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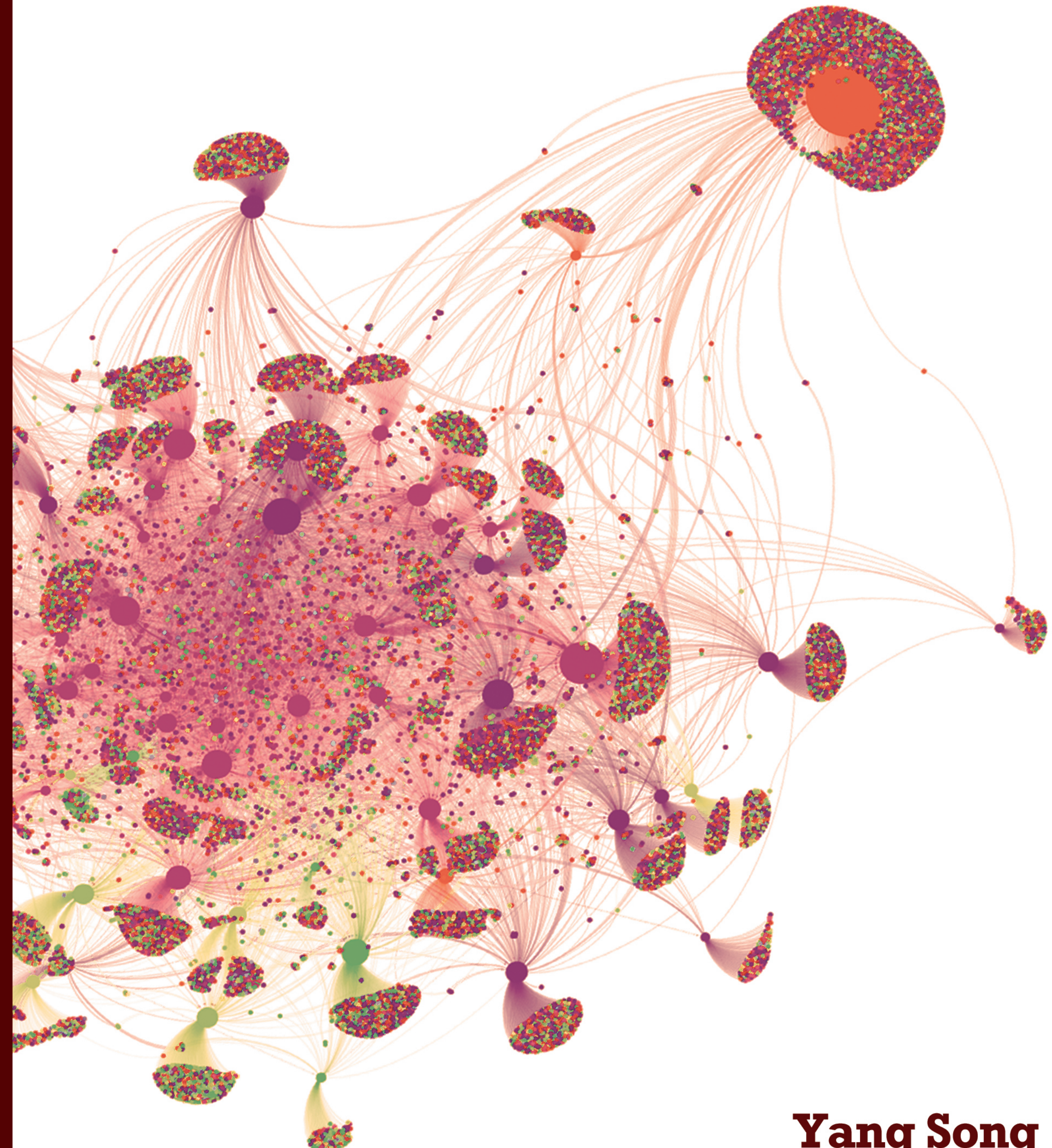
Network of Networks

Yang Song



Yang Song

Network of Networks

Uncovering the Secrets of Entrepreneurs' Networks

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Network of Networks:

Uncovering the Secrets of Entrepreneurs' Networks

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Faculteit der Economie en Bedrijfskunde

献给我亲爱的爸爸妈妈

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Yang Song

1 October 2012

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ENGLISH SUMMARY

Introduction

The popularity and universal use of online social network sites such as LinkedIn, Facebook and Twitter has become an important phenomenon attracting research in various disciplines. Entrepreneurs also use social networks to access and acquire resources, with online social networks also providing many opportunities for entrepreneurs to share and organize knowledge through their contacts among these networks. The role and importance of social networks for entrepreneurs has been recognized in previous studies. However, the study of online social networking by entrepreneurs is just starting. This study is intended to fill a gap in the literature concerning the structure, characteristics and use of online social networks by entrepreneurs.

We developed a novel approach to extract data on the online social networks of entrepreneurs through the use of the Application Programming Interfaces (APIs) of social network sites such as LinkedIn, Facebook and Twitter. The data concerning entrepreneurs' profiles and network connections was entered into a MySQL database for further analysis to determine the characteristics of entrepreneurs' online social networks such as size, structure, diversity and the role of these networks in the entrepreneurial process. Based on our findings concerning the structure of these networks, we also developed a simulation model to predict their contribution to entrepreneurial survival.

Structure and main findings

Following an introduction in Chapter 1, the dissertation is divided into a theoretical part (Chapter 2) and three empirical parts (Chapters 3, 4 and 5). The main findings of each chapter are presented below.

In Chapter 2, we extended the theory of a Network of Networks (NoN) to entrepreneurship and developed a novel method to collect online social network data from online social network sites.

In Chapter 3 we studied the diversity of entrepreneurs' online social networks by analysing the different industries represented in networks and their geographical locations. Our findings suggest that an entrepreneur's LinkedIn network size has a positive relationship with entrepreneurial survival. However, the size of their Facebook network is not related to their survival, while the size of their Twitter network has a negative relationship with performance. In addition, we created a visualization of the entrepreneurs' LinkedIn online social network which represents industry diversity, and reflected on the implications for future research regarding the structure of these networks.

In Chapter 4, we found that entrepreneurs' NoNs follow an 'exponential degree distribution', which implies that weak ties between individual networks play an important role in forming these NoNs. Additionally, we found overlaps between an entrepreneur's neighbours across their NoN, which suggested that entrepreneurs develop and use NoNs to support the entrepreneurial process.

Finally, in Chapter 5 we investigated the growth of the entrepreneurs' businesses in a given network and the latter's impact on the entrepreneurial process. We assume entrepreneurs are interested in starting up new businesses in collaboration with others in the given network. The decision regarding collaboration depends on the information and resources that can be obtained from the network. We developed a simulation model of the entrepreneurial process in terms of the growth of entrepreneurial wealth. The use of simulation supports the study of network dynamics and we used these models to identify the survival rate of entrepreneurs in the network after a certain period. Our results imply that both the extent of networks and the start-up wealth positively influence entrepreneurial growth. The simulation model can also infer the longest survival time based on a given start-up time.

Main contributions

This dissertation contributes to both the entrepreneurship and social network fields by studying the structure of the online social networks of entrepreneurs. First, by extending NoN theory to entrepreneurship, we found that entrepreneurs are using multiple online social networks. We suggest that NoN theory can be applied as a novel approach to the study of networks in entrepreneurship. Moreover, NoN can also be used to explain phenomena in multiple disciplines. For example, we can infer human behavioural patterns and social network structures by focusing on the entrepreneurs' behavioural data gathered from online social networks.

Second, we find that entrepreneurs tend to build a very diverse network during the start-up period of their business. We use the data we collected to study the structure and diversity of their networks and to conduct an analysis of the impact of the network on entrepreneurial performance, measured in terms of survival. We found that the LinkedIn network size is positively correlated with performance in terms of a venture's survival and that network diversity does not have an impact on performance.

Third, by analysing the structure of the online social networks of entrepreneurs, we found that these networks follow an exponential distribution and suggested that the networks used by entrepreneurs formed a NoN, rather than being single networks. This entrepreneurial NoN is formed as a random network with an exponential degree distribution and features a high degree of overlap between the individual networks. We were able to identify communities of networks by removing the edges with the highest betweenness values, which normally means weak ties.

Finally, we presented a network simulation model to describe the entrepreneurial growth process as dependent on the position in the given network. The network structure we used was extracted from the LinkedIn network. This simulation model can predict entrepreneurs' maximum survival time based on a given start-up time and the resources available. In our model, we found that entrepreneurial growth is not only related to capital investment but also to the extent of networks. While we were not able to determine the threshold for entrepreneurial survival at a given time, we could still infer the probability of survival from the amount of start-up wealth and the start-up time frame.

In conclusion, this dissertation provides a novel methodology to study entrepreneurship and online social networks. We suggest that online social network data can be used as behavioural data to study entrepreneurial processes. Furthermore, our simulation model can be used as an additional approach to predict the growth of new ventures in a fixed network structure. Using the simulation model we can also explore the dynamics and impact of online social networks on the entrepreneurial process over time. This study demonstrates that the online social network can be used to study various aspects of entrepreneurship, and it is thus worthy of further investigation in future research.

NEDERLANDSE SAMENVATTING

Introductie

De populariteit en het algemeen gebruik van online sociale netwerksites zoals LinkedIn, Facebook en Twitter, zijn uitgegroeid tot een belangrijk verschijnsel dat onderzoek uit verschillende disciplines aantrekt. Ook ondernemers gebruiken online sociale netwerken om middelen te verwerven en om kennis te delen en te organiseren door middel van hun contacten in deze netwerken. De rol en het belang van sociale netwerken voor ondernemers is erkend in eerdere studies. Echter, de studie van het gebruik van online sociale netwerken door ondernemers is nog maar kortgeleden begonnen. Dit onderzoek is bedoeld om een hiaat op te vullen in de literatuur met betrekking tot de structuur, de eigenschappen en het gebruik van online sociale netwerken door ondernemers.

We ontwikkelden een nieuwe benadering voor de selectie van gegevens over de online sociale netwerken van ondernemers door het gebruik van Application Programming Interfaces (API's) van sociale netwerksites zoals LinkedIn, Facebook en Twitter. De gegevens met betrekking tot profielen en netwerkverbindingen van ondernemers werden opgenomen in een MySQL database voor verdere analyse van de kenmerken van online sociale netwerken van ondernemers zoals de grootte, de structuur, de diversiteit en de rol van deze netwerken in het proces van ondernemen. Op basis van onze bevindingen met betrekking tot de structuur van deze netwerken, ontwikkelden we ook een simulatiemodel om hun bijdrage aan het overleven van de onderneming te voorspellen.

