables (Model 3) and the moderating variables (Models 4–9). The within R^2 for Model 3 reveals that it captures 6.5% of the within variance in the dependent variable for start-ups' fundraising performance. Nevertheless, there is a small increment (i.e. 0.07%) of the within R^2 from Model 2, which indicates that the very minor variation in the funding amounts within the start-up units is predicted by the model when adding the network nonredundancy. Yet, a small increment of R^2 seems possible when adding independent variables of interest into the fixed-effect panel model. In Stock and Watson's (2014, p.415) econometric textbook, an example presents a 0.6% R^2 increment while adding two independent variables of interest (i.e. unemployment rate (significant) and real income (not significant)) into the fixed-effect regression in order to predict the traffic fatality rate. However, I acknowledge that the small within R^2 increment is a limitation of the study, even though these three R^2 "do not have all the properties of the OLS R^2" (Stata.com n.d., p.10).

On the other hand, even though the addition of network nonredundancy captures very little of the outcome variable's variance, the effect size (beta=0.73) appears to present at a fair level. Therefore, a 10% increase in network nonredundancy is predicted to increase the funding amount received by 7.3%. For example, if network nonredundancy equal to 5 can receive (USD) $100,000, then improving the network nonredundancy from 5 to 5.5 can increase the predicted funding amount by $7,300, to $107,300 in total. Therefore, this increment of funding cannot be neglected. In addition, a further example is presented in the discussion chapter (see section 6.2) in order to explain the ease or difficulty of achieving a 10% increase in network nonredundancy.

Table 5.2 Panel fixed-effects results

DV: funding amounts (log)	Model 1 Venture Control	Model 2 Venture + team Control	Model 3 Main effect	Model 4 Moderation effect (Team tenure × non-redundancy)	Model 5 Moderation effect (Heterogeneity of education × non-redundancy)	Model 6 Moderation effect (Industry experience × non-redundancy)	Model 7 Moderation effect (Founding experience × non-redundancy)	Model 8 Moderation effect (Gender diversity × non-redundancy)	Model 9 Moderation effect (All)
Number of patents	0.293	0.278	0.258	0.257	0.268	0.258	0.258	0.258	0.266
	(0.236)	(0.231)	(0.228)	(0.245)	(0.232)	(0.228)	(0.228)	(0.228)	(0.249)
Number of trademarks	0.019	0.018	0.017	0.008	0.018	0.017	0.017	0.017	0.010
	(0.083)	(0.083)	(0.082)	(0.083)	(0.081)	(0.082)	(0.082)	(0.082)	(0.082)
Early stage	4.580***	4.788***	4.805***	4.400***	4.754***	4.805***	4.805***	4.804***	4.350***
	(0.432)	(0.437)	(0.436)	(0.435)	(0.437)	(0.436)	(0.436)	(0.437)	(0.435)
Venture size (log)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team size		-0.238	-0.412*	-0.416*	-0.412*	-0.410*	-0.412*	-0.412*	-0.414*
		(0.174)	(0.194)	(0.192)	(0.195)	(0.194)	(0.194)	(0.194)	(0.195)

Team tenure	-0.911**	-0.905**	-0.956**	-0.859*	-0.909**	-0.905**	-0.906**	-0.921**
	(0.331)	(0.332)	(0.331)	(0.333)	(0.331)	(0.334)	(0.332)	(0.335)
Heterogeneity of education	0.182	0.140	0.112	0.363*	0.138	0.140	0.140	0.325*
	(0.147)	(0.148)	(0.148)	(0.160)	(0.148)	(0.148)	(0.148)	(0.160)
Founding experience	0.069	0.066	0.099	0.049	0.067	0.066	0.066	0.070
	(0.176)	(0.175)	(0.175)	(0.176)	(0.176)	(0.177)	(0.175)	(0.177)
Industry experience	0.364	0.116	0.077	0.050	0.107	0.116	0.116	0.012
	(0.274)	(0.291)	(0.290)	(0.293)	(0.292)	(0.291)	(0.291)	(0.293)
Gender diversity	-0.132	-0.139	-0.121	-0.134	-0.138	-0.139	-0.137	-0.113
	(0.275)	(0.275)	(0.276)	(0.275)	(0.276)	(0.276)	(0.283)	(0.283)
Network nonredundancy (log)		0.726*	0.621*	0.891**	0.705*	0.726*	0.726*	0.759*
		(0.293)	(0.289)	(0.300)	(0.309)	(0.297)	(0.293)	(0.309)
Team tenure × nonredundancy (log)			-0.530***					-0.527***
			(0.089)					(0.089)

Heterogeneity of education × nonredundancy (log)					-0.306**				-0.295**
					(0.108)				(0.108)
Industry experience × nonredundancy (log)						0.050			0.024
						(0.223)			(0.232)
Founding experience × nonredundancy (log)							0.0001		0.047
							(0.151)		(0.158)
Gender diversity × nonredundancy (log)								-0.007	-0.002
								(0.236)	(0.233)
Constant	2.487***	0.098	0.022	0.052	0.206	-0.002	0.022	0.022	0.202
	(0.635)	(1.044)	(1.042)	(1.037)	(1.043)	(1.046)	(1.048)	(1.042)	(1.046)
Year, industry, and location dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F	44.42***	30.61***	29.38***	29.00***	28.28***	27.87***	27.89***	27.84***	24.41***
Observations	12,247	12,247	12,247	12,247	12,247	12,247	12,247	12,247	12,247
Number of start-ups	3,083	3083	3,083	3,083	3,083	3,083	3,083	3,083	3,083

Within R-squared	0.0628	0.0645	0.0652	0.0690	0.0661	0.0652	0.0652	0.0652	0.0699
Between R-squared	0.0705	0.0625	0.0348	0.0278	0.0283	0.0346	0.0348	0.0348	0.0221
Overall R-squared	0.0004	0.0024	0.0065	0.0089	0.0074	0.0066	0.0065	0.0065	0.0100

Robust standard errors in parentheses. Two tailed tests. + p< 0.1; * p<0.05; ** p<0.01; *** p<0.001

Note: Since venture size is a time-invariant variable, it was dropped because it is constant within groups from the panel fixed-effects model.

Table 5.3 Panel random-effects results

DV: funding amounts (log)	Model 10 Venture Control	Model 11 Venture + team Control	Model 12 Main effect	Model 13 Moderation effect (Team tenure × non-redundancy)	Model 14 Moderation effect (Heterogeneity of education × non-redundancy)	Model 15 Moderation effect (Industry experience × non-redundancy)	Model 16 Moderation effect (Founding experience × non-redundancy)	Model 17 Moderation effect (Gender diversity × non-redundancy)	Model 18 Moderation effect (All)
Number of patents	-0.032	-0.025	-0.053	-0.057	-0.052	-0.053	-0.054	-0.056	-0.057
	(0.135)	(0.136)	(0.128)	(0.133)	(0.130)	(0.128)	(0.128)	(0.128)	(0.135)
Number of trademarks	-0.057	-0.054	-0.055	-0.054	-0.054	-0.055	-0.056	-0.054	-0.054
	(0.084)	(0.085)	(0.084)	(0.083)	(0.084)	(0.084)	(0.084)	(0.084)	(0.083)
Early stage	0.214	0.341	0.532	0.348	0.516	0.532	0.524	0.525	0.313
	(0.334)	(0.329)	(0.331)	(0.329)	(0.332)	(0.331)	(0.332)	(0.331)	(0.330)
Venture size (log)	1.444***	1.405***	1.359***	1.357***	1.359***	1.359***	1.357***	1.360***	1.359***
	(0.095)	(0.094)	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)
Team size		-0.011***	-0.135^{+}	-0.125	-0.132^{+}	-0.138^{+}	-0.135^{+}	-0.136^{+}	-0.133^{+}

	(0.105)	(0.079)	(0.079)	(0.079)	(0.079)	(0.079)	(0.079)	(0.080)
Team tenure	-1.323***	-1.305***	-1.285***	-1.306***	-1.305***	-1.308***	-1.309***	-1.290***
	(0.105)	(0.104)	(0.104)	(0.104)	(0.104)	(0.104)	(0.104)	(0.104)
Heterogeneity of education	0.204*	0.172*	0.160⁺	0.216*	0.173*	0.170*	0.169*	0.201*
	(0.085)	(0.085)	(0.085)	(0.095)	(0.085)	(0.085)	(0.084)	(0.095)
Founding experience	0.084	0.097	0.103	0.098	0.096	0.085	0.097	0.087
	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)
Industry experience	-0.075	-0.307**	-0.313***	-0.309***	-0.309**	-0.302**	-0.306**	-0.312***
	(0.080)	(0.088)	(0.088)	(0.088)	(0.089)	(0.088)	(0.088)	(0.089)
Gender diversity	0.067	0.056	0.052	0.054	0.057	0.056	0.078	0.072
	(0.079)	(0.079)	(0.079)	(0.079)	(0.079)	(0.079)	(0.081)	(0.081)
Network nonredundancy (log)		0.573***	0.456***	0.577***	0.590***	0.564***	0.572***	0.496***
		(0.088)	(0.088)	(0.088)	(0.103)	(0.090)	(0.088)	(0.103)
Team tenure × nonredundancy (log)			-0.469***					-0.473***
			(0.071)					(0.071)

Heterogeneity of education × nonredundancy (log)					-0.068				-0.066
					(0.067)				(0.068)
Industry experience × nonredundancy (log)						-0.028			-0.083
						(0.084)			(0.086)
Founding experience × nonredundancy (log)							0.052		0.060
							(0.066)		(0.067)
Gender diversity × nonredundancy (log)								-0.112	-0.108
								(0.078)	(0.078)
Constant	4.753***	-0.151	-0.549	-0.639	-0.583	-0.513	-0.539	-0.621	-0.620
	(0.656)	(1.476)	(1.318)	(1.344)	(1.313)	(1.325)	(1.316)	(1.327)	(1.360)
Year, industry, and location dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wald chi2	-	-	-	-	-	-	-	-	-
Observations	12,247	12,247	12,247	12,247	12,247	12,247	12,247	12,247	12,247
Number of start-ups	3,083	3,083	3,083	3,083	3,083	3,083	3,083	3,083	3,083

Within R-squared	0.0483	0.0448	0.0465	0.0520	0.0469	0.0465	0.0465	0.0465	0.0524
Between R-squared	0.0907	0.1149	0.1180	0.1167	0.1176	0.1181	0.1181	0.1183	0.1167
Overall R-squared	0.0744	0.0916	0.0960	0.0984	0.0960	0.0961	0.0961	0.0963	0.0988

Robust standard errors in parentheses. Two tailed tests. + p< 0.1; * p<0.05; ** p<0.01; *** p<0.001

Note: Estimates of the year (8), industry (43), and location (405) dummies are not reported here due to the lack of space.

In order to provide a more direct impression of the predicted relationship between network nonredundancy and funding amounts, I plot the relationship for the predicted funding amount and network nonredundancy. Figure 5.1 illustrates the log–log relationship and indicates a clear positive association between the network nonredundancy and funding amounts.

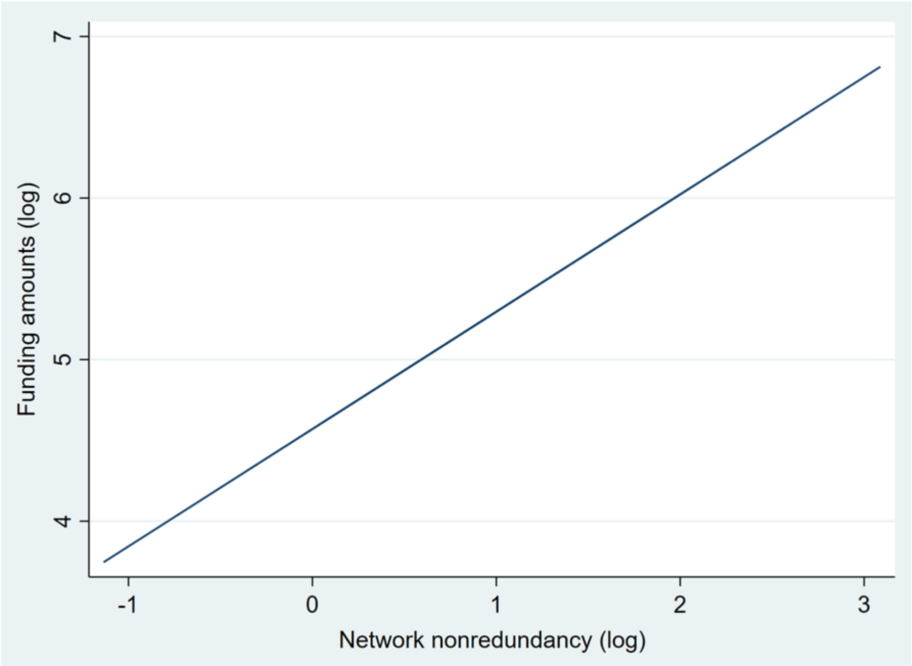

Figure 5.1 Illustration of the main effect: the log–log relationship of network nonredundancy and funding amounts.

Similarly, the interaction effects are plotted in the entrepreneurial team's network structure to depict how team tenure and heterogeneity of education influence the network nonredundancy and funding relationship, respectively. As suggested by Aiken and West (1991), two regression equations are generated for each moderator to represent their level difference, and illustrate this on the plot of network nonredundancy (log) versus predicted funding amount (log). As shown in Figure 5.2, the dash line presents the relationship between network nonredundancy (log) and funding amount (log) with short team tenure, calculated via its mean minus one standard deviation; while the solid line indicates the relationship between network nonredundancy (log) and funding amount (log) with long team tenure, measuring from its mean plus one standard deviation. The figure clearly illustrates that an entrepreneurial team with long team tenure reduces the effect of nonredundancy on raising funding (Hypothesis 2b).

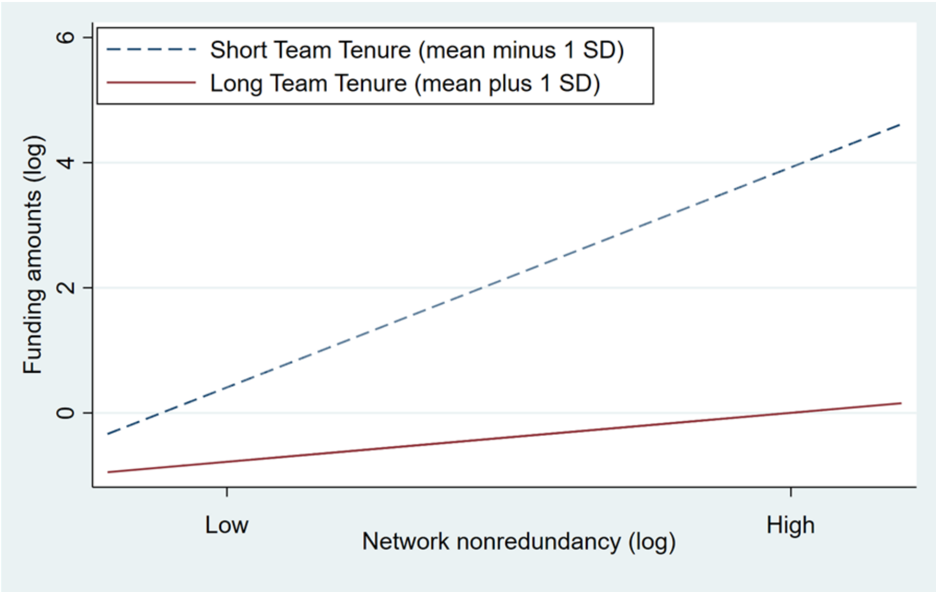

Figure 5.2 Moderating effects of team tenure on the relationship between network nonredundancy (log) and the funding amounts (log).

In Figure 5.3, I plot the relationship between network nonredundancy (log) and funding amount (log) for less and greater heterogeneity of education, using the same approach (i.e. mean ±1 standard deviation) to present the level difference. The dash line refers to entrepreneurial teams with less heterogeneity of education, and the solid line shows teams with greater educational diversity. Therefore, it can be seen that greater heterogeneity of education in the entrepreneurial team reduces the impact of network nonredundancy on obtaining funding, since the solid line has a smaller slope than the dash line (Hypothesis 3b).

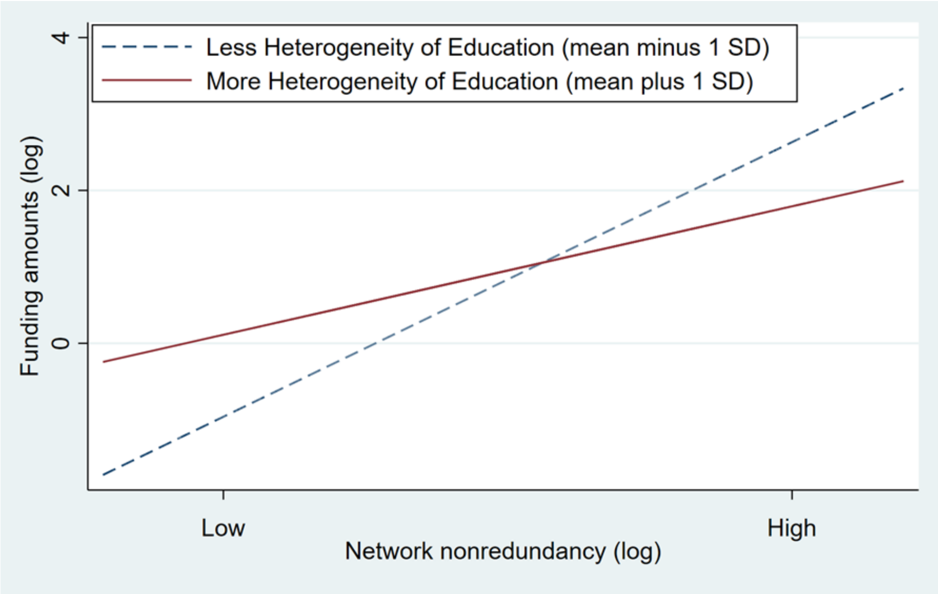

Figure 5.3 Moderating effects of heterogeneity of education on the relationship between network nonredundancy (log) and the funding amounts (log).