Structuur en belangrijkste bevindingen

Na een inleiding in hoofdstuk 1, wordt het proefschrift opgedeeld in een theoretisch deel (hoofdstuk 2) en drie empirische delen (hoofdstukken 3, 4 en 5). De belangrijkste bevindingen van elk hoofdstuk staan hieronder weergegeven.

In hoofdstuk 2 hebben we de theorie van Netwerk van Netwerken (NvN) uitgebreid naar ondernemerschap en hebben we een nieuwe methode ontwikkeld om gegevens van online sociale netwerk sites te verzamelen.

In Hoofdstuk 3 onderzochten we de diversiteit van de online sociale netwerken van ondernemers door het analyseren van de verschillende sectoren die vertegenwoordigd zijn in de netwerken en van hun geografische ligging. Onze bevindingen suggereren dat de grootte van het LinkedIn netwerk van een ondernemer een positieve relatie heeft met de overlevingskansen van de onderneming. De omvang van hun Facebook netwerk is echter niet gerelateerd aan de overlevingskansen, terwijl de grootte van hun Twitter netwerk een negatieve relatie heeft met de prestaties van de onderneming. Daarnaast hebben we een visualisatie gemaakt van de sectordiversiteit van de LinkedIn online sociaal netwerken van ondernemers en hebben we nagedacht over de implicaties voor toekomstig onderzoek met betrekking tot de structuur van deze netwerken.

In hoofdstuk 4 hebben we gevonden dat het Netwerk van Netwerken (NvN) van ondernemers exponentiële distributie laat zien, wat betekent dat zwakke banden tussen individuele netwerken een belangrijke rol spelen bij het vormen van deze NvN's. Daarnaast vonden we overlappingen tussen de netwerken van de 'netwerk-buren' een ondernemer en zijn eigen NvN, waaruit kan blijken dat ondernemers NvN's ontwikkelen en gebruiken om het proces van ondernemen te ondersteunen.

Tenslotte hebben we in hoofdstuk 5 onderzoek gedaan naar de groei van de bedrijven van de ondernemers in een bepaald netwerk en het effect ervan op het proces van ondernemen. We gaan ervan uit dat ondernemers geïnteresseerd zijn in het starten van nieuwe bedrijven in samenwerking met anderen in het netwerk. De beslissing over de samenwerking hangt af van de informatie en middelen die kunnen worden verkregen uit het netwerk. We ontwikkelden een simulatiemodel van het proces van ondernemen gemeten in termen van de groei en het financiële vermogen. Het gebruik van simulatie ondersteunt de studie van de dynamiek van netwerken en we gebruikten deze modellen om de overlevingskansen van ondernemingen na een bepaalde periode in het netwerk te identificeren. Onze resultaten impliceren dat zowel de omvang van de netwerken als de grootte van het startkapitaal een positieve invloed hebben op de groei van de onderneming. Het simulatiemodel kan ook de langste overlevingstijd afleiden uitgaande van een bepaald start-up moment.

Belangrijkste bijdragen

Door het bestuderen van de structuur van de online sociale netwerken van ondernemers draagt dit proefschrift bij aan de onderzoeksvelden van ondernemerschap en sociale netwerken. Ten eerste, door de uitbreiding van NvN-theorie naar ondernemerschap vonden we dat ondernemers meerdere online sociale netwerken gebruikten. We stellen voor dat de NvN-theorie kan dienen als een nieuwe benadering voor de studie van de ondernemersnetwerken. Bovendien kan de NvN-theorie gebruikt worden om fenomenen in verschillende disciplines te verklaren. Zo kunnen we menselijke gedragspatronen en sociale netwerkstructuren afleiden door ons te richten op data over ondernemersgedrag uit de online sociale netwerken.

Ten tweede vonden we dat ondernemers geneigd zijn om tijdens de start-up periode van hun bedrijf een zeer divers netwerk op te bouwen. We gebruikten de verzamelde gegevens om de structuur en de diversiteit van hun netwerken te bestuderen en een analyse uit te voeren op het effect van het netwerk op de resultaten van de ondernemer, gemeten in overlevingskans van het bedrijf. We vonden dat het LinkedIn netwerkformaat een positieve correlatie vertoont met de overlevingskans van een onderneming en dat de netwerkdiversiteit geen invloed heeft op deze prestaties.

Ten derde, door het analyseren van de structuur van de online sociale netwerken van ondernemers, vonden we dat deze netwerken een exponentiële verdeling volgen en stelden we voor dat de netwerken een NvN vormen, in plaats van een individueel netwerk. Dit ondernemende NvN wordt gevormd als een willekeurig netwerk met een exponentiële verdelingsgraad en laat een hoge mate van overlap tussen de afzonderlijke netwerken zien. We waren in staat om ‘communities’ van netwerken te identificeren door het verwijderen van de randen met de hoogste ‘betweenness’ waarden, die meestal duiden op zwakke verbindingen.

Tenslotte presenteerden we een netwerk-simulatiemodel om de groei van de onderneming te beschrijven als afhankelijk van de positie in het gegeven netwerk. De netwerkstructuur hebben we afgeleid uit het LinkedIn netwerk. Dit simulatiemodel kan de maximale overlevingstijd van de onderneming voorspellen, gegeven de startdatum en de beschikbare middelen. In ons model, vonden we dat de groei van de onderneming niet alleen samenhangt met kapitaalsinvesteringen, maar ook met de omvang van de netwerken. Hoewel we niet in staat waren om de drempel voor overleving van de onderneming op een gegeven moment te bepalen, konden we toch de kans op overleving afleiden op basis van de omvang van het startkapitaal en het start-up tijdpad.

Tot slot, dit proefschrift biedt een nieuwe methodologie om ondernemerschap en online sociale netwerken te bestuderen. Wij stellen voor dat gegevens van online sociale netwerken gebruikt kunnen worden om ondernemersgedrag te bestuderen. Bovendien kan ons simulatiemodel gebruikt worden als aanvullende benadering om de groei van nieuwe bedrijven in een vaste netwerkstructuur te voorspellen. Met behulp van het simulatiemodel kunnen we ook de dynamiek en de impact van online sociale netwerken op het proces van ondernemen in de tijd verkennen. Deze studie toont aan dat het online sociale netwerk gebruikt kan worden om verschillende aspecten van ondernemerschap te bestuderen en dat het waardevol is om dat verder te onderzoeken.

中文摘要

导言

在线社交网络网站（如LinkedIn, Facebook和Twitter）的普及现象已经吸引各学科领域的研究者。创业者可以通过使用社交网络访问和获取资源，与此同时,在线社交网络通过社交网络中的关系为创业者提供大量共享和整理知识的机会。现有文献已经确立了社交网络对于创业者的作用和重要性，然而，针对创业者使用社交网络的研究才刚刚开始。本研究旨在填补这一空白，探讨创业者如何使用社会网络，并发掘创业者社会网络的结构与基本特点。

通过使用在线社交网络如LinkedIn, Facebook和Twitter的应用程序编程接口(API)，我们开发了一种全新的研究方法来提取创业者的在线社交网络数据。创业者的个人资料和网络关系被自动收录到MySQL数据库中作进一步分析，例如,在线社交网络的大小、结构、多样性以及在线社交网络在创业过程中扮演的角色。通过研究这些网络的结构，我们还开发了一个模拟模型来预测在线社会网络对创业贡献。

结构和主要成果

本论文的结构如下：第1章为介绍，第2章为理论部分，3、4、5章为实证部分。其中，每章的主要研究成果如下：

第2章，我们将网中网的理论扩展到创业领域，并开发了一个全新方法从在线社交网络中收集创业者的社交网络数据。

第3章，通过分析创业者所处的不同行业和地理位置，我们研究了创业者社交网络的多样性。研究结果表明，创业者在LinkedIn的网络规模与新创企业的存活时间呈正相关；创业者在Facebook的网络规模却与新创企业的存活时间不相关；Twitter的网络规模与新创企业的存活时间呈负相关。此外，我们创建了可以体现创业者LinkedIn在线社交网络多样性的可视化图形，并阐述了这些网络结构对今后研究的影响。

第4章的研究表明，创业者的网中网服从“指数分布”。这意味着各个网络之间的弱连接对于形成网中网发挥极为重要的作用。此外，创业者网中网的邻接关系存在重叠，这说明创业者发展并通过使用网中网来支持创业过程。

第5章，我们研究了在特定的网络结构下新创企业增长以及特定网络对创业过程的影响。我们假设，在特定的社交网络结构中，创业者有意愿与网络中的人进行合作并开始创业。合作的决定取决于可以在网络中获取的信息和资源。根据创业资本的变化，我们建立了创业发展过程的模拟模型。该模型支持对社会网络动态的研究，在本论文中，我们采用这个模型来确定创业者经过一段时期后的创业存活率。结果表明，创业网络的规模和初期资本影响创业成长。给定创业的起始时间，我们还能通过该模型推断创业家的最长存活时间。

主要贡献

通过对创业者在线社交网络结构的探讨，本论文对创业以及社会关系网络研究起到了如下贡献：

首先，通过将网中网模型扩展到创业领域，我们发现创业者在使用多个在线社交网络。我们主张，网中网理论可以作为一个新的研究方法应用到创业研究领域。此外，网中网理论还可以用来解释涉及多重学科领域的社会现象。例如，通过对创业者在线社交网络关系的数据分析，我们可以推断他们的行为模式以及社交网络结构。

其次，我们认为，创业者在创业初期倾向于建立一个多样化的网络。我们使用收集的数据来研究他们的社交网络结构和多样性，以创业存活时间衡量创业绩效，分析了网络对创业绩效的影响。结果表明，LinkedIn网络规模与创业者的创业绩效，也就是创业存活时间呈正相关；而网络的多样性对创业绩效没有任何影响。

第三，通过分析创业者在线社交网络的结构，我们发现，这些网络在一起形成网中网，创业者所使用的并非单一网络。并且，这个网中网随机生成并服从指数分布，网络之间存在着较高程度的重叠。通过消除网络中的最弱关系，我们可以识别网络中的群落。

最后，我们提出了一个基于网络的模拟模型来研究新创企业的成长过程，其中创业者在网络中所处的位置决定新创企业的成长。模型中给定的网络为LinkedIn网络结构。根据给定的创业时间点以及其他变量，该模型可以预

测最长的创业存活时间。我们发现，在该模型中新创企业的成长，不仅与创业资本有关，还与网络规模有关。尽管根据给定的创业时间点，我们不能预测创业存活的临界点，但是我们还是可以根据给定的创业资本以及创业初始时间点推测最长存活时间。

总之，本文为我们提供了一个全新的方法研究创业和在线社交网络。我们认为，在线社交网络数据可以作为行为数据来分析创业过程。此外，我们的模拟模型可以作为一个新的方法用以预测新创企业在给定网络结构下的增长。通过使用模拟模型，可以观察在线社交网络对创业成长随时间变化的动态增长。这一研究表明，在线社交网络可以运用到创业领域的多方面研究，并值得进行深入研究。

CHAPTER 1

Introduction

1.1 Online social network sites

The history of online social networking can be traced back to the late 1990s, with the last decade seeing its full emergence. The increasing popularity of the internet makes it possible for people to interact and communicate with each other through a variety of online social networks. Previous studies suggest that information exchange and social contact are the central reasons why people join and remain in virtual social networks (D'Andrea, Ferri, & Grifoni, 2010). According to a recent report by comScore (2012), more than half of the local online population engages in social networking, with nearly one in five minutes spent online today being allocated to social networking. Social networking sites (SNSs) such as LinkedIn, Facebook and Twitter provide a private online space for individuals and the tools for interacting with others on the internet (Ahn, Han, Kwak, Moon, & Jeong, 2007). It is already a universal phenomenon for human beings to use online social networking sites and an essential part of their social life.

With the growth of social networking and sharing, more and more information is becoming available online about how people interact with each other (Chin & Chignell, 2010). Online social networks help people find others with common interests, establish a forum for discussion, exchange photos and personal news, and much more (Ahn et al., 2007). Online social networks also provide opportunities for individuals to share and organize knowledge through contacts among networks. Previous research on online social networking has primarily examined private interactions (Boyd, 2007; Boyd & Ellison, 2007; Ellison, Steinfield, & Lampe, 2007; Junghee Lee & Hyunjoo Lee, 2010; B. Wellman, Haase, Witte, & Hampton, 2001).

Online social networks contain important sources of information, such as profile information and connections with friends and family. The information included in online social networks can help individuals to build and maintain their formal and informal relationships with other people. Previous research has shown that online social networks, in particular LinkedIn, can also assist entrepreneurs maintain business networks (Nann et al., 2010; O'Murchu, Breslin, & Decker, 2004). Online social networking sites support both the maintenance of existing social ties and the formation of new social connections (Ellison et al., 2007), and thus the influence of social ties can be studied through online social networks (Song & Vinig, 2012; Tchuente et al., 2010). It has also been found that the internet neither increases nor decreases face-to-face engagement but instead supplements social capital (Junghee Lee & Hyunjoo Lee, 2010; B. Wellman et al., 2001).

Online social networking sites have exploded in popularity all over the world, and on this basis, the wide usage of online social networking services is reshaping the organizational landscape. The ubiquitous usage of the internet has increased human interactions and opportunities for the emergence of social networks, while the power of individuals to interact with others in an online setting now drives the success or failure of many organizations on the internet (Kumar, Novak, & Tomkins, 2010). Previous research has shown that there are different motives for using online social networks, such as information exchange, social support, friendship, recreation, common interests and technical support (D'Andrea et al., 2010; Ridings & Gefen, 2004). In particular, the socially interactive aspect plays a more important role than the entertainment and information-seeking aspects (Junghee Lee & Hyunjoo Lee, 2010). We adapt individual motives for using online social networks from D'Andrea et al. (2010) and Ridings and Gefen (2004). Furthermore, we divide the users into entrepreneurs and non-entrepreneurs. We list the motives for individuals using online social networks in Table 1.

Table 1 Motives for using online social networks (adapted from D'Andrea et al. (2010) and Ridings and Gefen (2004))

Category	Users	Description	Examples
Information exchange	Entrepreneurs	Obtain and transfer information about a topic	To learn about new technologies for my business To share my knowledge of something with others
	Non-entrepreneurs	Educate about a topic Learn things	To learn about new things To get new ideas
Social support	Entrepreneurs	Help entrepreneurs' leverage their business networks	To organize and gain economies of scale through social networks
	Non-entrepreneurs	Obtain and give emotional support	A way for me to express my anger to others who will sympathize with me
Social Networking without boundaries	Entrepreneurs	Accessibility to suppliers and consumers	Find international suppliers and consumers
	Non-entrepreneurs	Expand social networks	Find international friends or people with common interests
Friendship	Entrepreneurs & Non-entrepreneurs	To make friends	To socialize, to talk to people with similar interests and values
Recreation	Entrepreneurs & Non- entrepreneurs	For entertainment	Because it is fun
Common Interest	Entrepreneurs & Non- entrepreneurs	Love of the topic of the community	I like talking about sport I like talking about baseball
Technical reason	Entrepreneurs & Non- entrepreneurs	Technical features in the community	The interface is easy to use The search function is really cool

Individuals and companies use online social network platforms for social interaction as well as for maintaining and expanding their professional networks. Consequently, many organizations have adopted the use of SNSs for purposes such as relationship building, information exchange and collaborative work. However, despite a growing number of studies of SNSs, their use in organizational contexts, particularly in the context of entrepreneurship, has been largely neglected. As we know, obtaining access to financial, social and other types of resources is crucial, and SNSs might be an important vehicle for obtaining such access.

Online social networking sites contain a large amount of data. Individuals from online social networks connect to each other for different reasons, such as similar interests (Bisgin, Agarwal, & Xiaowei, 2010) or friendship (Ellison et al., 2007). Despite the large amount of research on online social networks (Boyd, 2007; Boyd & Ellison, 2007; Ellison et al., 2007; Junghee Lee & Hyunjoo Lee, 2010; B. Wellman et al., 2001), there is very limited research that focuses on entrepreneurship and online social networking. Understanding the structure of entrepreneurs' online social networks is important, not only because of the ubiquitous use of the internet and online communications, but also because the online social network may reflect the real behaviour of entrepreneurs. Investigating the theory of online social networks has significant implications, not only with respect to entrepreneurship but also with regard to other social behaviour related to online communication and interaction.

It is now possible to access data from entrepreneurs' online social networks and analyse their behavioural and longitudinal data. Using a novel approach, this dissertation addresses the challenge of linking online social networks to entrepreneurship. Considering the characteristics of online social networks, we will examine online social networking sites as a tool used by entrepreneurs to engage with others. In the following sections we will introduce our research questions, provide the theoretical framework of our study of entrepreneurship and social networks, discuss the value of social networks and outline the structure of this dissertation. Finally, the chapter provides an assessment of the contribution made by this dissertation.

1.2 Social networks and entrepreneurship

The essential act of entrepreneurship is a new entry into the market, that is, the act of launching a new venture, either by a start-up firm, through an existing firm, or via 'internal corporate venturing' (Lumpkin & Dess, 1996). Building a new company is a highly competitive and risky endeavour (Stuart, Hoang, & Hybels, 1999), hence, entrepreneurs who start new ventures need to continuously seek opportunities and mobilize resources (Aldrich & Auster, 1986). Accessing financial, social and other types of resources is an inherently social process, with resources acquired primarily through relationships with parties beyond the boundaries of these start-ups (Stuart et al., 1999). Entrepreneurship remains as important to the economy as ever (Vinig & van der Voort, 2005). Thus, studying entrepreneurship from the perspective of networks becomes a very important research topic. In particular, studying the structure of online social networks (Kumar et al., 2010; Socievole & Marano, 2012) and linking online social networks to entrepreneurship is a very interesting research topic.

A network consists of a set of actors connected by a set of ties. The actors can be people, teams, organizations, or even concepts. Ties connecting pairs of actors can be directed or undirected and can be dichotomous or valued (Borgatti & Foster, 2003). Social network analysis is based on the assumption of the importance of relationships among interacting units. The relationships, defined by the connections between units, are a fundamental component of network theories. Actors and their actions are viewed as interdependent rather than independent (Wasserman & Faust, 1994).

Previous research on social networking and entrepreneurship has been conducted from three main perspectives. First, from the perspective of collaborations among large numbers of individuals: the more collaborators an individual has, the higher the chances are that he or she will be invited to participate in subsequent collaborations (Barabási, 2005; Raz & Gloor, 2007). Second, from the organizational perspective, social networking affects entrepreneurial performance and actions and thus entrepreneurial networking (E. L. Hansen, 1995; Larson, 1992). In the organizational context, a network is a collection of voluntary agreements between firms, which entail exchanges of information and the sharing of existing knowledge (Gulati, 1998). Third, from the individual perspective, the focus will be on individual entrepreneurs, in other words, the nodes and ties of the networks which consist of every form of communication or exchange between entrepreneurs (Brüderl & Preisendörfer, 1998; M. S. Granovetter, 1973). In addition, research based on social capital and the theories of structural holes and brokerage (Burt, 1992) are still the main topics of research.

Each entrepreneurial firm is a hub organization with a small number of stable exchange relationships that are maintained with favourite external companies (Larson, 1991). According to Bouchikhi (1993), the entrepreneurial outcome is determined neither by the entrepreneur nor by the context, but emerges in the process of their interaction. This view is supported by Sarasvathy and Venkataraman (2011), who suggest that the entrepreneurial process, the interaction, is an important source of opportunities. However, due to the lack of large amounts of data, as well as the sensitive nature of extracting information from entrepreneurial networks, empirical studies focus more on self-reported network data using offline questionnaires, and thereby lack information on the behavioural aspects of networking.

Online social networks can provide a large amount of behavioural data, with the communication and interaction between members of online social networks making it possible to collect an abundant supply of data on the behaviour of entrepreneurs.

1.3 The value of social networks

Social networks are a key component of entrepreneurial networks, generating firm legitimacy and reputation (Burt, 1992; Deeds, Decarolis, & Coombs, 2000). Entrepreneurial social networks play an important role in the start-up period of businesses. According to Brüderl and Preisendörfer (1998), social networks stimulate entrepreneurship by making use of these networks to establish new entrepreneurial ventures. Entrepreneurs attempt to organize and actually benefit from social network resources in terms of their venture's performance in the start-up period. The findings of Brüderl and Preisendörfer (1998) are supported by several researchers, who argue that entrepreneurs require valuable resources such as information, advice, finance, skills and labour (Arent Greve & Salaff, 2003) when starting business activities to be able to realize entrepreneurial opportunities. A key benefit of entrepreneurial social networks in the start-up period is the access they provide to these resources and in gathering valuable information. In conclusion, entrepreneurs who can rely on a broad and diverse social network and who receive much support from it are more successful (Brüderl & Preisendörfer, 1998).