In order to mitigate the endogeneity concern regarding the endogenous regressor network nonredundancy (as discussed in section 4.7), I lag all the independent variables by 1 year and employ the instrumental variables' 2SLS regression with robust standard error to control for heteroskedasticity. The function of the instrument variable is intrinsically to break the correlation between the independent variables and the error term. Accordingly, the succinct criteria for selecting an instrument is that the instrument variable should correlate with the endogenous variable and not correlate with the error term. In the first stage, we estimate the instrument, along with other independent and control variables on the endogenous variable, through fixed-effects regression (with robust standard error). If the coefficient of the instrument is significant, then this suggests that our selected instrument is statistically correlated with our endogenous regressor. After the first stage, we can obtain a predicted value of the endogenous variable by using instruments. Then, in the second stage, this predicted value becomes a proxy in the original fixed-effects regression to acquire the estimated coefficient of the endogenous variable. If the instrument is strong and valid, suggesting that it is strictly exogenous, then the endogeneity concern can be alleviated.

Finally, following Lev and Sougiannis (1996), Friedberg (2003), Cheng, Ioannou, and Serafeim (2014), and Symeonidou and Nicolaou (2018), I use the mean network nonredundancy in the same industry category per year as an instrument. It is possible that entrepreneurial teams might impersonate other start-up teams in the same industry's networking strategies (i.e. to imitate how others construct their external network structure) in leveraging the resource and information in terms of making the strategic decision to obtain funding. On the basis of such intuition, it is inferred that focal entrepreneurial teams' network nonredundancy is influenced by the average value of other start-up teams' network nonredundancy in the same industry. Besides, the industry's average network nonredundancy should not directly link to the fundraising performance of the focal start-up. Accordingly, the industry mean should be theoretically valid to be a proper instrument in this case.

Table 5.4 presents both the first and second stage results of the fixed-effects instrumental 2SLS regression (by utilising the xtivreg2 command in Stata), while Model 19 reports the result of the main effect. In the first stage, the coefficient of the instrument variable (i.e. the industry category's mean network nonredundancy) is positive ($\beta = 0.251$) and highly significant ($p<0.001$), which meets my expectation that the instrument statistically correlates with the endogenous independent variable's network nonredundancy. In addition, several tests are also performed to ascertain whether the chosen instrument is valid or not. It is necessary to examine the instrument validity prior to interpreting further results in order to assure that the IV estimation results are reliable. The first check is to apply the ordinary rule of thumb to inspect if the first stage F statistic is larger than 10 (Staiger & Stock 1997). If the first stage F is greater than 10, we can say that the instrument is valid. The first stage F of Model 19 is 628.09 ($p<0.001$), thus suggesting that the instrument is a very strong predictor of network nonredundancy. Secondly, I conduct the underidentification test to report the Kleibergen–Paap rk LM statistic (Baum, Schaffer, & Stillman 2007). The Kleibergen–Paap statistic in Model 19 rejects the null ($p<0.001$), thus suggesting that the instrument is robust and not weak. Third, the weak identification test (i.e. Stock and Yogo test reporting the Cragg–Donald Wald F statistic) is applied. If the Cragg–Donald Wald F exceeds the critical values (proposed by Stock and Yogo (2005)), the instrument is not weak. Model 19 reports that the Cragg–Donald Wald F is 2285.05, which strongly exceeds the Stock and Yogo critical values. Therefore, the industry mean instrument is not weak. Furthermore, the results of weak-instrument robust inference (Anderson–Rubin Wald test and Stock–Wright LM S test) approve ($p<0.05$) the above inference that the chosen instrument is strong and valid. Since we have confirmed the validation of the chosen instrument in Model 19, we can continue checking the results in the second stage. The coefficient of network nonredundancy in the second stage also presents a positive ($\beta = 1.817$) and strong statistical significance ($p<0.01$), as per the fixed-effects results in Model 3.

From Models 20 to 25, I test for moderation effects via the 2SLS IV regression. The first stage results suggest that the instruments are robust and valid. Moreover, the second stage results suggest that team tenure (Model 20: $\beta = -0.6$; $p<0.001$) and the heterogeneity of education (Model 21: $\beta = -0.359$; $p<0.05$) both negatively moderate the relationship between network nonredundancy and funding amounts, with the moderation results consistent in Model 25. The reported centred R^2 of Models 20 and 21 also show a rise from the IV used in the main model (Model 19). It should be noted that the reported R^2 in 2SLS IV regression (using the xtivreg2 Stata command) is the same as the within R^2 from the fixed-effects panel model. Models 22, 23, and 24 find that there are no significant moderating effects of industry experience, founding experience, or gender diversity, respectively. Moreover, these moderation test results represent the same direction of interaction as the fixed-effects model. In addition, I also plot for the effective interaction effects (see Figure 5.4, team tenure; and Figure 5.5, heterogeneity of education) estimated in the 2SLS IV regression for visualisation. Likewise, Aiken and West (1991) are followed by generating two regression equations for each moderator to illustrate their level difference (i.e. calculated via the moderator's mean minus one standard deviation and plus one standard deviation). Then, these are presented on the plot of network nonredundancy (log), with endogeneity correction versus the predicted funding amount (log). Figure 5.4 represents the same trend shown in Figure 5.2, suggesting that an entrepreneurial team with long team tenure decreases the effect of nonredundancy on securing funding (Hypothesis 2b). Likewise, the results illustrated in Figure 5.5 suggest that greater heterogeneity of education in the entrepreneurial team reduces the effect of network nonredundancy on awarding funding, thus presenting a consistent result, as shown in Figure 5.3 (Hypothesis 3b).

Table 5.4 Panel fixed-effects models with endogeneity correction (fixed-effects 2SLS instrumental regression)

First stage (endogenous variable: team network nonredundancy)							
	Model 19 Main effect	Model 20 Moderation effect (Team tenure × non-redundancy)	Model 21 Moderation effect (Heterogeneity of education × non-redundancy)	Model 22 Moderation effect (Industry experience × non-redundancy)	Model 23 Moderation effect (Founding experience × non-redundancy)	Model 24 Moderation effect (Gender diversity × non-redundancy)	Model 25 Moderation effect (All)
Number of patents	0.023^{+}	0.023^{+}	0.023^{+}	0.023^{+}	0.023^{+}	0.023^{+}	0.023^{+}
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Number of trademarks	0.001	0.001	0.002	0.001	0.001	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Early stage	-0.017	-0.017	-0.016	-0.017	-0.018	-0.017	-0.015
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Venture size (log)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team size	0.184***	0.184***	0.183***	0.183***	0.184***	0.184***	0.183***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Team tenure	-0.009	-0.009	-0.012	-0.006	-0.009	-0.007	-0.009
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Heterogeneity of education	0.051***	0.051***	0.039***	0.052***	0.051***	0.051***	0.038***

	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)
Founding experience	0.005	0.005	0.005	0.004	0.003	0.005	0.001
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Industry experience	0.273***	0.274***	0.277***	0.279***	0.274***	0.274***	0.285***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Gender diversity	0.006	0.006	0.007	0.006	0.007	-0.002	-0.002
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Year, industry, and location dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Instrumental variable(s)							
Industry category mean nonredundancy	0.251***	0.251***	0.247***	0.258***	0.250***	0.252***	0.253***
(log)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Industry category mean × Team		0.001					0.00002
tenure		(0.002)					(0.002)
Industry category mean × Heterogeneity			0.017***				0.017***
of education			(0.004)				(0.004)
Industry category mean × Industry				-0.015*			-0.019**
experience				(0.007)			(0.007)
Industry category mean × Founding					0.004		0.010^{+}
experience					(0.006)		(0.005)
Industry category mean × Gender						0.016*	0.018**
diversity						(0.007)	(0.007)
Second stage (dependent variable: funding amounts (log)							

	Model 19	Model 20	Model 21	Model 22	Model 23	Model 24	Model 25
Number of patents	0.228	0.233	0.243	0.227	0.228	0.215	0.232
	(0.258)	(0.272)	(0.261)	(0.259)	(0.259)	(0.259)	(0.277)
Number of trademarks	0.015	0.006	0.017	0.018	0.014	0.013	0.008
	(0.084)	(0.085)	(0.083)	(0.084)	(0.084)	(0.084)	(0.084)
Early stage	4.831***	4,367***	4.768***	4.838***	4.844***	4.798***	4.307***
	(0.458)	(0.468)	(0.460)	(0.458)	(0.458)	(0.458)	(0.471)
Venture size (log)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team size	-0.672**	-0.619**	-0.644**	-0.674**	-0.675**	-0.674**	-0.602**
	(0.229)	(0.227)	(0.228)	(0.229)	(0.229)	(0.230)	(0.227)
Team tenure	-0.897**	-0.956**	-0.843*	-0.939**	-0.860*	-0.921*	-0.919**
	(0.336)	(0.337)	(0.134)	(0.338)	(0.337)	(0.337)	(0.340)
Heterogeneity of education	0.077	0.060	0.345^{+}	0.052	0.079	0.069	0.292
	(0.152)	(0.152)	(0.196)	(0.153)	(0.152)	(0.152)	(0.196)
Founding experience	0.061	0.099	0.041	0.071	0.120	0.059	0.166
	(0.184)	(0.184)	(0.184)	(0.184)	(0.192)	(0.184)	(0.194)
Industry experience	-0.257	-0.219	-0.294	-0.392	-0.271	-0.257	-0.389
	(0.362)	(0.362)	(0.363)	(0.375)	(0.363)	(0.363)	(0.380)
Gender diversity	-0.151	-0.128	-0.144	-0.139	-0.163	0.008	0.070
	(0.273)	(0.273)	(0.273)	(0.274)	(0.273)	(0.294)	(0.293)
Team network nonredundancy (log)	1.817**	1.457*	1.895**	1.665*	1.869**	1.818**	1.488**
	(0.671)	(0.666)	(0.672)	(0.669)	(0.678)	(0.673)	(0.674)

Team tenure ×		-0.600***					-0.577***
nonredundancy (log)		(0.114)					(0.116)
Heterogeneity of education ×			-0.359*$^{+}$				-0.349^{+}
nonredundancy (log)			(0.179)				(0.180)
Industry experience ×				0.580			0.488
nonredundancy (log)				(0.384)			(0.406)
Founding experience ×					-0.215		-0.291
nonredundancy (log)					(0.247)		(0.264)
Gender diversity ×						-0.452	-0.567
nonredundancy (log)						(0.353)	(0.352)
Year, industry, and location dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Second-stage F-statistic	30.42***	29.65***	29.04***	28.96***	28.90***	28.90***	24.99***
Observations	11,862	11,862	11,862	11,862	11,862	11,862	11,862
Number of start-ups	2,698	2,698	2,698	2,698	2,698	2,698	2,698
Centred R-squared	0.0637	0.0681	0.0649	0.0628	0.0635	0.0632	0.0676
Uncentered R-squared	0.0637	0.0681	0.0649	0.0628	0.0635	0.0632	0.0676
Tests for weak instruments							
	Model 19	Model 20	Model 21	Model 22	Model 23	Model 24	Model 25
1. First-stage F-statistic	628.09***	314.53***	332.76***	320.69***	314.79***	317.80***	114.90***
2. Underidentification test -Kleibergen-Paap rk LM statistic	286.94*** p-value = 0.000	286.18*** p-value = 0.000	289.06*** p-value = 0.000	266.81*** p-value = 0.000	287.12*** p-value = 0.000	281.11*** p-value = 0.000	284.60*** p-value = 0.000

3. Weak identification test (Stock and Yogo test) -Cragg-Donald Wald F statistic	2285.05 (exceeds the critical values)	1134.52 (exceeds the critical values)	1160.17 (exceeds the critical values)	1071.01 (exceeds the critical values)	1142.37 (exceeds the critical values)	1135.30 (exceeds the critical values)	350.34 (exceeds the critical values)
4. Weak-instrument-robust inference - 4.1 Anderson-Rubin Wald test (Chi-sq)	7.46** p-value = 0.006	34.37*** p-value = 0.000	10.72** p-value = 0.005	9.27** p-value = 0.009	7.98* p-value = 0.019	8.73* p-value = 0.013	41.22*** p-value = 0.000
- 4.2 Stock-Wright LM S statistic (Chi-sq)	7.49** p-value = 0.006	34.21*** p-value = 0.000	10.65** p-value = 0.005	9.15* p-value = 0.010	8.02* p-value = 0.018	8.78* p-value = 0.012	40.28*** p-value = 0.000
Tests for regressor endogeneity							
	Model 19	Model 20	Model 21	Model 22	Model 23	Model 24	Model 25
1. *C* test: difference-in-Sargan statistic	3.41+	2.09	2.77+	3.89*	3.39+	3.39+	1.88
(Chi-square & P-value)	0.065	0.148	0.096	0.049	0.066	0.066	0.171
2. Durbin-Wu-Hausman test	3.56	3.35	2.99	5.96	4.82	6.22	9.30
(Chi-square & P-value)	0.965	0.985	0.991	0.876	0.939	0.858	0.862

Robust standard errors in parentheses. Two tailed tests. + p< 0.1; * p<0.05; ** p<0.01; *** p<0.001

Note: Venture size is a time-invariant variable. Thus, it was dropped because it is constant within groups from the fixed-effects model.

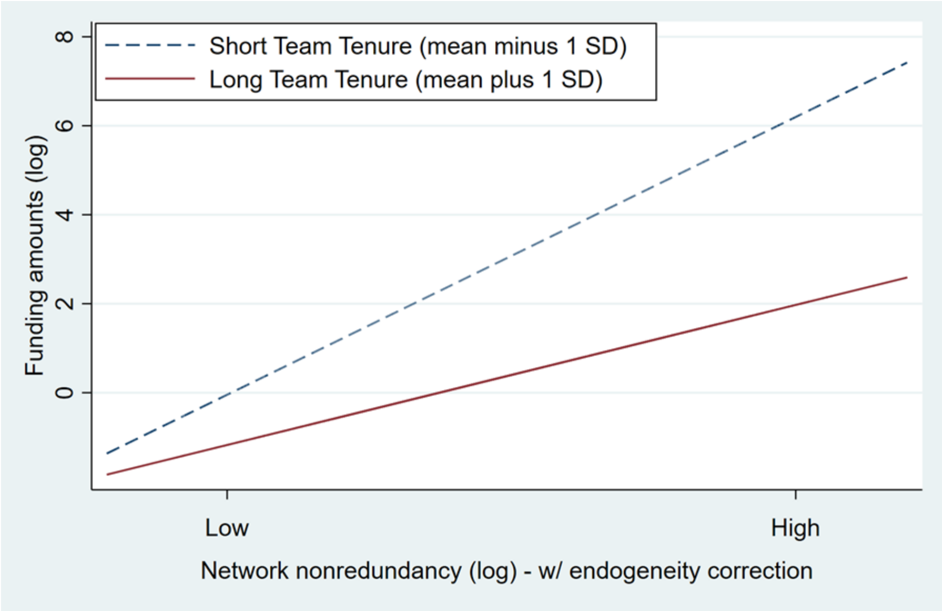

Figure 5.4 Moderating effects of team tenure on the relationship between network nonredundancy (log) and the funding amounts (log) – with endogeneity correction.

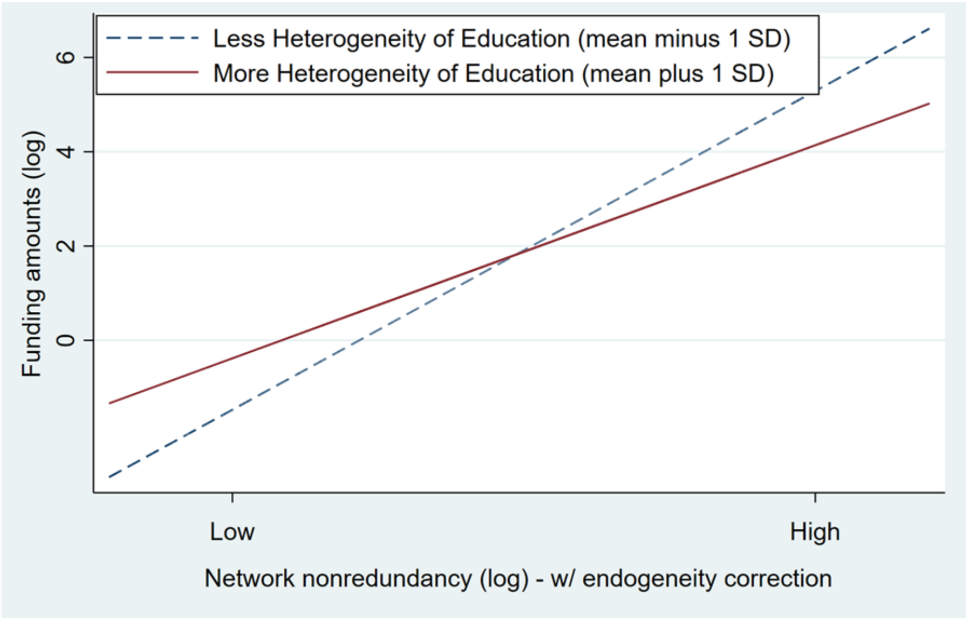

Figure 5.5 Moderating effects of heterogeneity of education on the relationship between network nonredundancy (log) and the funding amounts (log) – with endogeneity correction.

Despite all the instrument tests suggesting that the industry category mean of network nonredundancy is a strong and valid instrument variable for network nonredundancy, we still need to examine whether the network nonredundancy is an endogenous regressor in the model or not, to enable us to decide which model's (i.e. fixed-effects or IV 2SLS fixed-effects) estimates are more appropriate. If the test for regressor endogeneity suggests that the network nonredundancy is exogenous, then we should report the fixed-effects model estimation; otherwise, we should report the IV 2SLS fixed-effects regression results if the endogeneity tests suggest that the network nonredundancy is endogenous. I finally conduct a C test (i.e. the difference-in-Sargan statistic) and Durbin–Wu–Hausman test to examine the endogeneity of network nonredundancy. The C test results (see Table 5.4, Model 20) suggest a partial significance ($p<0.1$) of the endogeneity of the network nonredundancy, which is not a very clear sign to determine whether it is endogenous or exogenous. However, the exogeneity of the network nonredundancy is clearly indicated in the Durbin–Wu–Hausman test ($p= 0.965$), and thus we cannot reject the null hypothesis of exogeneity. Therefore, this suggests that reporting the panel fixed-effects estimates (non-instrumented) is more appropriate than the instrument 2SLS fixed-effects regression.

Furthermore, scholars also suggest we should be cautious in interpreting the moderation models when there is a potential endogeneity concern in the model (Angrist & Pischke 2008; Wooldridge 2010). The debate involves whether researchers might have problems in interpreting the interaction effects (interaction term coefficient) properly if both the independent variable (denotes x afterwards) and moderator (denotes m afterwards) are endogenous (Anderson 2018).

Nevertheless, it is claimed that such a concern is not an issue in this study. First, the endogeneity test already suggests that the network nonredundancy (x) is exogenous in the models. Second, all the independent variables have been lagged in all the estimation models. As we know, scholars typically apply lagged independent variables in their panel regression model in order to minimise the endogeneity concern. In this technique, we can assume that the lagged x variables by 1 year (including moderators) play the role of the instruments, namely, implying that the x_t-1 and m_t-1 are exogenous, while retaining the insight of x_t and m_t (i.e. still preserving the information of the original x and m). Thus, the interaction terms' coefficient (β x_t-1*m_t-1) in this study should not be problematic in terms of practical and meaningful interpretation based on the above argument.

5.1 Robustness tests

Several robustness tests are conducted to examine the accuracy of the results. First, I apply the same fixed-effects panel model to those start-ups that received second round funding and beyond (i.e. to track the funding obtained after the first round). It is argued that some start-ups 'pull themselves up by their own bootstraps' (i.e. they rely on the founders or entrepreneurial team's personal savings or assets, or receive financial support exclusively from their friends and family) and never participate in seeking funding from external investors (Ter Wal et al. 2016; Jin, Wu, & Hitt 2017). Accordingly, if start-ups have received first round funding, this means that the start-up has built a record for venture capitalists to track, and we can expect such start-ups will follow this route to secure additional funds for their further operations. Thus, focus on the funding amounts that start-ups received after the second funding round could help to control for the potential 'bootstraps' effect.

Considering the above argument, the dependent variable of robustness test 1 is the total funding amounts received after the second funding round on a yearly basis (between the 2009–2018 study period). As per the main analysis, I carry out natural log transformation on both the outcome variable (funding amounts) and the independent variable (network nonredundancy) to correct the positive skew and for the underlying economic grounds.

The Hausman test is also performed to examine whether the fixed-effects is the preferred model rather than the random-effects under this sample condition (see Appendix 3). The result suggests that we should reject the null hypothesis, and thus the fixed-effects panel model is more appropriate.

Table 5.5 presents the results of the panel fixed-effects estimation. Model 26 is the base model for the different dependent variable presenting the venture control regression, while Model 27 is the venture plus team control regression. Model 28 represents the results of the main effect. The coefficient of network nonredundancy (log) is positive (β = 0.838) and significant ($p<0.01$), which presents a consistent main effect, as shown in Table 5.2, Model 3. The main effect plot of this robustness test is presented graphically below in Figures 5.6.

Models 29–34 introduce the interaction effect. The overall results are consistent, as seen in Models 4–9 presented in Table 5.2. The team tenure (β = -0.416; $p<0.001$) negatively moderates the network nonredundancy and funding amounts' relationship, as does the heterogeneity of education (β = -0.369; $p<0.01$). Model 34 presents the combined significance involving all the moderators in the regression. Moreover, following the same procedure as the main analysis, the plots of the interaction effects of team tenure and endogeneity of education are illustrated in Figure 5.7 and Figure 5.8, respectively. These two figures present the same direction of moderating effect results shown in Figure 5.2 and Figure 5.3, respectively, suggesting a consistent finding emerging from the main analysis.

Similarly, I also run the instrumental 2SLS regression and test the endogeneity for the network nonredundancy for this robustness check condition, where the results are also consistent with the instrumental 2SLS estimation for the main analysis.

Table 5.6 presents the IV 2SLS fixed-effects results for robustness test 1. Model 35 shows the main effect via applying the industry category mean as the instrument. The first stage in Model 35 suggests that the coefficient of the instrument is positive and significant ($\beta = 0.248$; $p<0.001$), indicating its statistical correlation to network nonredundancy. All tests to ensure a robust instrument are passed, and hence the industry category mean is also a strong and valid instrument for robustness check 1. Similarly, the endogeneity test for network nonredundancy suggests that it is exogenous, which is consistent with the main analysis. Therefore, under the robustness test 1 condition, reporting the fixed-effects panel estimates is more appropriate than the random-effects model and the IV 2SLS regression model.

Overall, all the test results for robustness test 1 are consistent with the main analysis.

Table 5.5 Robustness test 1: Panel fixed-effects results

DV: 2nd and later rounds funding amounts (log)	Model 26 Venture Control	Model 27 Venture + team Control	Model 28 Main effect	Model 29 Moderation effect (Team tenure × non-redundancy)	Model 30 Moderation effect (Heterogeneity of education × non-redundancy)	Model 31 Moderation effect (Industry experience × non-redundancy)	Model 32 Moderation effect (Founding experience × non-redundancy)	Model 33 Moderation effect (Gender diversity × non-redundancy)	Model 34 Moderation effect (All)
Number of patents	0.414*	0.395*	0.371*	0.371*	0.383*	0.371*	0.371*	0.376*	0.387*
	(0.187)	(0.183)	(0.179)	(0.188)	(0.183)	(0.179)	(0.179)	(0.179)	(0.190)
Number of trademarks	0.089	0.089	0.087	0.081	0.089	0.087	0.088	0.088	0.083
	(0.070)	(0.070)	(0.070)	(0.070)	(0.069)	(0.070)	(0.070)	(0.070)	(0.069)
Early stage	4.959***	5.232***	5.254***	4.937***	5.192***	5.253***	5.252***	5.268***	4.882***
	(0.428)	(0.431)	(0.430)	(0.429)	(0.430)	(0.430)	(0.430)	(0.431)	(0.428)
Venture size (log)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team size		0.010	-0.190	-0.193	-0.191	-0.193	-0.189	-0.189	-0.195
		(0.166)	(0.186)	(0.185)	(0.187)	(0.187)	(0.187)	(0.187)	(0.187)
Team tenure		-0.552+	-0.543+	-0.584+	-0.487	-0.537+	-0.551+	-0.533+	-0.531+
		(0.319)	(0.318)	(0.317)	(0.319)	(0.318)	(0.321)	(0.318)	(0.321)
Heterogeneity of education		0.265+	0.219	0.196	0.485**	0.222	0.219	0.222	0.457**
		(0.143)	(0.144)	(0.144)	(0.153)	(0.144)	(0.144)	(0.144)	(0.153)
Founding experience		-0.023	-0.027	-0.0002	-0.049	-0.028	-0.039	-0.025	-0.054

		(0.166)	(0.166)	(0.165)	(0.166)	(0.166)	(0.166)	(0.166)	(0.166)
Industry experience		0.392	0.105	0.074	0.025	0.120	0.108	0.105	0.027
		(0.265)	(0.283)	(0.281)	(0.285)	(0.280)	(0.283)	(0.282)	(0.281)
Gender diversity		-0.096	-0.102	-0.090	-0.094	-0.104	-0.100	-0.171	-0.150
		(0.259)	(0.260)	(0.261)	(0.259)	(0.261)	(0.260)	(0.259)	(0.259)
Network nonredundancy			0.838**	0.756**	1.040***	0.871**	0.826**	0.836**	0.968**
(log)			(0.287)	(0.283)	(0.290)	(0.307)	(0.291)	(0.287)	(0.304)
Team tenure ×				-0.416***					-0.419***
nonredundancy (log)				(0.082)					(0.083)
Heterogeneity of education ×					-0.369**				-0.352**
nonredundancy (log)					(0.106)				(0.106)
Industry experience ×						-0.081			-0.121
nonredundancy (log)						(0.223)			(0.229)
Founding experience ×							0.045		0.117
nonredundancy (log)							(0.145)		(0.152)
Gender diversity ×								0.195	0.206
nonredundancy (log)								(0.235)	(0.233)
Constant	-1.310*	-2.876**	-2.956**	-2.930**	-2.732**	-2.918**	-2.971**	-2.949**	-2.691**
	(0.578)	(0.989)	(0.986)	(0.979)	(0.986)	(0.992)	(0.990)	(0.986)	(0.989)
Year, industry, and location dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F	24.73***	17.99***	17.64***	17.49***	17.52***	16.72***	16.72***	16.80***	15.16***

Observations	12,380	12,380	12,380	12,380	12,380	12,380	12,380	12,380	12,380
Number of start-ups	3,086	3,086	3,086	3,086	3,086	3,086	3,086	3,086	3,086
Within R-squared	0.0392	0.0413	0.0423	0.0450	0.0438	0.0423	0.0423	0.0424	0.0466
Between R-squared	0.1171	0.0783	0.0383	0.0313	0.0276	0.0386	0.0381	0.0390	0.0230
Overall R-squared	0.0051	0.0009	0.0005	0.0012	0.0011	0.0005	0.0005	0.0004	0.0018

Robust standard errors in parentheses. Two tailed tests. + $p< 0.1$; * $p<0.05$; ** $p<0.01$; *** $p<0.001$

Note: Since venture size is a time-invariant variable, it was dropped because it is constant within groups from the panel fixed-effects model.

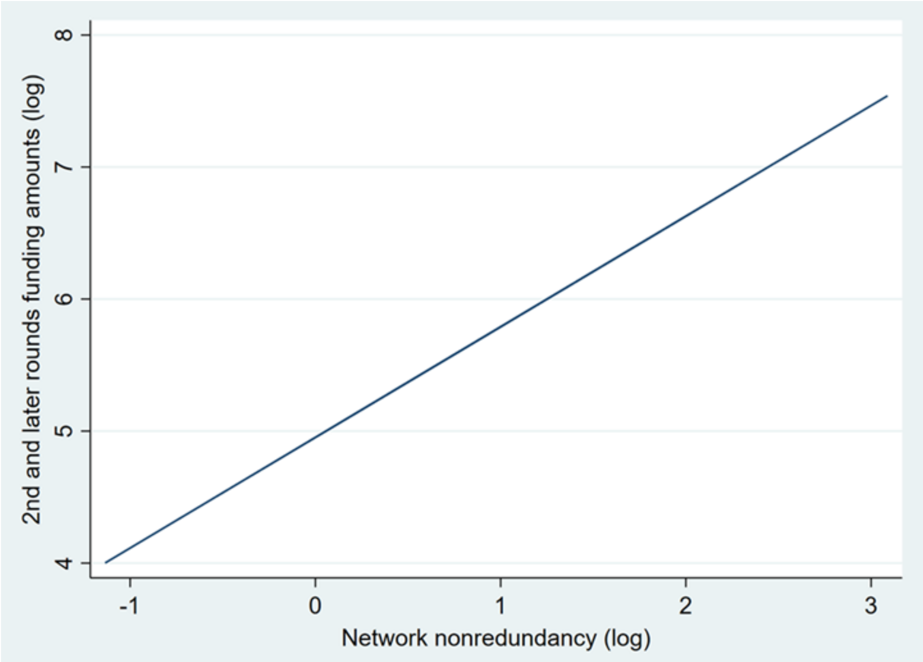

Figure 5.6 Illustration of the main effect: the log–log relationship of network nonredundancy and funding amount (summation of the second round and beyond on a yearly basis).

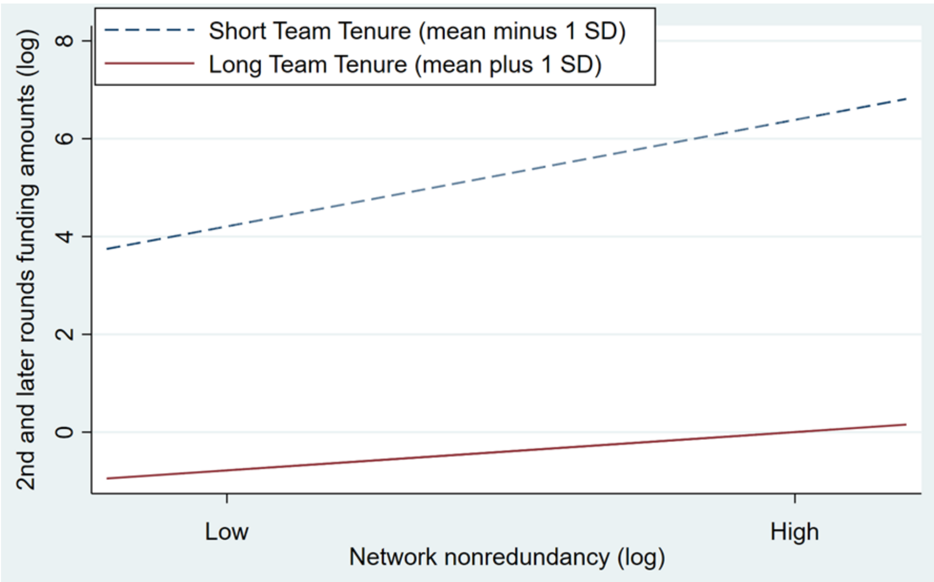

Figure 5.7 Moderating effects of team tenure on the relationship between network nonredundancy (log) and the second and later rounds' funding amounts (log).

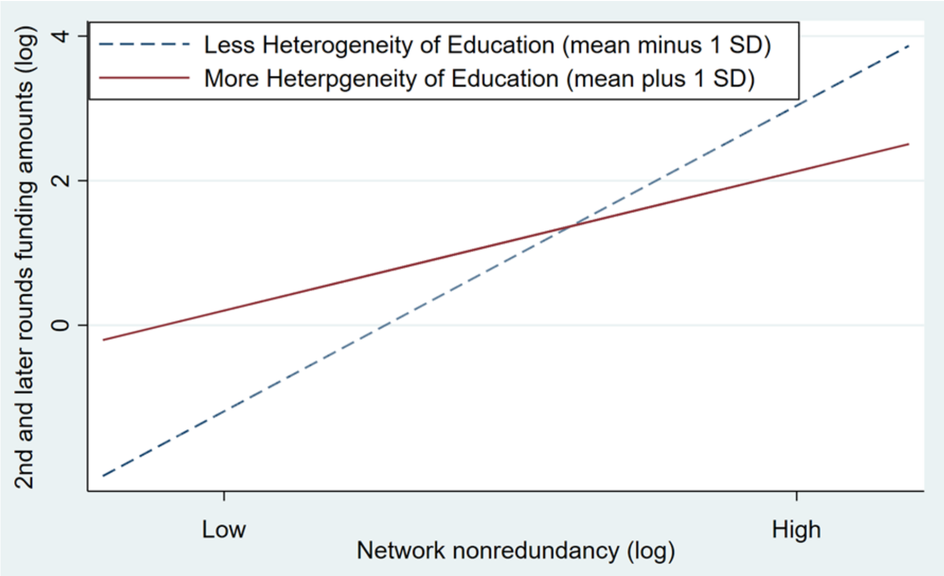

Figure 5.8 Moderating effects of heterogeneity of education on the relationship between network nonredundancy (log) and the second and later rounds' funding amounts (log).