Based on previous studies, we consider that networks are critical to entrepreneurship. Online social networks, as a special form of entrepreneurial network, provide an opportunity for us to explore entrepreneurs' behaviour. As mentioned at the beginning of this chapter, the use of online social networks is expected to increase in the future. In order to study how online social networks can affect the entrepreneurial process, as well as the relationship between entrepreneurship and online social networks, we raise the following research questions:

- What methodology can be used to study entrepreneurs' behaviour?
- What influence do the size and diversity of entrepreneurs' online social networks have on entrepreneurial survival?
- What patterns are apparent in entrepreneurs' online social networks?
- What influence does an online social network have on entrepreneurial performance?

In order to address our research questions and fill the gap in research on entrepreneurship and online social networks, this dissertation mainly uses the theory of a Network of Networks (NoN), applying it to online social networking and entrepreneurship. This will be discussed below. In addition, we use two methodologies to analyse entrepreneurs' online social networks. In this regard, we first had to solve the problem of how to collect the data on entrepreneurs' behaviour from the online social networks. We developed the novel approach of using the online social network API to extract data on online social networking behaviour, and used this data to address the issue of the influence of online social network size and diversity on entrepreneurial survival. The empirical research not only proved the value of our novel data collection approach but also allowed us to develop a simulation model which can be used to explore the influence of online social networks on entrepreneurial survival. Using this model we can predict entrepreneurs' maximum survival time based on a given start-up time frame.

The aim of this dissertation is threefold. First, we develop a methodology to analyse entrepreneurs' online network data that automatically extracts entrepreneurs' behavioural data. Second, we aim to analyse the structure of entrepreneurs' online social networks. Finally, we explore how entrepreneurs use online social networks to maintain their entrepreneurial venture. The following section provides an outline of each chapter.

1.4 Dissertation overview

This dissertation is comprised of six chapters. This chapter introduces the motives for studying online social networks and the aims of the dissertation as a whole. In Chapter 2 we will develop a methodology to study entrepreneurs' online social networks, which includes a methodology for collecting online social network data and a brief introduction to simulation. Chapter 3 and Chapter 4 will present the results of our analysis of network data from different perspectives, while in Chapter 5 we used a simulation model to study the entrepreneurial process based on a given network.

Drawing on the literature on social network analysis, Chapter 2 argues that entrepreneurs are embedded in different kinds of social networks, which can be considered a Network of Networks (NoN). We developed a novel method to extract and compare data on entrepreneurs' profiles and their online social networks on LinkedIn, Facebook and Twitter. The methodology can also be applied in other fields to study entrepreneurs' online social networks. We summarize the characteristics of the data collected and, in order to study the influence of entrepreneurs' networks, we also review simulation models that can be used to further study entrepreneurship and online social networks.

In Chapter 3, we assume that entrepreneurs use multiple online social networks that form their Network of Networks (NoN). We investigate the diversity of entrepreneurs' online social networks by analysing their online network's industry and location diversity. We examined network size and diversity to gauge their impact on performance in terms of survival. Our findings suggest that the size of an entrepreneur's LinkedIn network has a positive relationship to entrepreneurial survival. However, the size of the entrepreneur's Facebook network is not related to survival, while the size of their Twitter network has a negative relationship with performance. We visualize the entrepreneurs' LinkedIn network in terms of industry diversity. Finally, we reflect on the implications for future research on the structure of entrepreneurs' online social networks.

Chapter 4, will primarily analyse the data collected using the methodology introduced in Chapter 2. We merged the data from the three online social networks to study the structure of the entrepreneurs' NoN. Our analysis suggests that this NoN follows an exponential degree distribution, which implies that weak ties between individual networks play an important role in forming such NoNs. Furthermore, we demonstrate overlaps between an entrepreneur's neighbours across the NoN, which suggests that entrepreneurs develop and use NoNs to support the entrepreneurial process.

Chapter 5, investigates the growth of entrepreneurs' businesses in a given network and the impact of the latter on the entrepreneurial process. We assume entrepreneurs are interested in starting up new businesses with others in a given network. They attempt to find information and resources through other entrepreneurs in their networks and decide on whether to collaborate with each other. We develop a simulation model of the entrepreneurial process in terms of growth, identifying the survival rate of entrepreneurs in the network after a certain period. Our results imply that both network degree and start-up wealth positively influence entrepreneurial growth. Our simulation model can also allow us to infer the longest survival time based on a given start-up time frame.

In Table 2, we highlight the main contributions of each chapter.

1.5 Contribution

By studying the structure of entrepreneurs' online social networks, this dissertation contributes to both the entrepreneurship and social network fields.

First, by extending NoN theory to entrepreneurship, we find that entrepreneurs are using multiple online social networks. We suggest that NoN theory is a novel approach to the study

Table 2 Overview of dissertation

	Overview
Chapter 1	Motivations, research questions, objectives
Chapter 2	NoN theory, methodology for studying NoN network, data collection
Chapter 3	Empirical study of entrepreneurs' network diversity
Chapter 4	Empirical study of entrepreneurs' network structure and distribution We found online social networks follow an exponential degree distribution
Chapter 5	The entrepreneurial process simulation model based on a given network We are able to predict the maximum survival time based on a given start-up time frame
Chapter 6	Discussion and implications Future directions for NoN theory and data collection

of networks in entrepreneurship. Our methodology for using entrepreneurs' online social networking data offers a new way of analysing entrepreneurial behaviour. NoN can also be used to explain phenomena in multiple disciplines. We can also infer behaviour patterns and social network structures by focusing on data gathered from the entrepreneurs' online social networks. The potential value of the online social network in terms of providing resources, opportunities, customers and financing, as well as recruitment, can also be uncovered.

Second, we find that entrepreneurs tend to build a very diverse network during the start-up phase of their business. We use the data we collected to study their network's structure and diversity, and to conduct an analysis of the network's impact on entrepreneurial performance, measured by survival. We find that the LinkedIn network size is positively correlated with performance in terms of a venture's survival and that network diversity does not impact on performance.

Third, by analysing the structure of entrepreneurs' online social networks, we find that these networks have an exponential distribution and suggest that the networks used by entrepreneurs form an NoN, rather than occurring as individual networks. This entrepreneurial NoN is formed as a random network with an exponential degree distribution. The NoN features a high degree of overlap between individual networks. We were able to identify the communities of networks by removing the edges with the highest betweenness values, which are normally connected through weak ties.

Finally, we present a network simulation model to describe the growth of the entrepreneurial process as dependent on the position of an entrepreneur in a given network. The network structure we use was extracted from the LinkedIn network. This simulation model can predict an entrepreneur's maximum survival time based on a given start-up time frame and wealth allocated (capital, resources, etc.). In our model, we found that entrepreneurial growth is not only related to wealth but also to the network degree. Although we are not able to determine the threshold for entrepreneurial survival at a given time, we can still infer the survival probability based on start-up wealth and the time required for start-up. The simulation model can be used to study other potential network structures that might be helpful to entrepreneurship.

In conclusion, this dissertation provides a novel methodology to study entrepreneurship and online social networks. We suggest that online social network data can be used as behavioural data to study entrepreneurial processes. Furthermore, our simulation model can be used as an additional approach to predict the growth of new ventures in a fixed network structure. Using the simulation model, we can also explore the dynamics and impact of online social networks on the entrepreneurial process over time. This study demonstrates that the online social network can be used to study various aspects of entrepreneurship and that it is thus worthy of further investigation in future research.

CHAPTER 2

Methodology for Extracting Entrepreneurs' Online Social Network Data[1]

Abstract

In this chapter we introduce and apply the theory of a Network of Networks (NoN) developed in previous research. We present a novel approach to collecting data on entrepreneurs' online social networks and propose that these are in fact NoNs. In an NoN, each node participates in one or more networks hosted by other nodes. We propose that none of these networks are independent, and rather than the individual network, it is the NoN that contributes to an entrepreneur's venture performance. Furthermore, we suggest that the NoN model can be applied in other social science disciplines. Our approach can be used to collect NoN data simultaneously from different online social networks, and we used this methodology to collect data from LinkedIn, Facebook and Twitter. The data collected is used for empirical studies in Chapters 3 and 4. In addition, the data is used to study entrepreneurial processes using a simulation model, which is briefly introduced in this chapter. We also suggest that this simulation model could be used to study the entrepreneurial process based on a given network.

1 This chapter is adapted from preliminary research presented at Babson College Entrepreneurship Research Conference (BCERC 2010), 'Entrepreneurs' network of networks: studying entrepreneurs' social network structure using smart-phone data', June 10, 2010, Lausanne, Switzerland.

2.1 Introduction

The network approach has been applied to explain different phenomena in the social sciences as well as physics. As social network analysis focuses more on relationships rather than the attributes of the research objects, it has also become a prominent theoretical perspective within the literature on entrepreneurship, and it has been suggested (Aldrich & Zimmer, 1986) that it is a relevant method for explaining why some entrepreneurs are more successful in starting and maintaining businesses than others. It is argued that entrepreneurs with a large and diverse network receive more support from their connections, and this can lead to greater success (Brüderl & Preisendörfer, 1998).

Social relationships and networking are key components of human life but historically they have been bound by time and space limitations (D'Andrea et al., 2010). Moreover, traditional social network analysis has generally been constrained in accuracy, breadth and depth due to a reliance on self-reported data (Eagle, Pentland, & Lazer, 2009), with the majority of studies only providing static snapshots and temporal mappings of networks. However, due to the vast growth of the internet and the use of computers, it is now possible for us to collect and analyse data on entrepreneurial behaviour extracted from records saved on computers and other devices that can access the internet. Research suggests that successful entrepreneurs have more online connections and in particular more connections with peers from their alumni network than less successful entrepreneurs (Nann et al., 2010).

Due to the multiple communication purposes and functions that can be fulfilled by online social networking sites (SNSs), different types of network data can be extracted from them and linked in order to study various types of networks simultaneously, such as friendship networks, advice networks, kinship networks and business networks networks (Song & Vinig, 2012). Moreover, online SNSs support automatic data collection, on the basis of which it is possible to study entrepreneurs' networks and their potential.