Table 5.6 Robustness test 1: Panel fixed-effects models with endogeneity correction (fixed-effects 2SLS instrumental regression)

First stage (endogenous variable: team network nonredundancy)							
	Model 35 Main effect	Model 36 Moderation effect (Team tenure × non-redundancy)	Model 37 Moderation effect (Heterogeneity of education × non-redundancy)	Model 38 Moderation effect (Industry experience × non-redundancy)	Model 39 Moderation effect (Founding experience × non-redundancy)	Model 40 Moderation effect (Gender diversity × non-redundancy)	Model 41 Moderation effect (All)
Number of patents	0.023^{+}	0.023^{+}	0.023^{+}	0.024^{+}	0.023^{+}	0.023^{+}	0.023^{+}
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Number of trademarks	0.001	0.001	0.002	0.001	0.001	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Early stage or not	-0.020	-0.019	-0.018	-0.019	-0.020	-0.019	-0.017
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Venture size (log)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team size	0.185***	0.185***	0.184***	0.184***	0.184***	0.185***	0.184***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Team tenure	-0.010	-0.010	-0.013	-0.008	-0.010	-0.008	-0.011
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Heterogeneity of education	0.050***	0.050***	0.037***	0.050***	0.050***	0.050***	0.037***
	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)

Founding experience	0.004 (0.010)	0.004 (0.010)	0.005 (0.010)	0.004 (0.010)	0.003 (0.010)	0.005 (0.010)	0.0003 (0.010)
Industry experience	0.276*** (0.017)	0.276*** (0.017)	0.279*** (0.017)	0.281*** (0.017)	0.276*** (0.017)	0.277*** (0.017)	0.287*** (0.017)
Gender diversity	0.004 (0.015)	0.004 (0.015)	0.004 (0.015)	0.005 (0.015)	0.005 (0.015)	-0.004 (0.015)	-0.004 (0.015)
Year, industry, and location dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Instrumental variable(s)							
Industry category mean nonredundancy (log)	0.248*** (0.010)	0.248*** (0.010)	0.243*** (0.010)	0.254*** (0.010)	0.247*** (0.010)	0.249*** (0.010)	0.250*** (0.010)
Industry category mean × Team tenure		0.001 (0.002)					0.00004 (0.002)
Industry category mean × Heterogeneity of education			0.017*** (0.004)				0.018*** (0.004)
Industry category mean × Industry experience				-0.015* (0.007)			-0.018* (0.007)
Industry category mean × Founding experience					0.004 (0.006)		0.009^{+} (0.005)
Industry category mean × Gender diversity						0.017* (0.007)	0.018** (0.007)

Second stage (dependent variable: funding amounts (log)

	Model 35	Model 36	Model 37	Model 38	Model 39	Model 40	Model 41
Number of patents	0.345	0.350	0.366	0.344	0.345	0.342	0.366
	(0.243)	(0.250)	(0.247)	(0.243)	(0.243)	(0.244)	(0.254)
Number of trademarks	0.086	0.079	0.089	0.088	0.086	0.086	0.083
	(0.072)	(0.072)	(0.071)	(0.072)	(0.072)	(0.072)	(0.072)
Early stage	5.289***	4.910***	5.187***	5.284***	5.280***	5.273***	4.819***
	(0.461)	(0.471)	(0.462)	(0.461)	(0.461)	(0.462)	(0.474)
Venture size (log)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team size	-0.418^{+}	-0.373^{+}	-0.380^{+}	-0.419^{+}	-0.418^{+}	-0.418^{+}	-0.338
	(0.224)	(0.222)	(0.222)	(0.224)	(0.224)	(0.224)	(0.222)
Team tenure	-0.533	-0.582^{+}	-0.455	-0.556^{+}	-0.532	-0.538	-0.525
	(0.329)	(0.329)	(0.330)	(0.329)	(0.329)	(0.328)	(0.331)
Heterogeneity of education	0.166	0.151	0.552**	0.152	0.166	0.164	0.516**
	(0.148)	(0.147)	(0.186)	(0.149)	(0.148)	(0.148)	(0.186)
Founding experience	-0.031	0.0001	-0.062	-0.026	-0.029	-0.032	-0.030
	(0.175)	(0.175)	(0.175)	(0.175)	(0.181)	(0.175)	(0.183)
Industry experience	-0.224	-0.190	-0.279	-0.298	-0.224	-0.223	-0.283
	(0.351)	(0.350)	(0.351)	(0.360)	(0.351)	(0.351)	(0.365)
Gender diversity	-0.110	-0.094	-0.097	-0.105	-0.110	-0.079	-0.028
	(0.261)	(0.261)	(0.260)	(0.261)	(0.261)	(0.280)	(0.279)
Team network nonredundancy	1.795**	1.500*	1.916**	1.710**	1.797**	1.795**	1.578*
(log)	(0.652)	(0.650)	(0.652)	(0.650)	(0.657)	(0.652)	(0.653)

Team tenure ×		-0.478***					-0.468***
nonredundancy (log)		(0.107)					(0.108)
Heterogeneity of education ×			-0.522**$^{+}$				-0.505**
nonredundancy (log)			(0.170)				(0.170)
Industry experience ×				0.321			0.166
nonredundancy (log)				(0.375)			(0.398)
Founding experience ×					-0.007		0.004
nonredundancy (log)					(0.241)		(0.257)
Gender diversity ×						-0.089	-0.146
nonredundancy (log)						(0.345)	(0.346)
Year, industry, and location dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Second-stage F-statistic	16.29***	16.21***	15.88***	15.44***	15.44***	15.43***	13.75***
Observations	12,016	12,016	12,016	12,016	12,016	12,016	12,016
Number of start-ups	2,722	2,722	2,722	2,722	2,722	2,722	2,722
Centred R-squared	0.0410	0.0442	0.0427	0.0405	0.0410	0.0409	0.0453
Uncentered R-squared	0.0410	0.0442	0.0427	0.0405	0.0410	0.0409	0.0453
Tests for weak instruments							
	Model 35	Model 36	Model 37	Model 38	Model 39	Model 40	Model 41
1. First-stage F-statistic	615.87***	308.52***	327.23***	314.09***	308.66***	312.00***	113.01***
2. Underidentification test	285.52***	284.71***	288.06***	267.37***	285.75***	279.77***	284.23***

-Kleibergen-Paap rk LM statistic	p-value = 0.000	p-value = 0.000	p-value = 0.000	p-value = 0.000	p-value = 0.000	p-value = 0.000	p-value = 0.000
3. Weak identification test (Stock and Yogo test) -Cragg-Donald Wald F statistic	2256.55 (exceeds the critical values)	1120.54 (exceeds the critical values)	1145.50 (exceeds the critical values)	1062.47 (exceeds the critical values)	1127.88 (exceeds the critical values)	1121.16 (exceeds the critical values)	347.04 (exceeds the critical values)
4. Weak-instrument-robust inference - 4.1 Anderson-Rubin Wald test (Chi-sq)	7.65** p-value = 0.006	27.42*** p-value = 0.000	16.07** p-value = 0.000	8.04* p-value = 0.018	7.66* p-value = 0.022	7.66* p-value = 0.022	34.84*** p-value = 0.000
- 4.2 Stock-Wright LM S statistic (Chi-sq)	7.70** p-value = 0.006	27.80*** p-value = 0.000	15.92** p-value = 0.000	8.04* p-value = 0.018	7.71* p-value = 0.021	7.71* p-value = 0.021	34.74*** p-value = 0.000

Tests for regressor endogeneity

	Model 35	Model 36	Model 37	Model 38	Model 39	Model 40	Model 41
1. *C* test: difference-in-Sargan statistic (Chi-square & P-value)	2.74^{+} 0.098	1.72 0.190	1.89 0.169	2.94^{+} 0.087	2.74^{+} 0.098	2.74^{+} 0.098	1.14 0.286
2. Durbin-Wu-Hausman test (Chi-square & P-value)	3.03 0.981	2.92 0.992	3.44 0.984	4.40 0.957	3.09 0.990	4.11 0.967	5.34 0.989

Robust standard errors in parentheses. Two tailed tests. + p< 0.1; * p<0.05; ** p<0.01; *** p<0.001

Note: Venture size is a time-invariant variable. Thus, it was dropped because it is constant within groups from the fixed-effects model.

Second, I employ a different operationalisation of the dependent variable, namely, a binary variable coding “1” or “0” indicating received funding (from all funding sources) or not, respectively.

In robustness test 2, a fixed-effects logit model is employed to verify the impact of network nonredundancy (along with the control variables) on the probability of funding being secured for start-ups. The fixed-effects model helps control the omitted variables such as firm-level heterogeneous effects, and the logit model applied as the dependent variable is binary. The general form of the model can be written as below:

$$P_r\left(y_{it}=1|x_{it}\right)=F\left(\alpha_i+x_{it}\beta\right)=\frac{e^{\alpha_i+\beta x_{it}}}{1+e^{\alpha_i+\beta x_{it}}}$$

where $Pr(y_{it} =1 | x_{it})$ is the logistic probability of receiving funding conditional on $\sum_{t=1}^{Ti} y_{it}$, F is the cumulative logistic distribution, $i = 1,2 \ldots, n$ denotes the start-ups, $t = 1,2 \ldots, T_i$ represents the observations for the ith start-ups, and α_i captures the heterogeneous effects (unobserved) among start-ups (Chamberlian 1980; Baltagi 2013; Longhi & Nandi 2015).

I choose not to employ the random-effects logit model because the potential for omitted variables could lead to inconsistent likelihood estimates (Greene 2012). As per the case of the linear fixed-effects panel model with a continuous dependent variable, “in the case of the logistic distribution, a particular conditional distribution of the dependent variable has been found to have the same property of independence of the unobserved heterogeneity” (Longhi & Nandi 2015, p.203). In other words, the probabilities are independent of α_i. Hence, the firm-level heterogeneous effects such as the corporate culture and its own core competitive advantage can be controlled, while unbiased and consistent estimates of β can be obtained when we adopt the fixed-effects model. I also utilise the Hausman test (Note: with the random-effects logit estimate, Mundlak correction is also carried out in order to produce consistent estimates of the parameter for comparison (Longhi & Nandi 2015) to help in terms of suggesting the preference for applying the fixed-effects logit or random-effects logit model. The results (see Appendix 4) reveal that we should reject the null hypothesis (i.e. the random-effects estimator is consistent and efficient in terms of the true population parameters (Hausman 1978)), and select the fixed-effects logit model.

In addition, the fixed-effects probit model should not be chosen because it applies unconditional maximum likelihood estimates, and thus will lead to inconsistent α_i and β values (Anderson 1970; Chamberlian 1980; Greene & Hensher 2010). Besides, as one of the mainstream software applications, Stata does not provide a command "for a fixed effects probit panel model because the probit distribution does not provide a 'sufficient statistic' that can be used in the modelling process" (Gayle & Lambert 2018, p.103).

Table 5.7 presents the results of robustness test 2 using the fixed-effects logit model, while Model 44 shows the main effect result. The coefficient of network nonredundancy is positive (β = 0.211) and significant ($p<0.05$), indicating a statistically positive relationship between network nonredundancy and the likelihood of receiving funding. Accordingly, the results of the main effect are consistent with the main analysis. Figure 5.9 presents the predicted relationship between network nonredundancy and the likelihood of receiving funding.

Models 45 to 50 are the results of the moderation effects. The overall results are consistent with the previous tests. The team tenure (β = -0.167; p<0.001) negatively moderates the relationship between network nonredundancy and the likelihood of receiving funding, as does the heterogeneity of education (β = -0.102; p<0.01). Model 50 presents the combined significance involving all the moderators in the regression, with the results being similarly consistent. The plots of the interaction effects of team tenure and heterogeneity of education are illustrated in Figure 5.10 and Figure 5.11, respectively.

Table 5.7 Robustness test 2: Panel fixed-effects logit predicting the probability of receiving funding

DV: receive funding (from all sources) or not	Model 42 Venture Control	Model 43 Venture + team Control	Model 44 Main effect	Model 45 Moderation effect (Team tenure × non-redundancy)	Model 46 Moderation effect (Heterogeneity of education × non-redundancy)	Model 47 Moderation effect (Industry experience × non-redundancy)	Model 48 Moderation effect (Founding experience × non-redundancy)	Model 49 Moderation effect (Gender diversity × non-redundancy)	Model 50 Moderation effect (All)
Number of patents	0.150^{+}	0.142^{+}	0.137	0.147^{+}	0.139	0.137	0.136	0.137	0.150^{+}
	(0.087)	(0.085)	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)
Number of trademarks	0.021	0.022	0.022	0.018	0.021	0.022	0.022	0.022	0.017
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
Early stage	0.868***	0.978***	0.981***	0.886***	0.968***	0.982***	0.981***	0.981***	0.875***
	(0.131)	(0.134)	(0.134)	(0.136)	(0.134)	(0.134)	(0.134)	(0.134)	(0.136)
Venture size (log)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team size		-0.045	-0.093^{+}	-0.095^{+}	-0.090^{+}	-0.092^{+}	-0.093^{+}	-0.093^{+}	-0.093^{+}
		(0.049)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.055)
Team tenure		-0.401***	-0.395***	-0.399***	-0.386***	-0.396***	-0.396***	-0.397***	-0.394***
		(0.096)	(0.096)	(0.096)	(0.097)	(0.097)	(0.097)	(0.097)	(0.097)
Heterogeneity of education		0.072	0.061	0.056	0.138**	0.060	0.061	0.060	0.124*
		(0.044)	(0.044)	(0.045)	(0.052)	(0.044)	(0.044)	(0.044)	(0.052)
Founding experience		-0.013	-0.014	-0.009	-0.018	-0.014	-0.017	-0.014	-0.018

		(0.063)	(0.063)	(0.063)	(0.063)	(0.063)	(0.066)	(0.063)	(0.066)
Industry experience		0.132	0.055	0.044	0.040	0.052	0.055	0.055	0.031
		(0.086)	(0.093)	(0.094)	(0.094)	(0.095)	(0.094)	(0.094)	(0.096)
Gender diversity		-0.024	-0.023	-0.022	-0.024	-0.023	-0.022	-0.016	-0.015
		(0.087)	(0.087)	(0.087)	(0.087)	(0.087)	(0.087)	(0.090)	(0.090)
Network nonredundancy			0.211*	0.166	0.269**	0.207*	0.209*	0.211*	0.218*
(log)			(0.101)	(0.101)	(0.103)	(0.104)	(0.101)	(0.101)	(0.107)
Team tenure ×				-0.167***					-0.163***
nonredundancy (log)				(0.034)					(0.034)
Heterogeneity of education ×					-0.102**				-0.095**
nonredundancy (log)					(0.036)				(0.036)
Industry experience ×						0.011			0.001
nonredundancy (log)						(0.073)			(0.076)
Founding experience ×							0.008		0.015
nonredundancy (log)							(0.057)		(0.060)
Gender diversity ×								-0.020	-0.023
nonredundancy (log)								(0.071)	(0.071)
Year, industry, and location dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log likelihood	-3506.49	-3491.83	-3489.62	-3477.50	-3485.43	-3489.61	-3489.61	-3489.58	-3473.86
LR chi2	649.8***	679.1***	683.5***	707.7***	691.9***	683.5***	683.5***	683.6***	715.0***
Observations	9,638	9,638	9,638	9,638	9,638	9,638	9,638	9,638	9,638

Number of start-ups	1,984	1,984	1,984	1,984	1,984	1,984	1,984	1,984	1,984

Standard errors in parentheses. Two tailed tests. + $p< 0.1$; * $p<0.05$; ** $p<0.01$; *** $p<0.001$

Note: Since venture size is a time-invariant variable, it was dropped because it is constant within groups from the panel fixed-effects model.

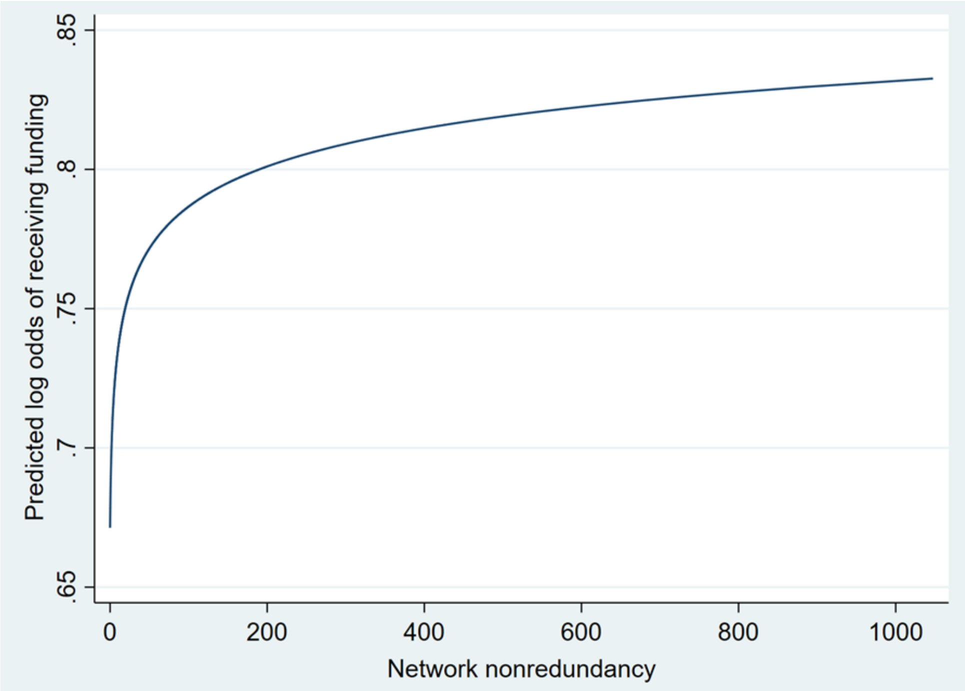

Figure 5.9 The predicted relationship between network nonredundancy and the likelihood of receiving funding.