In this chapter, we present a novel approach for studying entrepreneurs' online social networks. This approach is based on the use of computers and the popularity of online SNSs and will examine to what extent they can be used to explain the behaviour of entrepreneurs and entrepreneurial processes over time. This approach automatically collects data on entrepreneur's behaviour from multiple online SNSs, which can be used to model and study the emergence, patterns, structures and dynamics of entrepreneurial networks. Moreover, it allows us to identify the main variables and important relationships vis-à-vis the entrepreneurial process and its outcome.

2.2 Network of networks (NoN)

Individuals are usually members of a number of different social networks, each based on different types of relationships and, perhaps, different communication media. We refer to the amalgamation of these networks as a Network of Networks (NoN) (Craven & Wellman, 1973; de Jesús Cruz Guzmán & Oziewicz, 2004; Garton, Haythornthwaite, & Wellman, 1997). Previous research has suggested that a network of networks should offer methodological support, promote sound design and standardization of practices, and generate up-to-date overviews of each field (Ioannidis et al., 2005). As a research approach to the study of social networks, the concept of an NoN implies that ties between individuals and ties between network clusters need to be included in the analysis of social networks (Craven & Wellman, 1973; Garton et al., 1997). For example, the concept of an NoN has been proposed in the context of human genome epidemiology studies, with the creation of an NoN which includes groups of investigators collecting data for human genome epidemiology research. Twenty-three networks of investigators addressing specific diseases or research topics and representing several hundreds of teams have already joined this initiative (Ioannidis et al., 2005). In addition, the notion of an NoN is also suggested as a new metaphor for the sociology of network society (Castells, 2000) and a dominant technological structure (De Jesús Cruz Guzmán & Oziewicz, 2004). Yet another example of the emergence of an NoN is related to the transformation of telecommunications worldwide from national network monopolies to a new system – the network of networks that it is today.

In this thesis, we draw upon previous work on NoN theory and apply this to networks in entrepreneurship. We propose that entrepreneurs' networks are in fact networks of networks. In such networks each node (e.g. entrepreneur) hosts and participates in one or more networks hosted by other nodes. We propose that none of these networks are independent, and rather than the individual network, it is the NoN that contributes to entrepreneurs' performance.

We assume that entrepreneurs use multiple online social networks. In this study, we refer to entrepreneur's online SNSs as NoNs, including LinkedIn, Facebook and Twitter. Nodes and links can overlap in an entrepreneur's NoN. We use those overlapping nodes to link the different online social networks of entrepreneurs into their NoNs. In this chapter, we will introduce a method to collect NoN data from the online social networking sites themselves.

2.3 Network data

Social network analysis provides a formal, conceptual means for thinking about the social world (Wasserman & Faust, 1994), and has been used as an approach in many fields. According to Wasserman and Faust (1994), relationships defined by linkages among units are a fundamental component of network theories. Thus, the unit of network analysis is an entity consisting of a collection of individuals and the relationships between them rather than the individual alone. Previous studies have addressed two approaches in social network analysis: socio-centric network analysis and ego-centric analysis. 'Socio-centric' or 'whole' networks comprise relationships between all the actors within a bounded group. 'Ego-centric' or 'personal' networks comprise the relationships among the people known by individuals. An 'ego' is an individual 'focal' node. Egos can be persons, groups, organizations, or whole societies (Hanneman & Riddle, 2005).

When analysing the social networks formed through online interaction, the focus can be on using a graph structure (nodes and links) or on semantics (content analysis and text analysis) (Chin & Chignell, 2010). Data collection can also be used for online social network studies. As mentioned, traditional social network analysis has generally been constrained in accuracy, breadth and depth due to a reliance on self-reported data (Eagle et al., 2009), and the majority of studies provide static snapshots and temporal mappings of networks. The internet serves as an instrument for expanding social networks in a number of ways (Ahn et al., 2007). We draw upon Boyd and Ellison's (2007) definition of online social networks as 'web-based services that allow individuals (1) to construct a semi-public profile within a bounded system, (2) to articulate a list of other users with whom they share a connection, and (3) to view and traverse their list of connections and those made by others within the system'.

Both socio-centric analysis and ego-centric analysis can be applied to online social networks to study and map the structure of virtual social networks (D'Andrea et al., 2010). The socio-centric data can be used to map the whole range of relationships between nodes, while an ego-centric analysis can be used to study the individual actors.

There are various ways of collecting data from online social networking sites. For data mining from online social networks, the techniques can be divided (according to the analysis target) into web-content mining, web-structure mining, oriented to the structure of websites, and web-usage mining, which focuses on how websites are used (Dráždilová, Obadi, Slaninová, Martinovič, & Snášel, 2010). As we proposed at the beginning of this chapter, it is the NoN rather than the individual network that contributes to entrepreneurial behaviour. In order to explore the structure and configurations of these NoNs, we collected data from the well-known online social network sites of LinkedIn, Facebook and Twitter. In the following section we will present the sources of our network data.

2.4 Data from online social network sites

Due to the widespread accessibility of the internet, more and more people have started using online social networking sites. Before we start our data mining, we will introduce the characteristics of the three online networking sites used in this dissertation. Each site uses its own mechanisms and security settings. Below, we will focus on the manner in which each online social network is used.

The ubiquitous use of computers makes it possible for people to communicate and interact with each other through online social networks such as LinkedIn, Facebook and Twitter. These three networks have become the standard social networks for contacting other people and for gathering information. Entrepreneurs find these networks especially useful for developing important contacts, which can also assist them in starting up a business. Online social networks make it easier for everybody to establish connections. Below we will discuss the main characteristics of each online social networking site.

LinkedIn is one of the major business-related social networking sites in the world. As of 2 August 2012, LinkedIn operated the world's largest professional network on the internet, with more than 175 million members in over 200 countries and territories.[2] LinkedIn encourages users to construct an abbreviated CV and to establish 'connections' (Skeels & Grudin, 2009). The users can decide what and how much data they want to share with other people. In the LinkedIn network, nodes represent people, while edges represent the connections among people. The LinkedIn online social networking site keeps a profile of each LinkedIn user. The profile information is available to the public unless the user setting is changed manually. The profile includes a user's full name, headline, location, current position, previous position, education and other information. The public can view a user's information only if the user wishes to share the data. Profiles are strictly professional, with little or no information about hobbies, political or religious affiliations, favourite music, books or movies (Skeels & Grudin, 2009). In addition to their basic profile information, the connection information for a user may also be available.

The LinkedIn graph is undirected. Edges between individuals are called 'connections', and are formed using the mutual consent model. The nodes of those who joined the LinkedIn

2 http://press.linkedin.com/about

online social network earlier have a higher connection number. This is not simply because they joined earlier but because the activity of LinkedIn users tends to slowly increase over time (Leskovec, Backstrom, Kumar, & Tomkins, 2008). The LinkedIn online social networking site can be used for employment pooling, career opportunities, consulting offers, new ventures, expertise requests, business deals, reference requests and instant messaging between contacts.

Facebook is a social networking site founded in 2004.[3] Connections among nodes in the Facebook network represent relationships of 'friendship' between people. In comparison with LinkedIn, Facebook profiles can be extensive and may include marital or relationship status, religious and political views, hobbies, birthday, favourite books, movies, music and quotations (Skeels & Grudin, 2009). Similar to the LinkedIn network, the connections on Facebook are also mutual. According to earlier research based on a Facebook graph, the Facebook network degree distribution does not follow a strict power-law model (Ugander, Karrer, Backstrom, & Marlow, 2011). The Facebook site has strict security mechanisms that protect user's data from unauthorized access, which in part accounts for its great popularity (Mavridis, Kazmi, & Toulis, 2010).

Twitter is a free social networking and micro-blogging service that enables its users to send and read messages known as 'tweets'.[4] The users of Twitter are only allowed to post 140 characters of text to display their current status. By default, these 'tweets' are available to everyone. A Twitter user can search these tweets and follow other Twitter users they are interested in without gaining their permission to do so.

The Twitter graph differs from that of the LinkedIn and Facebook networks, since the edges are directed. However, the Twitter network clearly shows that it is more likely (88%) for users to be connected in a balanced two-way relationship, which might indicate strong ties when the edges are reciprocal.

The three online social networks have an official application programming interface (API) for developers who are interested in the data arising from online social networks. The online social network API can offer access to a large amount of information depending on the target or the purpose of the developer. Table 3 depicts the information that we will collect through the API of each online social network. However, the online social networks we use do not included the removal of nodes or edges, thus in this research we did not address the loss of connections between different nodes.

3 http://newsroom.fb.com/content/default.aspx?NewsAreaId=22
4 http://en.wikipedia.org/wiki/Twitter

Table 3 Summary of data for each online social network

	Online network users	Their connections
LinkedIn	First name, last name, headline, location, country, industry, current status, picture-url	First name, last name, headline, location, country, industry, picture-url
Facebook	First name, last name, user name, gender, location, picture-url	First name, last name, user name, gender, location, picture-url
Twitter	Name, user name, description, location, time-zone, friend number, follower number, picture-url	Name, user name, description, location, time-zone, friend number, follower number, picture-url

2.5 Extracting NoN from online social networking sites

In order to extract an NoN from online social networking sites and explore the functions and structures of entrepreneurs' online social networks, we designed an online survey to collect data on entrepreneurs' online social networks. The survey website used the official Application Programming Interface (API) to collect data from the different online social networks. We used the API of each of the online social networks we studied to extract the entrepreneurs' profile and network data. Using the official API, we were able to collect actual behavioural data on the entrepreneurs – including profile information and connection information – from different social networking sites. We did not use self-reported data on networks.

We first received permission from the online social networking sites to allow us to use the official API. We then used the online social network API to obtain entrepreneurs' profiles and connection information by building a feature into our data collection website which leverages the respondent's online network data. To achieve this, respondents were asked to log onto their online social network using their own login credentials after they had been informed about the purpose of the study and how the data would be used. In other words, the network data could only be obtained after consent by the entrepreneurs, that is, after they logged in. Subsequently, the network data was transferred automatically to our server, where we stored the data from different points in time in order to allow us to model the structural network dynamics.