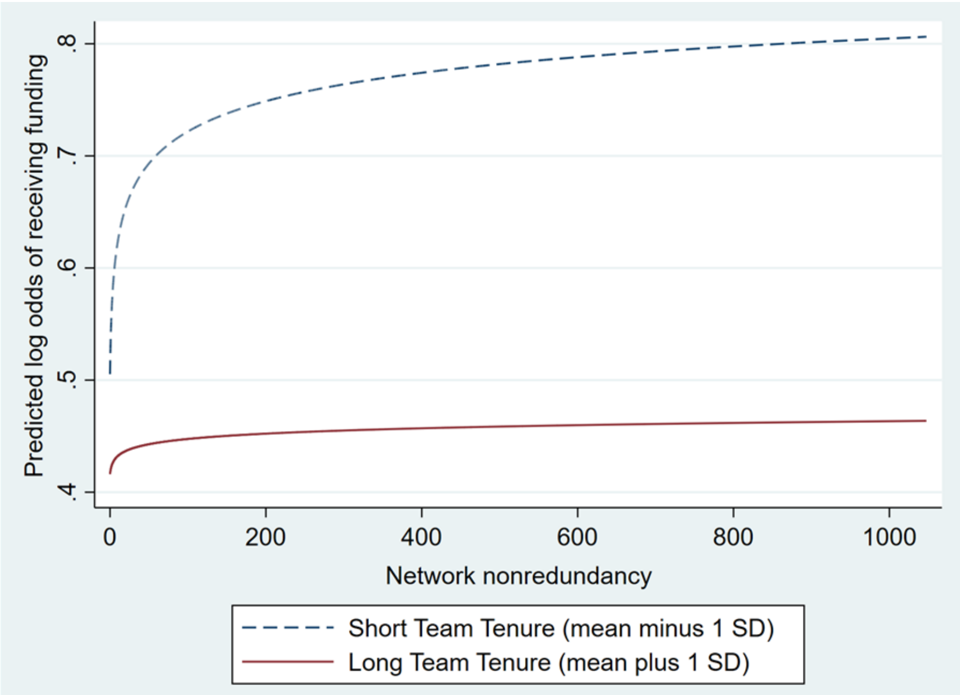

Figure 5.10 Moderating effects of team tenure on the relationship between network nonredundancy (log) and the likelihood of receiving funding.

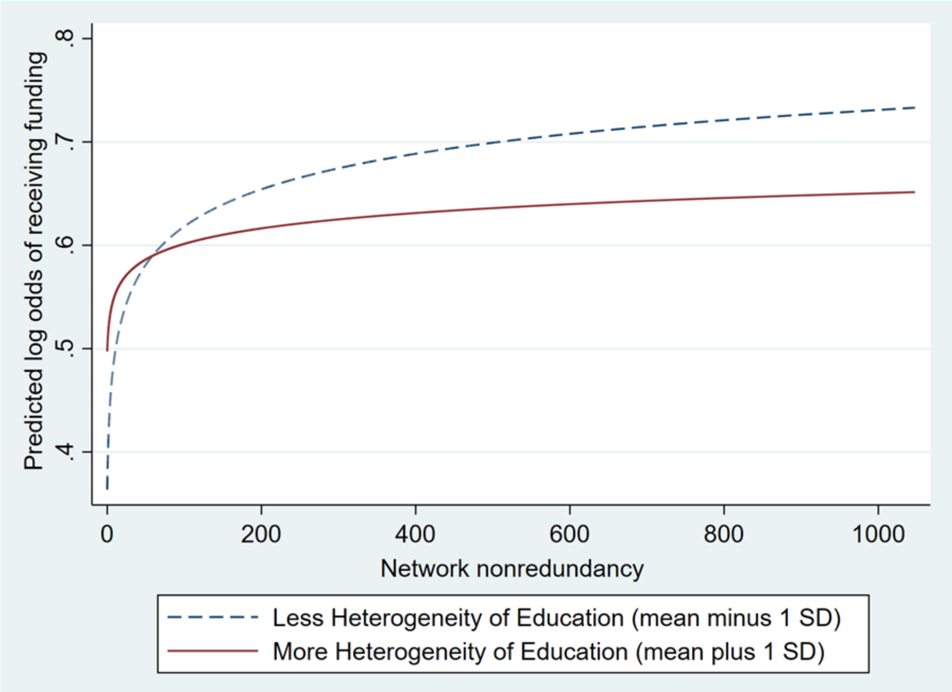

Figure 5.11 Moderating effects of heterogeneity of education on the relationship between network nonredundancy (log) and the likelihood of receiving funding.

Third, I employ another binary dependent variable of receiving funding, with 1 referring to start-ups receiving the second and later rounds of funding, and 0 otherwise. This robustness test corresponds to the different dependent variable's operationalisation of robustness test 1, applying the same theoretical reason for this design.

I run the same analysis model (i.e. fixed-effects logit) as robustness test 2 to obtain the results, with consistent results also emerging. The Hausman test suggests employing the fixed-effects logit model (see Appendix 5).

Table 5.8 presents the robustness test 3 results of applying the fixed-effects logit model, where Model 53 introduces the main effect result, with the coefficient of network nonredundancy being both positive (β = 0.259) and significant ($p<0.05$).

Similarly, it indicates a statistically positive relationship between the network nonredundancy and the likelihood of receiving second and later rounds of funding. Accordingly, the results of the main effect are consistent. Figure 5.12 presents the predicted relationship between network nonredundancy and the likelihood of receiving second and later rounds of funding.

Models 54 to 59 present the moderation effect results, which overall are consistent with the previous tests. The team tenure (β = -0.153; p<0.001) negatively moderates the relationship between network nonredundancy and the likelihood of receiving second and later rounds of funding, as per the heterogeneity of education (β = -0.148; p<0.001). Model 59 reports the combined significance involving all moderators in the regression, where the interaction results are consistent with Models 54 to 58. I also plot the interaction effects of team tenure and heterogeneity of education in Figure 5.13 and Figure 5.14, respectively.

Table 5.8 Robustness test 3: Panel fixed-effects logit predicting the probability of receiving second and later rounds of funding

DV: receive 2nd and later rounds funding (from all sources) or not	Model 51 Venture Control	Model 52 Venture + team Control	Model 53 Main effect	Model 54 Moderation effect (Team tenure × non-redundancy)	Model 55 Moderation effect (Heterogeneity of education × non-redundancy)	Model 56 Moderation effect (Industry experience × non-redundancy)	Model 57 Moderation effect (Founding experience × non-redundancy)	Model 58 Moderation effect (Gender diversity × non-redundancy)	Model 59 Moderation effect (All)
Number of patents	0.159^{+}	0.151^{+}	0.143	0.150^{+}	0.147	0.143	0.143	0.143	0.153^{+}
	(0.091)	(0.090)	(0.090)	(0.089)	(0.090)	(0.090)	(0.090)	(0.090)	(0.089)
Number of trademarks	0.067^{+}	0.067^{+}	0.067^{+}	0.061	0.062	0.066^{+}	0.067^{+}	0.067^{+}	0.057
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
Early stage	1.008***	1.119***	1.122***	1.040***	1.108***	1.122***	1.121***	1.123***	1.028***
	(0.127)	(0.130)	(0.130)	(0.132)	(0.130)	(0.130)	(0.131)	(0.130)	(0.132)
Venture size (log)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team size		0.036	-0.023	-0.025	-0.016	-0.024	-0.023	-0.023	-0.019
		(0.049)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)
Team tenure		-0.234*	-0.226*	-0.218*	-0.211*	-0.222*	-0.229*	-0.223*	-0.203*
		(0.098)	(0.098)	(0.098)	(0.099)	(0.098)	(0.098)	(0.098)	(0.099)
Heterogeneity of education		0.094*	0.079^{+}	0.075	0.198***	0.081^{+}	0.079^{+}	0.081^{+}	0.187**
		(0.045)	(0.046)	(0.046)	(0.055)	(0.046)	(0.046)	(0.046)	(0.055)
Founding experience		-0.012	-0.012	-0.007	-0.017	-0.013	-0.022	-0.012	-0.029

		(0.068)	(0.068)	(0.068)	(0.068)	(0.068)	(0.072)	(0.068)	(0.072)
Industry experience		0.171^{+}	0.078	0.068	0.058	0.090	0.078	0.076	0.066
		(0.088)	(0.095)	(0.096)	(0.096)	(0.098)	(0.096)	(0.095)	(0.099)
Gender diversity		-0.045	-0.047	-0.043	-0.046	-0.047	-0.046	-0.064	-0.057
		(0.089)	(0.090)	(0.090)	(0.090)	(0.090)	(0.090)	(0.094)	(0.094)
Network nonredundancy			0.259*	0.219*	0.340**	0.275*	0.253*	0.259*	0.309**
(log)			(0.103)	(0.104)	(0.106)	(0.107)	(0.103)	(0.103)	(0.110)
Team tenure ×				-0.153***					-0.150***
nonredundancy (log)				(0.036)					(0.036)
Heterogeneity of education ×					-0.148***				-0.137***
nonredundancy (log)					(0.037)				(0.038)
Industry experience ×						-0.045			-0.057
nonredundancy (log)						(0.075)			(0.079)
Founding experience ×							0.027		0.046
nonredundancy (log)							(0.060)		(0.063)
Gender diversity ×								0.045	0.042
nonredundancy (log)								(0.070)	(0.072)
Year, industry, and location dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log likelihood	-3087.25	-3072.78	-3069.58	-3060.28	-3061.66	-3069.40	-3069.48	-3069.37	-3052.57
LR chi2	291.0***	319.9***	326.4***	344.9***	342.2***	326.7***	326.6***	326.8***	360.4***
Observations	8,026	8,026	8,026	8,026	8,026	8,026	8,026	8,026	8,026

Number of start-ups	1,625	1,625	1,625	1,625	1,625	1,625	1,625	1,625	1,625

Standard errors in parentheses. Two tailed tests. + p< 0.1; * p<0.05; ** p<0.01; *** p<0.001

Note. Venture size is a time-invariant variable. Thus, it was dropped because it is constant within groups from the panel fixed-effects model.

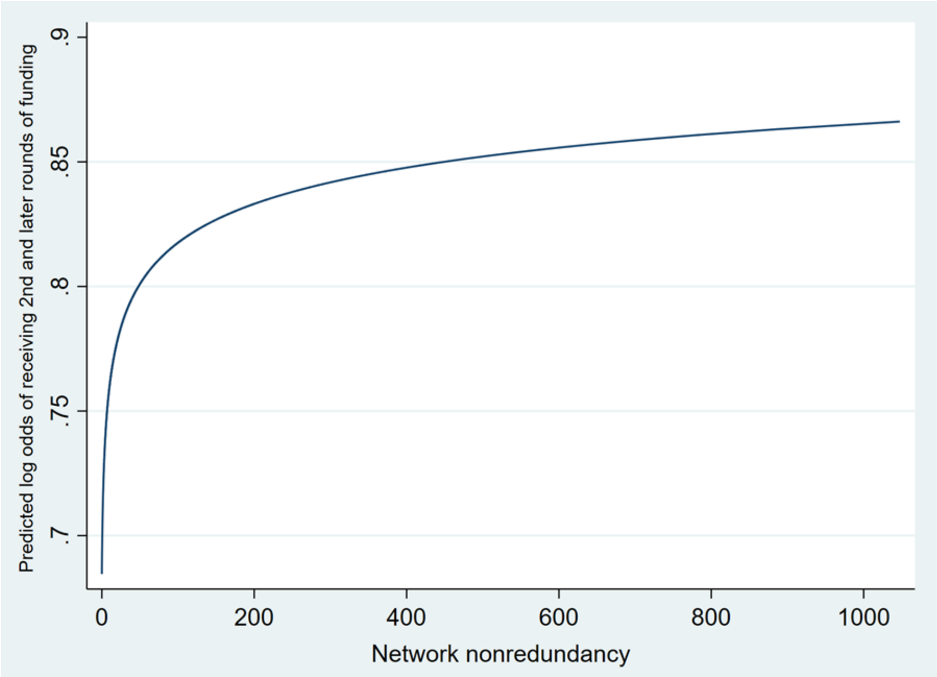

Figure 5.12 The predicted relationship between network nonredundancy and the likelihood of receiving second and later rounds of funding.

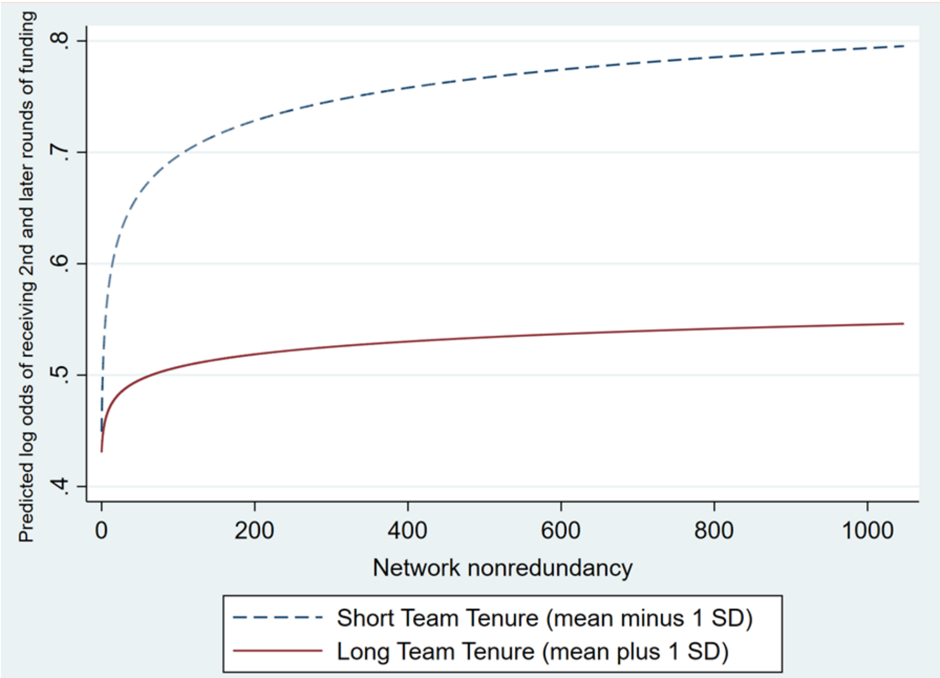

Figure 5.13 Moderating effects of team tenure on the relationship between network nonredundancy (log) and the likelihood of receiving second and later rounds of funding.

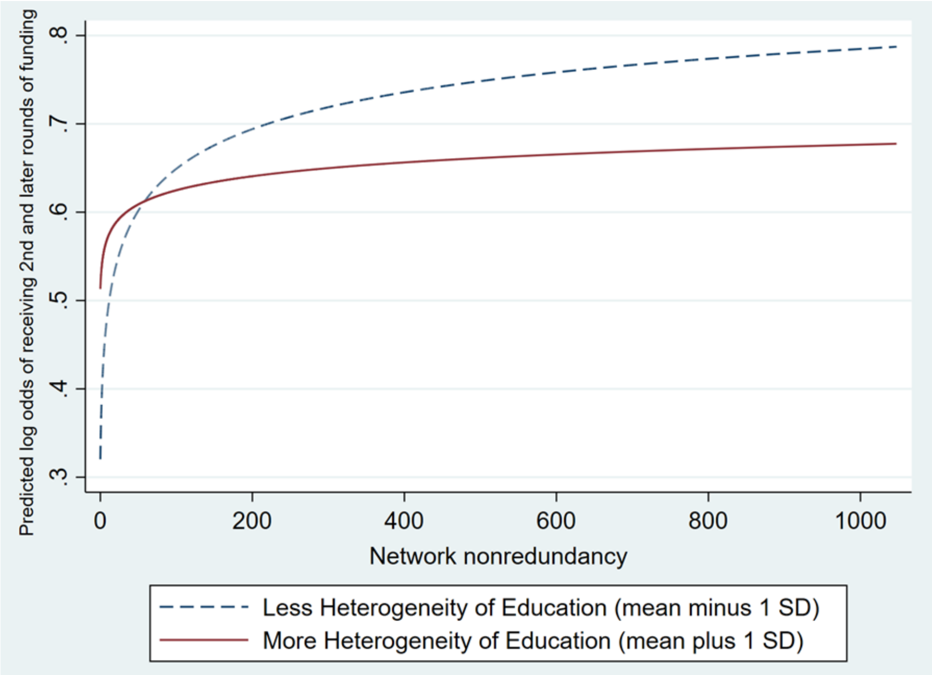

Figure 5.14 Moderating effects of heterogeneity of education on the relationship between network nonredundancy (log) and the likelihood of receiving second and later rounds of funding.

Fourth, I conduct the fixed-effects logit model on another alternative binary dependent variable of receiving funding. For robustness test 4, the examination involves whether start-ups can obtain funding from venture capital, coding “1” as yes, and “0” otherwise. As venture capitalists invest in start-ups from their early to late stages, I use venture capital funding as an alternative operationalisation to examine the relationship between network nonredundancy and the probability of receiving funding with longitudinal research design. Similarly, according to the Hausman test (see Appendix 6), the panel fixed-effects logit model is applied in this robustness check.