In order not to violate privacy regulations, our survey asked for the consent of the respondents before they logged into their online social networks. The participants first logged into their online social networks through links embedded in our online survey. Then we automatically generated a coded ID to be used rather than the respondent's name. The data was coded and stored in our database for analysis. The survey was distributed to entrepreneurs from different industries in the Netherlands. We used three ways of contacting entrepreneurs to participate our survey: (1) we invited entrepreneurs randomly through the people we had in our own networks, (2) we administered surveys through entrepreneur organizations such as consulting and social media companies and (3) we made personal visits to entrepreneurs to overcome their reluctance to participate. In addition, we put the survey website link on the server of the University of Amsterdam (UvA), and thus the domain name of the survey link contained 'UvA', which proved its legitimacy to entrepreneurs. In total the full online survey had twenty questions, the details of which are presented in Table 4.

As shown in Table 4, we first asked for the participants' gender and age. For the purposes of this study we defined people as entrepreneurs by asking whether they were the owner/founder or co-owner/co-founder of one or more ventures. If a participant was an entrepreneur, we then asked for venture demographic information to measure entrepreneurial performance in terms of the founding year, company name, revenue at the launch of the company and current situation, employee numbers at the launch of the company and current situation. Before entrepreneurs logged into their online social network sites, they consented to us using their online social network data. The online social networks used in this dissertation were LinkedIn, Facebook and Twitter. Figure 1 depicts the flow chart of the entire data collection process. The screenshots of the survey are presented in the Appendix of this dissertation.

The whole data collection process lasted for six months from April 2011 to September 2011, with 345 respondents participating in our survey. The online social networks analysed in our study consisted of LinkedIn, Facebook and Twitter, with 95,076, 59,365 and 114,907 connections respectively (see Table 5). In Chapters 3–5, we will investigate the data using different methodologies.

2.6 Simulation of entrepreneurial processes

The entrepreneurial process can be complicated in many ways. From an organizational perspective, the entrepreneurial process involved in starting and running a new venture can be described by various managerial and development life-cycle theories (Mueller, 1972; Quinn & Cameron, 1983; Smith & Miner, 1983; Torbert, 1987; Vinig, Blocq, Braafhart, & Laufer, 1998). We found that all the models follow the S-diagram. According to Torbert (1987), the entrepreneurial process can be divided into six stages: 1) Conception, 2) Investment, 3) Incorporation, 4) Experimental, 5) Systematic productivity and 6) Collaborative. In particular, entrepreneurs tend to expand their networks during the second stage of their firm's life cycle, which includes building up relationships, making personal, structural and financial commitments. Thus, we conclude that entrepreneurs tend to find their collaborators during a search period prior to starting up their business.

Table 4 Survey for data collection

Survey question	Answer & question purpose
1) Please choose your gender	• Female • Male
2) Please select your year of birth	Range from 1940-2000
3) Are you the (co)founder or (co)owner of a company?	• Yes->continue to question 5) • No->jump to 12)
4) Please state the name of your company	Name of the company (optional)
5) Please select the year when your company was launched	Range is from 1953–2011
6) How many employees (full-time and part-time) were involved at the launch of your company 7) Please choose current employee numbers (both full-time and part-time employees) at your company	• 1–5 • 6–10 • 11–20 • 21–50 • 51–100 • 101–500 • More than 501
8) What was the percentage of annual revenue growth from the first fiscal year to the second fiscal year after the launch of your company 9) Please choose the annual revenue growth of your company in the last fiscal year 10) What is the average annual revenue growth since the launch of your company	• 1%–10% • 11%–20% • 21%–30% • 31%–40% • 41%–50% • more than 50%
11) Do you have a LinkedIn account?	• Yes->continue to question 12) • No->jump to 14)
12) Please click the LinkedIn icon to log into your LinkedIn account	Note: By logging into your LinkedIn account, you will allow us to use your online data
13) For what purpose do you use the LinkedIn network?	• Personal • Business • Personal & Business
14) Do you have a Facebook account?	• Yes->continue to question 15) • No->jump to 17)
15) Please click the Facebook icon to log into your Facebook account	Note: By logging into your Facebook account, you will allow us to use your online data
16) For what purpose do you use the Facebook network?	• Personal • Business • Personal & Business
17) Do you have a Twitter account?	• Yes->continue to question 18) • No->jump to 20)
18) Please click the Twitter icon to log into your Twitter account	Note: By logging into your Twitter account, you will allow us to use your online data
19) For what purpose do you use Twitter network?	• Personal • Business • Personal & Business
20) Please enter your email address	Optional

Although we know that entrepreneurs obtain information and resources from their networks across the entire entrepreneurial process, the extent to which social networks or online social networks contribute to the entrepreneurial process remains a gap to be filled in the fields of entrepreneurship and social networks. In order to determine the influence of social networks

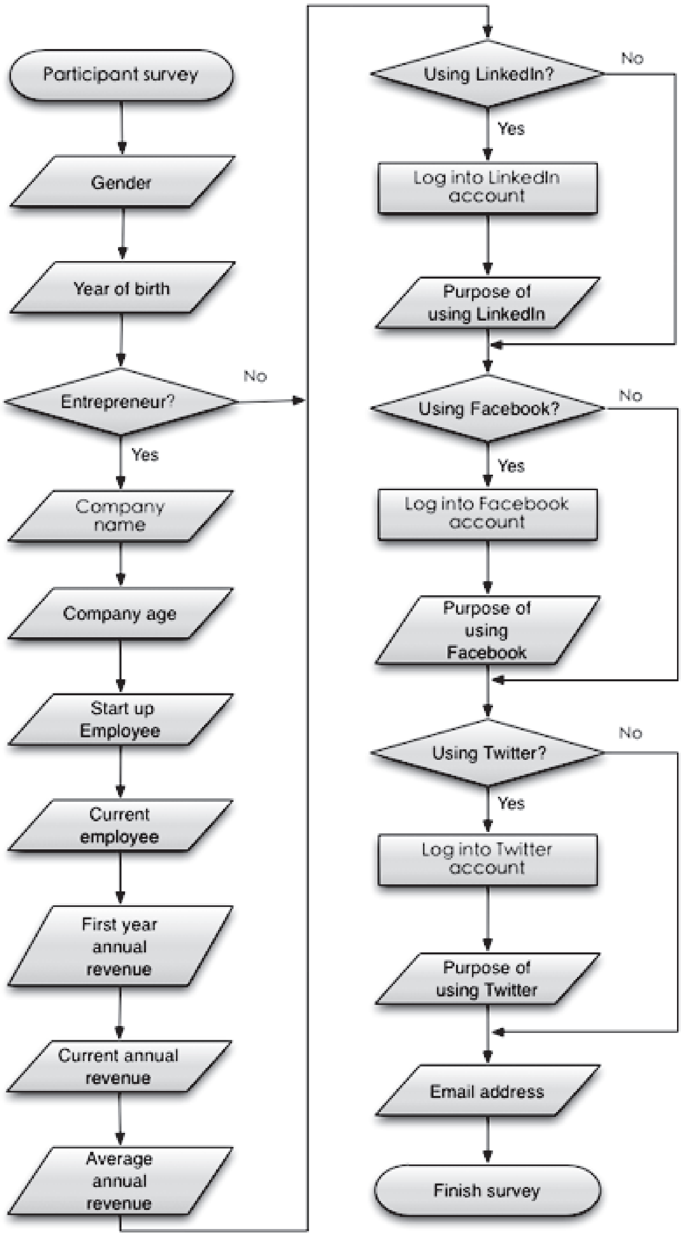

Figure 1 Survey flow chart.

Table 5 Raw data

	LinkedIn	Facebook	Twitter
Entrepreneur profiles	261	188	174
Links	95,076	59,365	114,907
Average/median links	364/249	272/215	*Following:* 396/174 *Followed by:* 628/238

on the entrepreneurial process, we focus solely on the networking part of the entrepreneurial life cycle. To do this we adapted the model of Arent Greve (1995) and Wilken (1979), rather than that of Torbert (1987). The former clearly explains the entire entrepreneurial life cycle in terms of a three-phase entrepreneurial process, which still accords with the six stages of Torbert's model but in a simplified form.

Entrepreneurs founding a business are assumed to go through three phases of entrepreneurship: 1) idea development, 2) organizing the founding of a firm, and 3) running a newly established firm (Arent Greve, 1995; Wilken, 1979). During the entire entrepreneurial process, the network supplies entrepreneurs with connections which could assist in finding information and resources. However, the mechanisms and processes whereby particular ties play a role in the development of an emerging firm remain unclear (Elfring & Hulsink, 2003). We suggest that the use of a simulation model could assist in evaluating the value of social networks in the entrepreneurial process.

According to the model developed in a previous study (Arent Greve, 1995; Wilken, 1979), entrepreneurs require different resources and information for different phases. At the beginning of the start-up phase, entrepreneurs need to find business ideas through their networks. In the first phase, they always face problems related to limited capacity, resources and new technologies. During the start-up phase, entrepreneurs search for potential collaborators from the network. The information and ideas they obtain come from strong ties in their network, such as friends, family and existing business contacts. In the second phase, entrepreneurs will start organizing their business based on the idea developed in the first phase, and strong network ties are still very important. However, during the third phase the entrepreneurial process is mainly driven by weaker ties (indirect contacts) and these become important. The connections supplied by the network assist entrepreneurs to find information and resources throughout the entire entrepreneurial process.

The simulation approach can be used to examine how entrepreneurs use networks to start up a business. We will present a network simulation model to describe entrepreneurial growth as dependent on the entrepreneur's position in a given network. The network structure that we used was extracted from the LinkedIn network. This simulation model can be used to predict entrepreneurs' maximum survival time based on a given start-up time frame and initial wealth allocated. In our model, we found that entrepreneurial growth is not only related to wealth but also related to the extent of an entrepreneur's network. Although we were not able to determine the threshold for entrepreneurial survival at a given time, we could still infer the survival probability from wealth allocated and time needed for start-up.

2.7 Discussion and conclusion

In this chapter we first reviewed the methodology used to collect social network data. Second, we introduced three online social network sites and the data stored on multiple websites. We analysed the reasons why people use online social networks and why we used the online social network to study NoNs. Third, we developed a methodology which can be used to collect NoN data. We also noted that NoN theory can be used to explain phenomena in other social science fields. In particular, we theorized that entrepreneurs' networks are networks of networks. We proposed that the structure of an NoN can be studied through data extracted from online social networking sites. NoN theory provides a new perspective for studying the entrepreneurial process throughout a venture's life.