Table 5.9 presents the predicted probability of receiving funding from venture capital, with Model 62 showing the main effect result. The coefficient of network nonredundancy is positive (β = 0.360) and significant ($p<0.01$), suggesting a statistically positive relationship between network nonredundancy and the likelihood of receiving funding from venture capital. This result is again consistent with previous tests. Furthermore, Figure 5.15 presents the predicted relationship between the network nonredundancy and the likelihood of receiving venture capital funds.

Models 63 to 68 present the moderation effect results, which are consistent. The team tenure (β = -0.174; $p<0.001$) negatively moderates the relationship between network nonredundancy and the likelihood of receiving funding from venture capital, while the heterogeneity of education (β = -0.092; $p<0.05$) also presents a harmful moderating effect. Model 68 introduces the results involving all moderators in the regression and presents a consistent result when compared with the individual moderating effects. The interaction effects of team tenure and heterogeneity of education are plotted for visualisation in Figure 5.16 and Figure 5.17, respectively.

Table 5.9 Robustness test 4: Panel fixed-effects logit predicting the probability of receiving venture capital funds

DV: receive funding from venture capital or not	Model 51 Venture Control	Model 52 Venture + team Control	Model 53 Main effect	Model 54 Moderation effect (Team tenure × non-redundancy)	Model 55 Moderation effect (Heterogeneity of education × non-redundancy)	Model 56 Moderation effect (Industry experience × non-redundancy)	Model 57 Moderation effect (Founding experience × non-redundancy)	Model 58 Moderation effect (Gender diversity × non-redundancy)	Model 59 Moderation effect (All)
Number of patents	0.025	0.018	0.006	0.015	0.008	0.006	0.006	0.005	0.015
	(0.079)	(0.079)	(0.079)	(0.081)	(0.079)	(0.079)	(0.079)	(0.079)	(0.081)
Number of trademarks	0.0003	0.001	0.0002	-0.004	-0.0003	0.0005	0.0002	-0.0001	-0.004
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Early stage	0.982***	1.072***	1.079***	0.978***	1.066***	1.081***	1.079***	1.077***	0.968***
	(0.135)	(0.139)	(0.139)	(0.141)	(0.139)	(0.139)	(0.139)	(0.139)	(0.141)
Venture size (log)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team size		-0.065	-0.147**	-0.149**	-0.143*	-0.147*	-0.147**	-0.149**	-0.146*
		(0.051)	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)
Team tenure		-0.389***	-0.380***	-0.378***	-0.367***	-0.385***	-0.381***	-0.386***	-0.379***
		(0.099)	(0.099)	(0.099)	(0.099)	(0.099)	(0.099)	(0.099)	(0.100)
Heterogeneity of education		0.057	0.036	0.031	0.111*	0.034	0.036	0.033	0.096^{+}
		(0.046)	(0.047)	(0.047)	(0.056)	(0.047)	(0.047)	(0.047)	(0.056)
Founding experience		0.018	0.016	0.021	0.010	0.016	0.011	0.016	0.013

		(0.067)	(0.067)	(0.067)	(0.067)	(0.067)	(0.071)	(0.067)	(0.071)
Industry experience		0.181*	0.053	0.044	0.038	0.039	0.053	0.055	0.021
		(0.088)	(0.096)	(0.096)	(0.096)	(0.098)	(0.096)	(0.096)	(0.099)
Gender diversity		-0.008	-0.008	-0.007	-0.009	-0.009	-0.008	0.022	0.024
		(0.090)	(0.091)	(0.091)	(0.091)	(0.091)	(0.091)	(0.095)	(0.095)
Network nonredundancy			0.360**	0.308**	0.409***	0.342**	0.358**	0.363**	0.340**
(log)			(0.105)	(0.105)	(0.107)	(0.108)	(0.105)	(0.105)	(0.112)
Team tenure ×				-0.174***					-0.168***
nonredundancy (log)				(0.036)					(0.037)
Heterogeneity of education ×					-0.092*				-0.087*
nonredundancy (log)					(0.038)				(0.039)
Industry experience ×						0.050			0.047
nonredundancy (log)						(0.076)			(0.080)
Founding experience ×							0.012		0.008
nonredundancy (log)							(0.059)		(0.062)
Gender diversity ×								-0.080	-0.087
nonredundancy (log)								(0.071)	(0.073)
Year, industry, and location dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log likelihood	-3130.53	-3118.17	-3112.18	-3100.61	-3109.24	-3111.97	-3112.16	-3111.55	-3097.31
LR chi2	537.6***	562.3***	574.3***	597.4***	580.2***	574.7***	574.3***	575.5***	604.0***
Observations	8,592	8,592	8,592	8,592	8,592	8,592	8,592	8,592	8,592

Number of start-ups	1,747	1,747	1,747	1,747	1,747	1,747	1,747	1,747	1,747

Standard errors in parentheses. Two tailed tests. + $p < 0.1$; * $p<0.05$; ** $p<0.01$; *** $p<0.001$

Note: Since venture size is a time-invariant variable, it was dropped because it is constant within groups from the panel fixed-effects model.

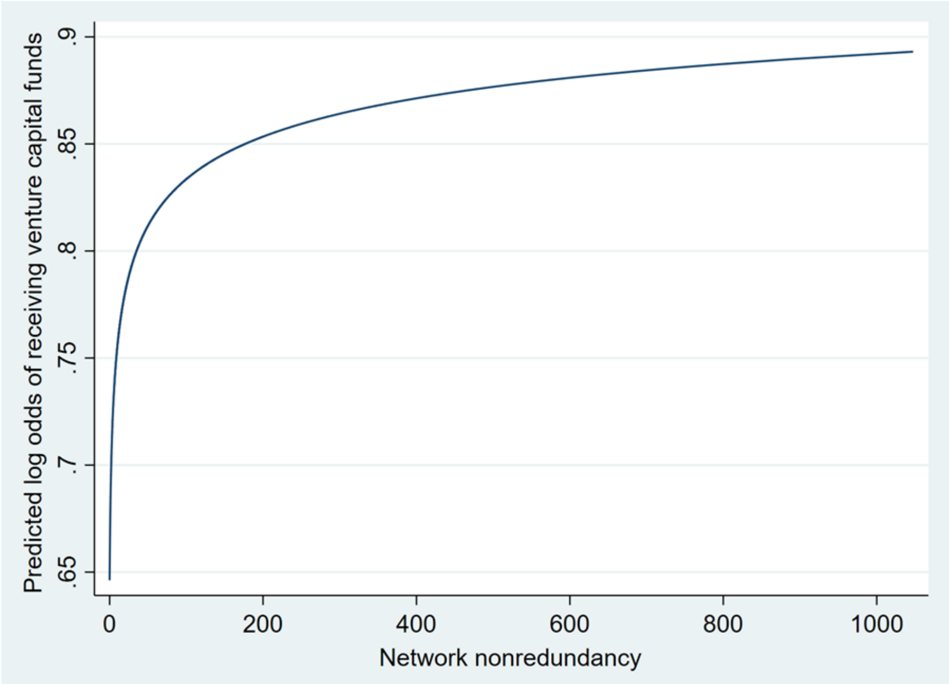

Figure 5.15 The predicted relationship between network nonredundancy and the likelihood of receiving venture capital funds.

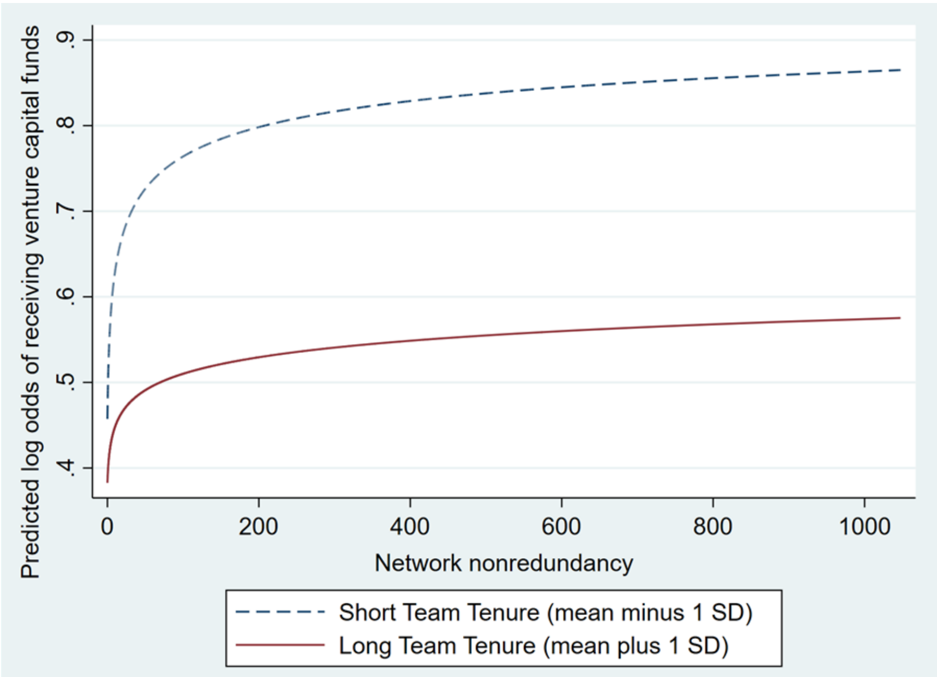

Figure 5.16 Moderating effects of team tenure on the relationship between network nonredundancy (log) and the likelihood of receiving venture capital funds.

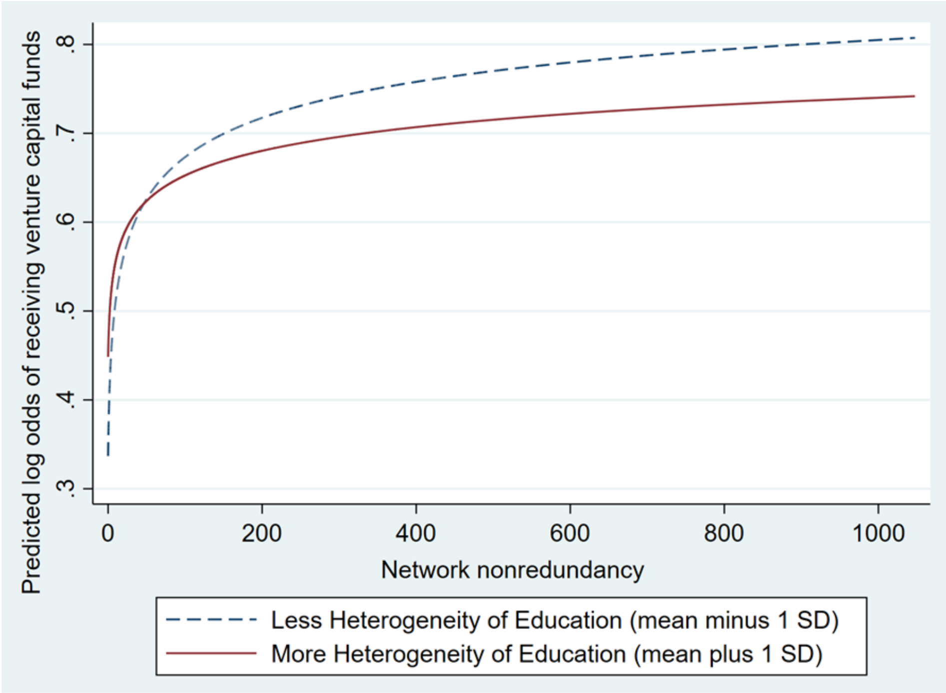

Figure 5.17 Moderating effects of heterogeneity of education on the relationship between network nonredundancy (log) and the likelihood of receiving venture capital funds.

Consequently, the above analysis includes a type (i.e. the Type 1 firm illustrated in Table 4.6) of sample firms that are continually operated by a sole entrepreneur through all the entrepreneurial stages. Accordingly, it might be questioned whether a single founder's network nonredundancy is distinct when compared to a team's network. In fact, since the network nonredundancy measure is ego-centric, the number of people inside the 'ego' does not appear to be central to this concept. Of most importance is that we can fully capture the ego's 'external' networks, and then calculate the nonredundancy in representing the network structure. However, it might be a necessity to demonstrate the robustness of the main results in responding to this potential argument. Thus, I drop the Type 1 firms from the original sample, and apply the same fixed-effects panel model on the sample of those start-ups founded or operated by multiple team members during the entrepreneurial stages as robustness test 5.

The Hausman test is also conducted to examine whether the fixed-effects is the appropriate model under this sample condition, as opposed to the random-effects (see Appendix 7). The result suggests that we should reject the null hypothesis, and thus the fixed-effects panel model is more appropriate.

Table 5.10 presents the results of the panel fixed-effects estimation. Model 60 is the base model, presenting the venture control regression, while Model 61 is the venture plus team control regression. Model 62 shows the results of the main effect under this robustness test 5 scenario. The coefficient of network nonredundancy (log) is positive (β = 0.675) and significant ($p<0.05$), which presents a consistent main effect, as shown in Table 5.2, Model 3. The main effect plot of this robustness test is presented graphically below in Figures 5.18.

Models 63–68 represent the interaction effect. The overall results are consistent, as seen in Models 4–9 presented in Table 5.2. The team tenure (β = -0.436; $p<0.001$) negatively moderates the network nonredundancy and funding amounts' relationship, as does the heterogeneity of education (β = -0.391; $p<0.01$). Model 68 presents the combined significance involving all the moderators in the regression. The plots of the interaction effects of team tenure and heterogeneity of education are illustrated in Figure 5.19 and Figure 5.20, respectively.

Table 5.10 Robustness test 5: Panel fixed-effects results

DV: funding amounts (log)	Model 60 Venture Control	Model 61 Venture + team Control	Model 62 Main effect	Model 63 Moderation effect (Team tenure × non-redundancy)	Model 64 Moderation effect (Heterogeneity of education × non-redundancy)	Model 65 Moderation effect (Industry experience × non-redundancy)	Model 66 Moderation effect (Founding experience × non-redundancy)	Model 67 Moderation effect (Gender diversity × non-redundancy)	Model 68 Moderation effect (All)
Number of patents	0.261	0.244	0.223	0.229	0.234	0.224	0.224	0.221	0.238
	(0.282)	(0.277)	(0.273)	(0.287)	(0.278)	(0.275)	(0.273)	(0.273)	(0.293)
Number of trademarks	0.019	0.019	0.017	0.010	0.019	0.018	0.018	0.017	0.014
	(0.107)	(0.107)	(0.107)	(0.107)	(0.105)	(0.107)	(0.107)	(0.107)	(0.106)
Early stage	4.417***	4.586***	4.603***	4.289***	4.536***	4.604***	4.598***	4.599***	4.226***
	(0.508)	(0.511)	(0.509)	(0.509)	(0.510)	(0.509)	(0.509)	(0.510)	(0.508)
Venture size (log)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team size		-0.241	-0.421^{+}	-0.434^{+}	-0.427^{+}	-0.416^{+}	-0.420^{+}	-0.421^{+}	-0.433^{+}
		(0.201)	(0.224)	(0.223)	(0.226)	(0.225)	(0.224)	(0.224)	(0.226)
Team tenure		-0.887*	-0.884*	-0.933*	-0.843*	-0.896*	-0.894*	-0.886*	-0.908*
		(0.360)	(0.363)	(0.365)	(0.364)	(0.362)	(0.366)	(0.363)	(0.368)
Heterogeneity of education		0.231	0.184	0.155	0.374*	0.178	0.183	0.182	0.337^{+}
		(0.182)	(0.184)	(0.184)	(0.189)	(0.184)	(0.184)	(0.184)	(0.189)
Founding experience		0.155	0.155	0.190	0.134	0.158	0.142	0.156	0.169

		(0.205)	(0.205)	(0.205)	(0.205)	(0.205)	(0.206)	(0.205)	(0.207)
Industry experience		0.240	0.038	0.011	-0.025	0.042	0.044	0.038	-0.046
		(0.258)	(0.274)	(0.274)	(0.277)	(0.275)	(0.275)	(0.274)	(0.277)
Gender diversity		-0.131	-0.135	-0.120	-0.131	-0.131	-0.134	-0.129	-0.107
		(0.251)	(0.251)	(0.253)	(0.251)	(0.252)	(0.252)	(0.251)	(0.252)
Network nonredundancy			0.675*	0.616*	0.760*	0.619^{+}	0.656*	0.675*	0.641*
(log)			(0.312)	(0.309)	(0.313)	(0.325)	(0.316)	(0.312)	(0.323)
Team tenure ×				-0.436***					-0.424***
nonredundancy (log)				(0.118)					(0.118)
Heterogeneity of education					-0.391**				-0.385**
× nonredundancy (log)					(0.139)				(0.139)
Industry experience ×						0.129			0.130
nonredundancy (log)						(0.217)			(0.232)
Founding experience ×							0.065		0.018
nonredundancy (log)							(0.176)		(0.188)
Gender diversity ×								-0.059	-0.056
nonredundancy (log)								(0.231)	(0.228)
Constant	3.553***	1.342	1.241	1.240	1.438	1.166	1.225	1.242	1.354
	(0.797)	(1.180)	(1.180)	(1.180)	(1.181)	(1.185)	(1.186)	(1.179)	(1.187)
Year, industry, and location dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F	30.38***	21.10***	20.25***	19.38***	19.61***	19.27***	19.19***	19.21***	16.49***

Observations	7027	7027	7027	7027	7027	7027	7027	7027	7027
Number of start-ups	1639	1639	1639	1639	1639	1639	1639	1639	1639
Within R-squared	0.0720	0.0742	0.0750	0.0774	0.0764	0.0751	0.0750	0.0750	0.0788
Between R-squared	0.0714	0.0526	0.0284	0.0240	0.0261	0.0285	0.0286	0.0283	0.0223
Overall R-squared	0.0018	0.0063	0.0125	0.0145	0.0129	0.0124	0.0124	0.0125	0.0149

Robust standard errors in parentheses. Two tailed tests. + p< 0.1; * p<0.05; ** p<0.01; *** p<0.001

Note: Since venture size is a time-invariant variable, it was dropped because it is constant within groups from the panel fixed-effects model.

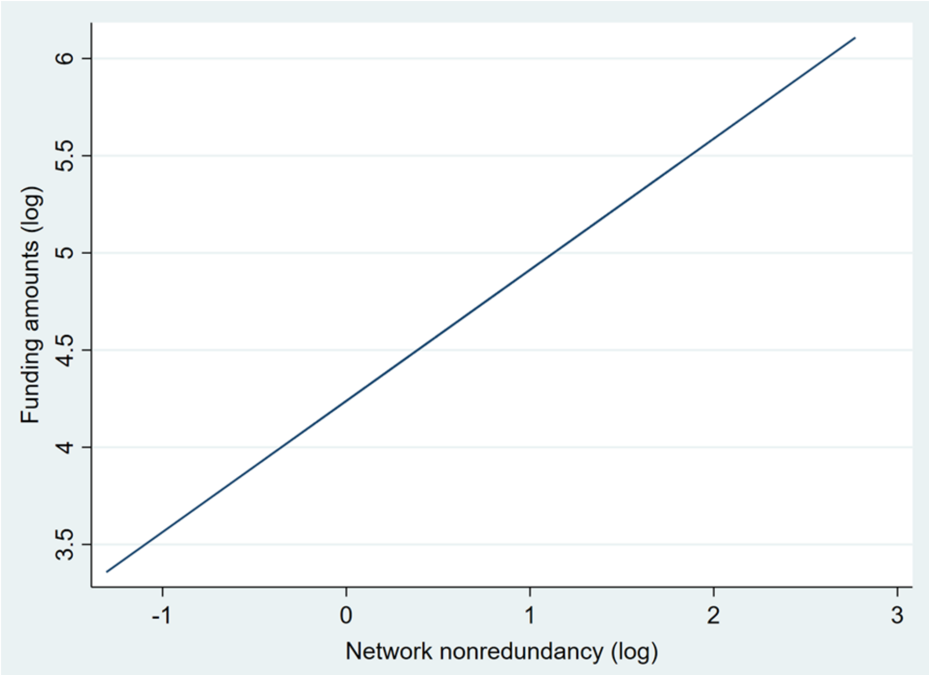

Figure 5.18 Illustration of the main effect: the log–log relationship of network nonredundancy and funding amounts (drop the Type 1 firms from the original sample).

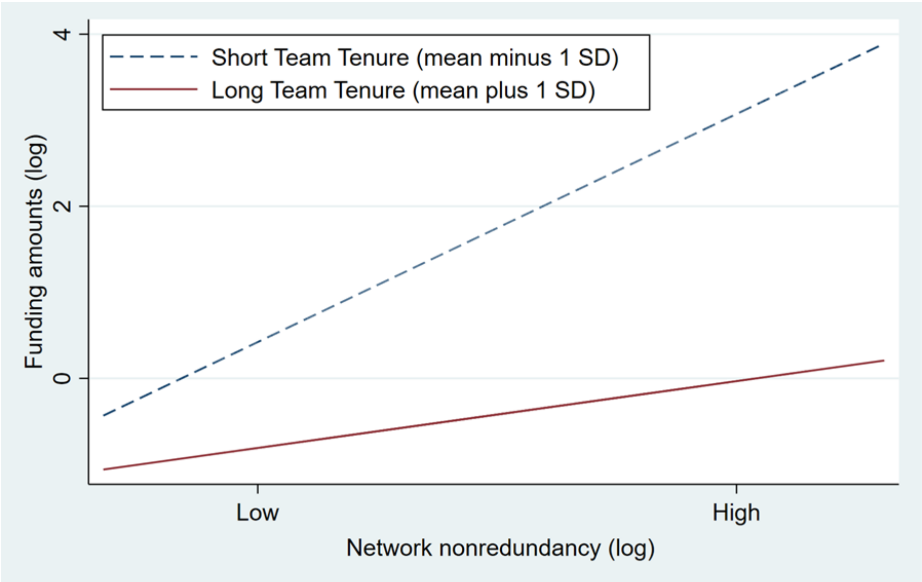

Figure 5.19 Moderating effects of team tenure on the relationship between network nonredundancy (log) and the funding amounts (log): drop the Type 1 firms from the original sample.

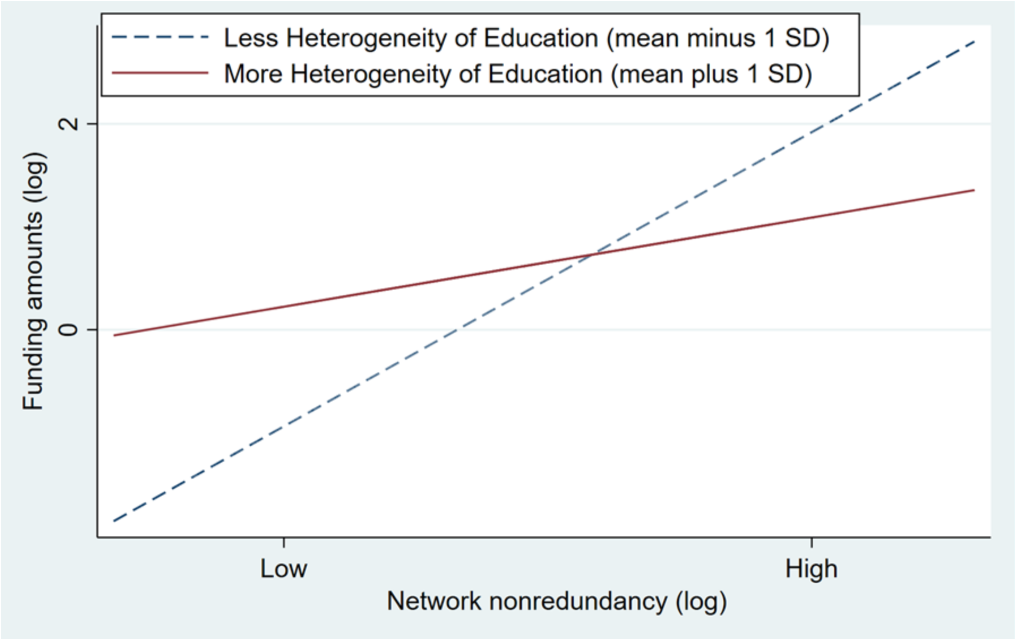

Figure 5.20 Moderating effects of heterogeneity of education on the relationship between network nonredundancy (log) and the funding amounts (log): drop the Type 1 firms from the original sample.

In sum, all the robustness checks present a consistent result in examining the impact of network nonredundancy on the start-ups' fundraising performance, along with the interaction effects of team tenure and heterogeneity of education. Thus, this thesis finds consistent results that support hypotheses 1, 2b, and 3b.

Chapter 6
Discussion

Although social networks research is flourishing, mixed and inconclusive findings are prevalent across the literature in terms of examining the network effects on new venture performance (as shown in Table 2.1), and also on financial capital acquisition (as shown in Table 2.2). Besides, prior social network and entrepreneurship research mainly draws attention to the solo entrepreneur's network effects, and thus our understanding of the entrepreneurial team's network impact remains limited (Hansen et al. 2001; Nicolaou & Birley 2003; Vissa & Chacar 2009). Recent developments in university venture spin-offs (Nicolaou & Birley 2003) and drivers for venture growth (Vissa & Chacar 2009) have endeavoured to focus their lens on the role of entrepreneurial teams' networks in new venture development. Building upon a large sample of start-ups operating in an extensive range of industries and with a broad distribution across the U.S., this study advances current understanding of the role that social networks play in the entrepreneurship field by examining the network nonredundancy's impact on the likelihood of attracting funding, as well as the funding amount. Likewise, this thesis sheds light on two key contingencies (i.e. team tenure and heterogeneity of education), which are predicted to alter the network nonredundancy effect on new ventures' ability to attract funding.

6.1 Contributions

This study provides several important contributions. First, this thesis contributes to the entrepreneurial team and entrepreneurial finance literature by attempting to disentangle the role that social networks play within the start-up fundraising process. The lens of contingency is utilised to extend our comprehension of the contingent value delivered by entrepreneurial teams' external network nonredundancy to their funding outcomes by following the pioneering entrepreneurial team-level egocentric network research (Nicolaou & Birley 2003; Vissa & Chacar 2009). The findings emerging from this study reveal that start-up teams with higher levels of network nonredundancy could obtain more heterogeneous information and diverse resource compared to lower nonredundancy-level teams, and thus make superior strategic decisions that would enhance the likelihood of receiving external financial support from investors. Therefore, a positive association was found that echoes previous research that examined the impact of the team's network structure on venture performance (Nicolaou & Birley 2003; Vissa & Chacar 2009). However, prior research regarding venture financing (Hall & Hofer 1993; Matusik et al. 2008) primarily focused on how investors or venture capitalists evaluate start-ups' quality, and typically identified the new venture's human capital and technical skills (e.g. number of patents) as key elements to influence the investors' assessment and the likelihood of receiving funding (Hsu 2007). Furthermore, some research based on the social capital perspective suggests that having a prior relationship with investors would increase the likelihood of obtaining venture capitalists' investment (e.g. Shane & Stuart 2002). Accordingly, this finding first indicates that the team's external network non-redundancy is another important factor associated with a start-up's fundraising outcomes. And further, by examining the teams' external structural network, the results of this sample extend previous research on ties to a particular sort of contact, namely, ties to angel investors (Shane & Cable 2002) and venture capitalists (Shane & Stuart 2002).

Secondly, this thesis makes a theoretical contribution through linking upper echelons and structural hole theory. After finding a positive association of entrepreneurial teams' network nonredundancy with start-ups' fundraising outcomes, this study sheds light on how entrepreneurial teams' external network structure interacts with their team demographic attributes. Top management team demography has been widely explored in terms of the influence on a team's strategic decision-making processes and organisational performance (e.g. Wiersema & Bantel 1992; Smith et al. 1994; Knight, Smith, Olian, Sims, Smith, & Flood 1999). Therefore, connecting the upper echelons perspective with structural hole theory led to the hypotheses suggesting that team demographics would alter the effectiveness of the entrepreneurial team's external nonredundant networks' usage in terms of influencing investors' investment decisions. Particularly, this thesis finds empirical support for the moderating role of team tenure and heterogeneity of education. This finding thereby extends Vissa and Chacar's (2009) study in terms of the interaction of entrepreneurial teams' internal dynamic conditions and external networks, where they found that teams with higher strategic consensus and superior cohesion would enhance the leverage of the teams' external networks on revenue growth. Overall, by applying the contingency perspective, this thesis makes a theoretical contribution to the social networks and entrepreneurship literature through extending the integration between structural hole theory and upper echelons theory via the consideration of both the team-level network structure and the team demographic attributes.

Third, and finally, this thesis makes a theoretical contribution to the team social network literature. The majority of team network studies draw samples from established firms' R&D teams (e.g. Reagans & Zuckerman 2001; Reagans et al.

2004; Tröster, Mehra, & Van Knippenberg 2014; Paruchuri & Awate 2017), while few explore the entrepreneurial team's social networks effect (e.g. Ruef, Aldrich, & Carter 2003; Aldrich & Kim 2007). Furthermore, these studies primarily estimated the team's internal network effect on the team's productivity performance, rather than studying the impact of the teams' external structure, since most studies on the external network effects focus on the inter-organisational collaboration ties (e.g. Baum et al. 2000; Stuart & Sorenson 2007; Wang & Chen 2016), which neglect the individuals' personal networks. However, nascent start-up teams may have only limited opportunities to build inter-firm connections, as some of them may not offer products or services at the infancy stage of their venture. Therefore, scanning new venture team members' networks could offer a relatively complete picture of start-ups' external network structure (Vissa & Chacar 2009). The first and only central finding that contributes to entrepreneurial teams' external networks is that high within-team cohesion and strategic consensus would positively moderate the relationship between the external network structure (i.e. network constraint in expressing the level of structural holes outside the team's network) and venture performance (Vissa & Chacar 2009). Nevertheless, Vissa and Chacar's (2009) study did not differentiate the factors (e.g. team demographic characteristics) that can induce teams' internal dynamics, or explore how such distinct components may moderate the main effect of the team's external networks on new venture performance. Notwithstanding a number of studies that investigated the interaction of social capital and human capital in shaping start-ups' performance outcome (e.g. Florin et al. 2003; Batjargal 2007; Klyver & Schenkel 2013; Semrau & Hopp 2016; Hernández-Carrión et al. 2017), these focused on the interaction effect with solo entrepreneur's network size, and thus cannot provide insight under the team's internal dynamic spectrum. Therefore, the debate in the team networks literature regarding how the internal team conditions influence the leveraging of external networks remains inconclusive. This study's finding on the moderating effect of team tenure and the team's heterogeneity of education thereby reveals certain facets of the mechanisms among entrepreneurial teams' social capital and human capital that influence the fundraising outcome, and thus contributes to the team social network theory and literature.

Consequently, following Vissa and Chacar's (2009) call, a longitudinal dataset is created to capture the complexity of team networks' development and the team formation dynamics. Thus, by demonstrating four types of evolution scenarios in this sample, I claim the consideration of the temporal effect also extends the prior research and represents a better attempt at reducing the reverse causality concern.

6.2 Implications in practice

The findings of this thesis also have a number of practical implications for building effective start-up teams in order to more effectively leverage the resources from their social networks. First, entrepreneurial teams should construct their external network structure with a high level of nonredundancy, which would offer advantages when pursuing external funding for venture development. The effect size[8] of the entrepreneurial team's network nonredundancy on funding amounts presented in this study is 0.73 (see Table 5.2), suggesting a 10% increase[9] in network

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[8] The 'effect size' usually refers to the 'marginal effect', which measures the impact of the instantaneous change in one independent variable on the dependent variable, while all other independent and control variables are held constant. The marginal effect size echoes the standardised correlation coefficient when applying the linear model to predict the relationship.

[9] The 10% increase of nonredundancy is not a fixed standard, whereby start-up teams should always seek to achieve this network nonredundancy level when striving to enhance the likelihood of

nonredundancy that is predicted to increase the funding amount received by 7.3%.[10] As stated earlier, if network nonredundancy equal to 5 can receive $100,000, then a network nonredundancy improvement from 5 to 5.5 can lead to a predicted funding amount of $107,300, representing an increase of $7,300. Therefore, this increment of funding cannot be neglected. However, the meaning of network nonredundancy level at '5' and increase to '5.5' might still be ambiguous, and thus another example should be delineated to further interpret the above results in detail.

Let us assume that entrepreneurial team X has a total non-overlap network size equal to 20. According to the formula introduced for measuring the team-level network nonredundancy in section 4.3 (i.e. nonredundancy = (number of potential ties - number of actual ties)/number of external contacts), we can then obtain the number of potential ties equal to ((20-1)*20)/2 = 190, which means there are a maximum of 190 connections among the entrepreneurial team's external contacts. Assuming there are 90 actual ties among these contacts, then we can calculate the level of network nonredundancy as (190-90)/20 = 5. Therefore, the question thus arises of how easy it would be to improve the nonredundancy level by 10% to 5.5, which might be reasonably straightforward if the entrepreneurial team has certain networking strategies. The following example illustrates how a team's network nonredundancy can increase. Considering the same example of entrepreneurial team X, if they can know 2 more people who are not acquaintances of the team's original

receiving additional external financial support. It is merely an interpretation from the standardised correlation coefficient estimated from the fixed-effect panel model in representing the predicted effect size of network nonredundancy on the funding amount received.

[10] Since natural log transformation is taken on both the independent variable (i.e. network nonredundancy) and the outcome variable (i.e. funding amount) in this study, the interpretation of the effect size via the standardised correlation coefficient thus applies the percentage change, rather than a unit change.

external contacts’ circle of friends, then the team could achieve the potential 10% nonredundancy increase without difficulty. If we assume that the additional network contacts are not close friends of the team’s existing external contacts, then this means that the number of actual ties will not increase considerably, even though team X adds 2 additional people into their external network structure. Let us assume that the number of actual ties in such a scenario sees a small increase from 90 to 110 in the above example. Then, the number of potential ties will be ((22-1)*22)/2 = 231, while the team’s network nonredundancy will be equal to (231-110)/22 = 5.5, which represents a 10% increase from the original scenario whereby team X had a network size of 20. Such an example thereby suggests that if an entrepreneurial team can further connect with a small number of additional network contacts outside of their existing circle, there is a greater probability that the team’s network nonredundancy will increase to a foreseeable level, which could lead to a considerable improvement in the funding amount received. Accordingly, perhaps start-up team members might consider attending more entrepreneurial events to connect with people distant from their current network structure.