The core idea related to NoNs is that entrepreneurs are embedded in multiple networks. Rather than individual networks, the NoN may contribute most to the entrepreneurial process in the future. We developed a methodology to collect NoN data through online social networks. However, in relation to this data, we can only observe when a new node is added to the existing network but not when connections are broken. Thus, we cannot predict from the online network whether connections will be maintained after two entrepreneurs become connected. Nonetheless, we can still test the structure of online social networks. We suggested that a simulation model can be used to study the influence of online social networks during different phases of the entrepreneurial process. In Chapter 5, we will use the simulation model to test the parameters that might be important for entrepreneurs' networks.

Our methodology and approach will contribute to the fields of entrepreneurship and social network analysis. First, we can infer entrepreneurial behaviour and social network structures. Second, our study will contribute to our understanding of how network structures influence entrepreneurial processes. Understanding the emergence of NoNs can improve our understanding of how new ventures, industries and, in fact, economies are interlinked. A deeper understanding of the structure of entrepreneurial networks can offer new ways of designing entrepreneurial business strategies and new ways of propagating new ventures, products, services and technologies. Last but not least, our methodology also contributes a novel way to access the internet to extract long-term, large-scale data on users' online social networks that can potentially be applied in other research areas. Furthermore, our approach resolves the privacy issue by inviting respondents to log onto their networks from within the online survey application, which we designed on the basis of the official API of each online social network.

This chapter introduced NoN theory and developed a novel approach to collecting data from online SNSs. In the next chapter, we will examine the data we collected through the above-mentioned approach. The aim of the next chapter is to test the methodology introduced in this chapter and explore the characteristics of each online social network.

CHAPTER 3

The Diversity of Entrepreneurs' Online Social Networks[1]

Abstract

This chapter is based on a pilot study undertaken during the data collection process. The purpose of this chapter is to test the methodology introduced in the previous chapter. We first study network diversity for entrepreneurs in the gaming industry. Based on our results, we decided to examine the structure of the online social networks of these entrepreneurs' in terms of their network size and the diversity of different online SNSs. In particular, we investigate the structure of entrepreneurs' social networks by analysing the diversity of their online network in relation to the industries in which their contacts are involved and their location. When we started this analysis, the data collection process was still continuing. Therefore, we used part of the data to explore the characteristics of entrepreneurs' online social networks. In total, data from 184 entrepreneurs was used in the analysis. Our findings suggest that entrepreneurs use multiple online social networks that form their NoN, which is consistent with the theory we presented in the previous chapter. We also examine the entrepreneurs' network size and diversity to gauge their impact on performance in terms of survival. We hypothesize that both the network size and its diversity are strongly related to the survival rate of entrepreneurs. Our findings suggest that the LinkedIn network size has a positive relationship with entrepreneurial survival, the size of an entrepreneurs Facebook network is not related to survival, while the size of their Twitter network has a negative relationship to entrepreneurial survival. We did not find any obvious influence of network diversity on venture survival. We then visualized the entrepreneurs' LinkedIn network using industry diversity, and reflect on the implications for future research on the structure of entrepreneurs' online social networks.

1 This chapter is based on a paper which was published in a special issue of *International Journal of Organisational Design and Engineering*, 'Entrepreneur online social networks – structure, diversity and impact on start-up survival', Vol. 2, No. 2, 2012.

3.1 Introduction

Social network analysis aims to uncover the complex relationships between groups and communities. As introduced in the previous chapter, social networking sites and recently online social networks such as LinkedIn, Facebook and Twitter are attracting the attention of many users. Entrepreneurs in particular are using different online social networking sites to share information and ideas with other people in their network as well as seek opportunities and resources. The increasing use of the internet means that the use of online social networks is becoming ubiquitous, making it an opportune time to study them. Meanwhile, the internet is also becoming a necessary platform for entrepreneurs to use in building their own networks (Baum, Calabrese, & Silverman, 2000; E. L. Hansen, 1995; Larson, 1991; Nann et al., 2010). Thus, it becomes possible to investigate their interactions and collaborations using data gathered from their online social networks. However, we need to know more about the structure of entrepreneurs' online social networks and the extent to which social networking contributes to their business success, if at all.

Entrepreneurs are connected with and embedded in a small number of stable exchange relationships, which can be understood as a network involving other entrepreneurs and potential collaborators. These relationships collectively form small yet dense networks of ties integrating a handful of firms. The individuals and companies in these networks provide critical information and resources required for the start-up period of entrepreneurial ventures. Thus, the nodes that entrepreneurs connect to tend to be those useful in accessing valuable information and resources at different stages of the start-up process.

Previous research suggests that economic opportunities are more likely to come from contacts outside a tightly knit local friendship group (Eagle, Macy, & Claxton, 2010). In other words, the diversity and composition of a nascent entrepreneur's social network will affect their access to information and resources and influence the likelihood of successfully starting a business (Renzulli, Aldrich, & Moody, 2000). In order to understand whether the structure of entrepreneurs' networks matters to entrepreneurship, in particular whether the diversity of entrepreneurs' social networks is relevant to entrepreneurial survival, we need to move beyond mere descriptive accounts to more in-depth explanations. Thus, we analysed the online social network data collected using the methodology we introduced in Chapter 2.

This chapter is based on a pilot study undertaken during the data collection process. The purpose of this chapter is to test the methodology introduced in the previous chapter. We first studied the diversity of the networks of entrepreneurs involved in the gaming industry.

Our pilot study showed that entrepreneurs in the gaming industry tend to have very diverse networks. Therefore, we continued to test the structure of entrepreneurs' online social networks in terms of network size and the diversity of their different online SNSs. In particular, we analysed the diversity of their online networks in relation to the industry in which their contacts were involved and the location of these contacts.

In the following, we first present the theory relating to network size and network diversity. We then introduce the results of our survey of the LinkedIn networks of entrepreneurs in the gaming industry and visualize this network. We further analyse the size and diversity of entrepreneurs' networks in relation to multiple online social networking sites, attempting to determine the effect of network diversity on entrepreneurial survival. In addition, we then compare the diversity of entrepreneurs' use of the online social networks, LinkedIn, Facebook and Twitter. Finally, we visualize the entrepreneurs' network across different industries.

3.2 Network measurement

3.2.1 Network size

Network size refers to the number of network actors (Burt, 1983). The larger the network is, the greater the amount of information that circulates in it. Previous studies have shown that the size of the network has a positive influence on entrepreneurial success (Baum et al., 2000; E. L. Hansen, 1995). It is suggested that smaller companies overcome some of the disadvantages of their limited size (information, resources, range within the network) by having an extensive network (Doloreux, 2004).

3.2.2 Network diversity

Network diversity refers to several dimensions and there are several definitions of diversity (Harrison & Klein, 2007). Diversity is a unit-level, compositional construct which can be used to describe the distribution of differences among members of a unit with respect to common attributes, such as tenure, ethnicity, gender, conscientiousness, task attitude, or pay (Harrison & Klein, 2007). The diversity of networks includes the diversity contributed by the nodes within a certain network. Diverse networks help people contact other social realms and restrict the amount of redundant information gathered (Renzulli et al., 2000).

The conclusions of previous work on the impact of network diversity on entrepreneurial performance are not unanimous. On the one hand, it is argued that entrepreneurs tend to become more successful if they gain access to diverse information and resources in their network (Brüderl & Preisendörfer, 1998). The resulting diversity of ideas expressed and the tolerance of competing viewpoints should, over time, facilitate group creativity and divergent thinking which would assist the generation of new business ideas (Goncalo & Staw, 2006). In other words, the diversity of a social network can enhance the breadth of a perspective, cognitive resources, and the overall problem-solving capacity of the group (Hambrick, Cho, & Chen, 1996) and thereby enhance entrepreneurial performance in relation to specific ventures and performance throughout the entire network. On the other hand, it has also been found that the diversity of demographic features can have a negative effect on team output (Harrison & Klein, 2007). Diverse social networks may contribute to communication problems and conflicts among different actors and thereby also decrease the performance of the networks.

Granovetter (1973) elaborated on the diversity of networks by distinguishing between strong ties, consisting of relationships with high levels of emotional underpinning, and weak ties, meaning relationships with a small emotional component but with greater rationality. In other words, weak ties are the source of network diversity. Network diversity describes the degree to which contacts are structurally 'non-redundant,' and there are both first-order and second-order dimensions of redundancy (Aral, Muchnik, & Sundararajan, 2009). The non-redundant nodes are connected by a structural hole. Individuals whose network is rich in structural holes have access to more opportunities, information and resources (Burt, 1992). Our research on network diversity will help us understand the configuration of entrepreneurs' online social networks as well as whether these kinds of structures can be of benefit to entrepreneurial survival.

3.3 The LinkedIn network for the gaming industry

Our first empirical study was based on the data collected from entrepreneurs in the gaming industry in the Netherlands. This section aims to test the methodology we developed in the previous chapter. To investigate the structure of entrepreneurs' online social networks, we used LinkedIn data to conduct our first test. We selected 63 entrepreneurs from our dataset, all from the gaming industry. This is because this industry is relatively unknown and young. The level of entrepreneurial activity of the firms involved in the gaming industry is very high, while more than half of the revenue derived from the industry comes from developing, producing, publishing or promoting games. There are many potential opportunities for entrepreneurs in the gaming industry.

All 63 entrepreneurs including their connections make up the network. In total, we found 23,067 unique nodes within the entire gaming industry network. The average number of employees is 12, and most of the firms were founded recently (young entrepreneurial ventures). As shown in Figure 2, we mapped the entrepreneurs' online social network by industry. We used Gephi (Bastian, Heymann, & Jacomy, 2009) for graph visualization and layout. Gephi is an open source software for exploring social networks especially for large amount of network data. Figure 3 colour-codes and lists the percentage involvement of an industry. As we can see, the gaming industry has a huge potential market, attracting connections from both gaming industry firms and firms in other industry fields. The graph of the entrepreneurs' online social networks implies that they have very diverse networks. In the next section, we will test these hypotheses with regard to both network size and network diversity.

Based on the visualization in Figure 2, the gaming industry is very heterogeneous. Within the industry there are several different kinds of companies active in different places within the value chain, with two distinctive kinds of company to consider in particular. On the one hand, we have companies who develop and produce games, and on the other, we have publishers who deliver the games to the market. Developers have a different online social network compared to publishers, and even within the developers' branch there are differences among the links within their networks. Previous research has shown that the personal social networks of people are influenced by socio-demographics, behaviour and other characteristics (McPherson, Smith-Lovin, & Cook, 2001).