Second, founders or entrepreneurs should consider the team diversity effects on their social networks while forming their entrepreneurial top management team. According to the findings in this study, both long team tenure and high heterogeneity of education could undermine the advantages that entrepreneurial teams can exploit from their external nonredundant networks in terms of their fundraising outcomes. Consequently, considering the addition of new members with similar educational background during the entrepreneurial stages might help to ease the negative effect caused by the team diversity factors while accessing nonredundant resources and information from their external networks. Overall, the empirical findings in this thesis emphasise the importance of specifically taking into account the team diversity (or human capital), which is vital for start-up teams to establish, prior to exploiting the benefits from the team's external network structure.

6.3 Limitations and future research directions

There are a number of limitations present in this study, which thereby suggest opportunities for future research directions. The first limitation is the accuracy of the network nonredundancy measure. The individual-level data are collected from Crunchbase in order to construct the team network and team characteristics' measures. This database obtains individuals' information through LinkedIn via Application Programming Interface (API) technology. However, I may not have precisely captured the complete composition of the team members if they did not register with LinkedIn or accurately complete their personal profiles. Therefore, it would be reasonable to assume that measurement errors will exist in these measures. However, even survey data could have a similar concern in terms of gathering inaccurate network data, where the respondent neglected to mention their important network contacts at certain stages during their entrepreneurial process, or failed to take questionnaires seriously, or was otherwise distracted, and thus delivered an incomplete answer (Nicolaou & Birley 2003). Nevertheless, with Brewer and Webster (1999) finding a strong correlation (i.e. Pearson correlation index: 0.93/0.89) between the individual recalled network structure (i.e. size and density) and the mixed recalled and forgotten network structure (i.e. size and density), this suggests that the limitation of inaccurate network data may not significantly influence the statistical analysis. Furthermore, some network research published in top management journals employed the Crunchbase data (e.g. Block and Sandner 2009; Alexy et al. 2012; Ter Wal et al. 2016; Butler et al. 2019), and thus the reliability of the data has been recognised and deemed suitable for conducting entrepreneurship research via the social networks' perspective.

Another concern regarding the measurement of the network nonredundancy stems from the assumption of applying individuals' overlapping prior employment to define a dyad relationship. Although the use of workplace dyad relationships is referred to in the literature (e.g. Nanda & Sørensen 2010; Balachandran et al. 2019), this assumption might not hold when the previous employment is in a large firm such as Google or Apple. Furthermore, network ties may not primarily come from previous employment, and hence this assumption of defining network relationship is highly likely to cause the measurement error of the network nonredundancy. This concern links to the next limitation I address below.

In addition, and as discussed in detail in section 4.7, endogeneity is a major limitation in this study, which primarily stems from the measurement error and simultaneity, and is common in organisational social network research (Carpenter et al. 2012). The measurement error concern is primarily induced from the challenges of capturing the real network structure (*ibid*), while the simultaneity issue is induced by the reverse causality. In this study, I applied several approaches in attempting to mitigate such concerns; for example, using an instrument variable to proxy network nonredundancy and lagging all independent variables by 1 year. The other form of endogeneity concern involves whether the level of non-redundancy affects not only performance, but also the entry to entrepreneurship. Individuals may decide to start a firm while they have non-redundant network ties that facilitate in obtaining diverse knowledge and information to drive the entrepreneurial orientation. Overall, it must still be acknowledged that the endogeneity issue is inevitable, and represents a chief limitation in this research field.

As discussed in Chapter 5, the small within R^2 increment while adding the network nonredundancy variable into the control-based fixed-effect panel model is another major limitation of this study. However, I have found evidence from an econometric source (Stock & Watson 2014) and a journal article (Florin et al. 2003) that such a phenomenon could occur when utilising the fixed-effect panel model and OLS model. Nevertheless, the fact remains that this study indeed captures very little variance in the funding amounts within the start-up units when adding the network nonredundancy into the fixed-effect panel regression model. Accordingly, I acknowledge that this limitation exists, and future studies could adopt a different research design and search for the most optimal model in confirming that the entrepreneurial team's network structure can capture important amounts of explanatory power on the outcome performance variable.

Future studies could also examine the impact of different types of network structure measures longitudinally on the start-up performance at the team level. As this thesis focuses on the ego-centric network structure measure, this variable construction only allows the examination of the first layer network effect of the entrepreneurial team. Other network measures such as the 'structural equivalence' could therefore facilitate understanding of the next layer of the network structure, as it examines whether an ego's current network contacts have identical ties to other nodes, and would thereby introduce more theoretical insight into the currently sparse domain of team network research. Moreover, future research might also explore how different entrepreneurial teams' network structures influence other important outcomes in new ventures, such as the likelihood of engaging with M&A, achieving IPO, or ensuring venture survival.

Furthermore, other variables that can also represent the entrepreneurial team's internal dynamics should be further examined to determine whether they are important contingencies that would moderate the network and start-up performance relationship. Further examination from this perspective could assist in uncovering more of the black box in terms of the mechanisms among entrepreneurial teams' social capital and the internal team dynamic interplay that shape the performance outcome. Different operationalisations of the team characteristics' measures are also encouraged to test the moderating effects, in order to further confirm the finding reported in this thesis.

Besides, the start-up firms in this study's sample are U.S. companies, and thus future studies should examine the entrepreneurs' network structure effects on the fundraising outcomes in other countries (e.g. Germany, Japan) or regions (e.g. Europe, East Asia). Another avenue in this domain could involve exploring the impact of teams' inter-country network structure on fundraising, since different nations have distinct institutional contexts and thus may show different results in terms of the investment decision.

Finally, as a quantitative study, while I indeed contribute to the generalisation of the phenomenon, the details of how team members cooperate, manage and develop their external social capital for seeking funding opportunities remain unclear, and thus could be investigated via qualitative research (Klotz et al. 2014).

Chapter 7
Conclusion

In sum, this study sheds important light on our understanding of the entrepreneurial team's network structure effect on external funding acquisition. In addition, it offers insights into the contingent value of how long team tenure and greater heterogeneity of education could weaken the positive advantage offered by nonredundant networks in terms of new ventures' fundraising outcomes.

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Appendices

Appendix 1. Hausman test results for determining the selection of fixed- or random-effects panel model – as applied to the main analysis

```
. hausman fixed random

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |     fixed        random       Difference          S.E.
-------------+----------------------------------------------------------------
Nonredundancy|    .7261702     .5733903        .1527799        .2755495
Team size    |   -.4117739    -.1352643       -.2765096        .1444922
Team tenure  |   -.9052099     -1.30547        .4002606         .265881
Educ.heter.  |    .1399789     .1721881       -.0322092        .1073782
Founding exp.|    .0656004     .0967943        -.031194        .1640124
Indust. exp. |    .1156781    -.3069794        .4226575        .2598081
  Gender di. |   -.1391838     .0563386       -.1955225        .2416053
No.of Patent |    .2580128    -.0533751         .311388        .2043946
Trademark    |    .0165207     -.054931        .0714518        .0383647
Early stage  |    4.804966     .5318856        4.273081        .2721502
        year |
       2011  |    1.253185     .9128618        .3403229         .189572
       2012  |    .8415958     .7458725        .0957233        .3120363
       2013  |    .3947054     .5748271       -.1801217        .4299936
       2014  |    .3975521      .821736       -.4241838         .548283
       2015  |    .2091993     .8399008       -.6307014        .6666962
       2016  |    -.053365     .6160048       -.6693698        .7829715
       2017  |    -.441028     .3489027       -.7899306        .9033654
       2018  |   -.4221298     .3895925       -.8117223         1.02348
------------------------------------------------------------------------------
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                 chi2(18) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       453.86
                Prob>chi2 =       0.0000
                (V_b-V_B is not positive definite)
```

Appendix 2. Results of the variance inflation factor test

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R-Squared
Nonredundancy	1.42	1.19	0.7059	0.2941
Team size	1.53	1.24	0.6533	0.3467
Team tenure	1.04	1.02	0.9651	0.0349
Edu. Heter.	1.37	1.17	0.7321	0.2679
Founding exp.	1.08	1.04	0.9287	0.0713
Ind.exp.	1.31	1.15	0.7624	0.2376
Gender div.	1.01	1.01	0.9870	0.0130
Patent	1.01	1.01	0.9882	0.0118
Trademark	1.00	1.00	0.9971	0.0029
earlystage	1.19	1.09	0.8395	0.1605
Firmsize	1.16	1.08	0.8587	0.1413
Mean VIF	1.19			

Appendix 3. Hausman test results for determining the selection of fixed- or random-effects panel model – for robustness test 1

```
. hausman fixed random

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |     fixed        random       Difference          S.E.
-------------+----------------------------------------------------------------
Nonredundancy|    .8378314     .6642557        .1735757        .2584597
   Team size |   -.1898588    -.0349689       -.1548898        .1351668
 Team tenure |   -.5432258    -.8738727        .3306469        .2501718
Educ. heter. |     .218848      .168554         .050294          .10002
Foundingexp. |   -.0266311      .087385       -.1140161         .153067
Ind. exp.    |    .1049033    -.2849576        .3898608        .2439133
 Gender div. |   -.1023765     .0561342       -.1585107        .2259574
Patent       |    .3713008    -.0254586        .3967593        .1922326
Trademarks   |    .0873525    -.0363425         .123695        .0342655
Early stage  |     5.25417     .4368446        4.817326        .2520734
        year |
       2011  |    1.601135     1.139171        .4619645        .1668142
       2012  |    1.819167     1.463998        .3551686        .2884414
       2013  |    1.769258     1.541978          .22728        .4012363
       2014  |    2.205946     2.126989        .0789573        .5138871
       2015  |    2.372322     2.420424       -.0481016        .6260524
       2016  |    2.155743     2.222902       -.0671586        .7358861
       2017  |    1.673155     1.819263        -.146108        .8494721
       2018  |    1.623147     1.783151        -.160004        .9628566
------------------------------------------------------------------------------
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                 chi2(18) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =      543.28
                Prob>chi2 =      0.0000
                (V_b-V_B is not positive definite)
```

Appendix 4. Hausman test results for determining the selection of fixed- or random-effects logit model – for robustness test 2

```
. hausman consistent efficient

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |   consistent   efficient       Difference        S.E.
-------------+----------------------------------------------------------------
Nonredundan. |    .2108212     .1073165        .1035046        .0966768
   Team size |    -.092625    -.0484769       -.0441481        .0490629
 Team Tenure |   -.3950584    -.6282435        .2331851        .0892504
  Edu. heter. |    .0606606     .0330812        .0275794        .0373972
Foundingexp. |   -.0141817     .0034831       -.0176648        .0588608
   Ind. exp. |     .054729    -.0634089        .1181379         .089582
 Gender div. |   -.0227134    -.0234285        .0007151        .0835732
 Patent      |    .1366526     .0963478        .0403049         .065875
Trademarks   |    .0218555     .0071921        .0146634        .0161085
Early stage  |    .9814253     .2801915        .7012338        .1019177
        year |
        2011 |    .3326675     .3642235        -.031556        .0429418
        2012 |    .1348219     .2361846       -.1013627        .1023483
        2013 |   -.0637553     .1760405       -.2397958        .1455096
        2014 |   -.1342997     .2436846       -.3779842        .1863895
        2015 |   -.2526108     .2380859       -.4906966        .2265566
        2016 |   -.3557272     .2026578        -.558385        .2648679
        2017 |   -.5376755      .074945       -.6126205        .3043938
        2018 |   -.5799122     .0427771       -.6226893        .3420618
------------------------------------------------------------------------------
                         b = consistent under Ho and Ha; obtained from xtlogit
          B = inconsistent under Ha, efficient under Ho; obtained from xtlogit

    Test:  Ho:  difference in coefficients not systematic

                 chi2(18) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       97.53
                Prob>chi2 =      0.0000
                (V_b-V_B is not positive definite)
```

Appendix 5. Hausman test results for determining the selection of fixed- or random-effects logit model – for robustness test 3

```
. hausman consistent efficient

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |   consistent   efficient      Difference          S.E.
-------------+----------------------------------------------------------------
Nonredundanc |    .2587039     .1014128        .1572911         .098178
   Team size |   -.0228866    -.0175345       -.0053521         .049037
 Team tenure |   -.2255717    -.4212262        .1956545        .0902007
  Edu.heter. |     .079203     .0476059        .0315971        .0379106
Foundingexp. |    -.011952     .0311495       -.0431014        .0632917
   Ind. exp. |    .0775604    -.0461289        .1236893        .0909138
 Gender div. |   -.0470235    -.0248201       -.0222034        .0853603
 Patent      |    .1430659     .0945468        .0485191        .0703694
Trademarks   |     .066545     .0609498        .0055952        .0169389
Early stage  |    1.122313     .3571524         .765161        .0967377
        year |
       2011  |    .5974824     .6003121       -.0028297         .052482
       2012  |    .6109794     .6482113       -.0372319         .104494
       2013  |    .5393356     .6293387        -.090003        .1473865
       2014  |    .6336204     .8060895       -.1724691        .1882607
       2015  |    .6469566     .8900836        -.243127        .2290503
       2016  |    .5279917     .8028822       -.2748906        .2676375
       2017  |     .286501     .5994984       -.3129974        .3078118
       2018  |    .2007052     .5262618       -.3255566          .34539
------------------------------------------------------------------------------
                          b = consistent under Ho and Ha; obtained from xtlogit
           B = inconsistent under Ha, efficient under Ho; obtained from xtlogit

    Test:  Ho:  difference in coefficients not systematic

                 chi2(18) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       87.51
                Prob>chi2 =      0.0000
                (V_b-V_B is not positive definite)
```

Appendix 6. Hausman test results for determining the selection of fixed- or random-effects logit model – for robustness test 4

```
. hausman consistent efficient

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |   consistent   efficient       Difference          S.E.
-------------+----------------------------------------------------------------
Nonredundanc |    .3599749      .148708        .2112669        .1001635
   Team size |    -.147275    -.0790542       -.0682208         .051104
 Team tenure |   -.3796116    -.6001325        .2205209        .0911255
 Edu. heter. |    .0356236     .0266961        .0089276        .0390458
Foundingexp. |    .0156948     .0263281       -.0106332        .0625039
   Ind. exp. |    .0529764    -.0568449        .1098213        .0914319
 Gender div. |   -.0082987    -.0326282        .0243295        .0867803
 Patent      |    .0059745      .003304        .0026705        .0584069
Trademarks   |    .0001587    -.0074557        .0076144        .0190216
Early stage  |    1.079407     .3510458        .7283613        .1053871
        year |
       2011  |    .2204477     .2018712        .0185765        .0459998
       2012  |    .1161296     .1427806        -.026651        .1037996
       2013  |   -.0145338     .1049192        -.119453        .1483006
       2014  |   -.0544428     .1640059       -.2184487         .190088
       2015  |    -.108688     .1970241       -.3057121        .2313309
       2016  |   -.1943963     .1645619       -.3589582        .2702501
       2017  |   -.3657179     .0550341       -.4207521        .3107283
       2018  |   -.5100124    -.1054858       -.4045266        .3484916
------------------------------------------------------------------------------
                         b = consistent under Ho and Ha; obtained from xtlogit
          B = inconsistent under Ha, efficient under Ho; obtained from xtlogit

    Test:  Ho:  difference in coefficients not systematic

                 chi2(18) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       94.04
                Prob>chi2 =      0.0000
                (V_b-V_B is not positive definite)
```

Appendix 7. Hausman test results for determining the selection of fixed- or random-effects panel model – for robustness test 5

```
. hausman fixed random

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |     fixed        random       Difference         S.E.
-------------+----------------------------------------------------------------
   lagz1lnNR |    .6746232     .5754703        .0991529        .2900924
     lagz1TS |   -.4212747    -.3730882       -.0481864        .1649468
     lagz1TT |   -.8843395    -1.155513        .2711733        .2824335
     lagz1EH |    .1837157     .1917139       -.0079982        .1342514
    lagz1PFE |    .1548661     .1457843        .0090819        .1756338
     lagz1IE |    .0382384    -.1926271        .2308655        .2382688
     lagz1GD |   -.1350031     .0507114       -.1857144        .2124416
 lagz1Patent |    .2234386    -.1176889        .3411274        .2410872
lagz1Trade~k |    .0169754    -.0325624        .0495378        .0414609
lagearlyst~e |    4.603166     1.072594        3.530572        .3014563
        year |
       2011  |    1.160861      .947067         .213794        .2147168
       2012  |    .7192911     .6304708        .0888203        .3487154
       2013  |    .2441647      .269635       -.0254704        .4778174
       2014  |    .2413364     .3054196       -.0640832        .6050456
       2015  |    .0908034     .3098622       -.2190588         .730005
       2016  |   -.5002217    -.3022511       -.1979707        .8513749
       2017  |   -.8809655    -.6892853       -.1916802        .9791077
       2018  |   -.6381158    -.4822538        -.155862        1.103392
------------------------------------------------------------------------------
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                 chi2(18) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =      245.91
                Prob>chi2 =      0.0000
```