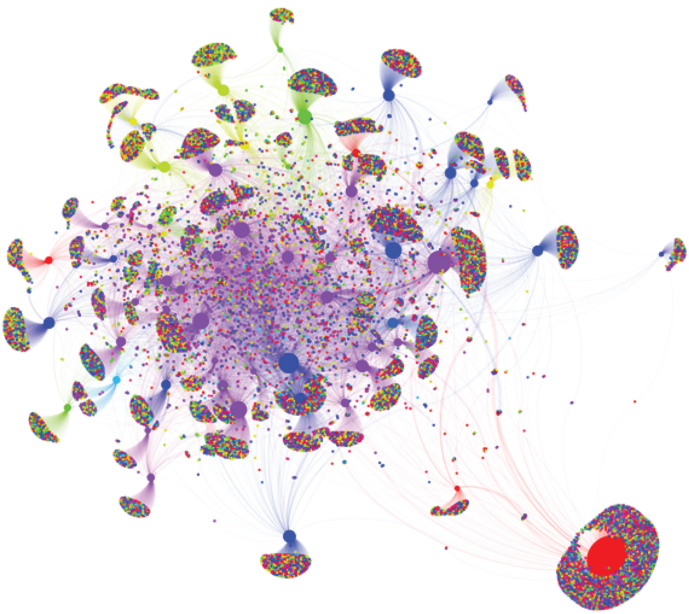

Figure 2 Gaming industry entrepreneurs' online social networks by industry.

Figure 3 Colour-coding and percentage involvement for each industry.

3.4 Multiple networks and entrepreneurial survival

3.4.1 Hypotheses

When we started the analysis of this chapter, the data collection process was still continuing. Therefore, we used part of the data to explore the characteristics of entrepreneurs' online social networks. In total, data from 185 entrepreneurs was used in the analysis. Each entrepreneur was involved in different online social networking sites. We tested the network diversity and entrepreneurial survival based on data from multiple online social networks. Before we start our analysis, we will review the literature on venture survival.

According to Geroski (1995), the survival rate for most market entrants is low, and a successful entrant may take more than a decade to achieve a size comparable to that of the average incumbent. Furthermore, the literature also suggests that the entry of innovative firms is more common but less successful than entry by diversification. Studies of offline social networks have shown that entrepreneurs who are well connected are more successful (Baum et al., 2000; Raz & Gloor, 2007; Schilling & Phelps, 2005; Uzzi, 1997; Uzzi & Spiro, 2005).

There is empirical evidence for the importance of social networks for entrepreneurial performance in offline settings. We aim to investigate if the same holds true in the online realm, by comparing online social network structures and entrepreneurial performance. We need to take into consideration that measuring the performance construct is difficult, given its multidimensional nature (Cameron, 1978; Chakravarthy, 1986). Furthermore, in the context of entrepreneurial start-ups, general performance measures, such as profit, are somewhat misleading, given initial (sunk) costs that need to be regained (Bosma, van Praag, Thurik, & de Wit, 2004).

Our data included a snapshot view at one particular point in time rather than longitudinal data. In cases where revenue information over time was not available, indirect performance measures such as the percentage change in revenues and number of employees was used. Network structure is one of the most frequently used approaches to evaluating the network role in entrepreneurship. We derived a set of hypotheses using network size and network diversity as proposed by Witt (2004).

Small social networks are effective in conserving resources, while large networks enable the acquisition of new resources (Garton et al., 1997). A high number of links means the possibility of obtaining diverse information (Arent Greve, 1995). In other words, larger social networks exhibit more heterogeneity in the social characteristics of the network members and more complexity in the structure of these networks. Hence, the first two hypotheses concern network size and network diversity:

- ***Hypothesis 1a:*** *Entrepreneurs' online* **network size** *is positively related to the survival of their new venture.*
- ***Hypothesis 1b:*** *Entrepreneurs' online* **network size** *is positively related to* ***network diversity****.*

If the network actors have similar backgrounds and work experience, they can share information and their experiences more easily. However, this will also limit the information and resources that they can obtain from their network. A variety of differences with respect to relevant dimensions (e.g., sex, age, race, occupation, talents) can assist the entire network to obtain new resources, which can contribute to entrepreneurship and innovation (Burt, 1983). Entrepreneurs with better and more diverse interpersonal connections tend to earn more income and are more frequently promoted (Burt, 1997; M. Granovetter, 1985). Organizations and entrepreneurs start networking with each other to gain access to critical resources, but they also rely on information from the industry network to determine whom to approach for any critical resources and the possibility of establishing new relationships (Gulati & Gargiulo, 1999).

Entrepreneurs, active agents who organize resources, are a critical element in the formation and viability of innovative industries and clusters (Feldman, Francis, & Bercovitz, 2005). According to Feldman et al. (2005), industrial clusters can best be defined as an agglomeration of mutually reinforcing ventures and aligned interests that play an important role in the development of entrepreneurial ventures. Several studies have found significant evidence of the positive impact of industrial clusters on entrepreneurship, with a high number of linkages with industry-related businesses (strong industrial clusters) having a positive influence on a venture's performance in the early stages by providing better access to valuable resources that assist in commercializing products and services (Delgado, Porter, & Stern, 2010; Feldman et al., 2005; Raz & Gloor, 2007). To further understand the structure of entrepreneurs' online social networks and whether entrepreneurs are also clustered in online social networks, we tested the following hypothesis regarding industry diversity:

- ***Hypothesis 2a: The industry diversity*** *of entrepreneurs'* ***LinkedIn networks*** *is positively related to their entrepreneurial survival.*

Entrepreneurs tend to become more successful if they gain access to most of the information and resources in their network (Brüderl & Preisendörfer, 1998). There is a common opinion that people share information with the people who are close to them. In offline networks, geographical proximity facilitates information sharing. We tested the following hypotheses on the relationship between the geographical diversity of online social networks and their performance in terms of survival. Most importantly, we investigated whether the geographical diversity of different online social networks influences their entrepreneurial survival. Thus we propose:

- ***Hypothesis 2b: The geographical diversity*** *of entrepreneurs'* ***LinkedIn networks*** *is positively related to their entrepreneurial* ***survival.***
- ***Hypothesis 2c: The geographical diversity*** *of entrepreneurs'* ***Facebook networks*** *is positively related to their entrepreneurial* ***survival.***

- ***Hypothesis 2d: The geographical diversity** of entrepreneurs' **Twitter networks** is positively related to their entrepreneurial **survival.***

Diversity is often used in research in the fields of sociology, ecology and most areas of communication. We adopted the Blau Index of Variability (Blau, 1977) to measure the diversity of entrepreneurs' online social networks. The Blau diversity index is defined as:

$$1 - \sum p_i^2$$

where p is the proportion of categories in a given category and i is the number of different categories of the feature across all groups. For example, if an entrepreneur has 100 connections from 50 different countries, then p is the proportion of the entrepreneurs coming from the city i (i is from 1 to 50). A perfectly homogenous network will have a diversity index of 0 (e.g. all entrepreneurs coming from the same city), and a perfectly heterogeneous network will have a diversity index of 1 (e.g. all entrepreneurs come from different cities). As the number of categories increases, the maximum value of the diversity index increases. Table 6 summarized our hypotheses.

Our data was collected using the methodology described in the previous chapter. In total, 345 respondents participated in our survey. We filtered out non-entrepreneurs and respondents from outside the Netherlands. We selected 185 entrepreneurs who shared their LinkedIn

Table 6 Overview of hypotheses

	Measurement	Hypotheses
Size	Online Social Network Size	**Hypothesis 1a:** Entrepreneurs' online network **size** is positively related to the **survival** of their new venture
		Hypothesis 1b: Entrepreneurs' online network **size** is positively related to network **diversity**
Diversity	Industry Diversity	**Hypothesis 2a:** The industry **diversity** of entrepreneurs' LinkedIn networks is positively related to their entrepreneurial **survival**
	Geographic Diversity	**Hypothesis 2b:** The **geographical diversity** of entrepreneurs' LinkedIn networks is positively related to their entrepreneurial **survival**
		Hypothesis 2c: The **geographical diversity** of entrepreneurs' Facebook networks is positively related to their entrepreneurial **survival**
		Hypothesis 2d: The **geographical diversity** of entrepreneurs' Twitter networks is positively related to their entrepreneurial **survival**

network information with us. We assume that the LinkedIn network would be more relevant to our study and thus we only selected entrepreneurs who had LinkedIn accounts. Of these 185 entrepreneurs, 114 had both a LinkedIn network and a Facebook network, while 78 used all three online social networks. Table 7 presents a detailed breakdown of our data.

Entrepreneurs' online social networks are highly heterogeneous, with an average industry diversity index of 0.65 and an average geographical diversity index of 0.67–0.97. Our data suggests that using multiple online social networks (NoNs), increases an entrepreneur's network heterogeneity, with a diversity index of 0.97. About 58–61% of entrepreneurs used two online social networks, while 42% used three online social networks, which suggests that entrepreneurs do not limit themselves to one online network but tend towards an NoN.

Table 7 Network data description

	LinkedIn	LinkedIn + Facebook	LinkedIn + Facebook + Twitter (NoN)
Number of Respondents	185	114 (61%)	78 (42%)
Average Network Size (Nodes)	316	137 (Facebook nodes)	281/481 (Twitter friends/followers)
Average Industry Diversity Index	0.65		
Average City Diversity Index	0.87	0.67	0.97

3.4.2 Entrepreneurial survival

As we reviewed in Chapter 1, building a new company is a highly competitive and risky endeavour (Stuart et al., 1999), hence, entrepreneurs who start new ventures need to continuously seek opportunities and mobilize resources (Aldrich & Auster, 1986). According to Geroski (1995), the survival rate for most entrants is low, and a successful entrant may take more than a decade to achieve a size comparable to that of the average incumbent. Furthermore, the results suggest that the entry of innovative firms is more common but less successful than entry by diversification.

There are three kinds of possible measurements to evaluate the success of an entrepreneurial endeavour (Witt, 2004). The first is based on self-evaluations by entrepreneurs of the success of their business. However, this is a somewhat subjective measure as different entrepreneurs are not equally satisfied about their performance, and therefore it is not suitable to study the success of start-ups (Chandler & Hanks, 1993). The second measure considers the survival year of new start-ups. The difficulty of taking firm survival into account is the determination of a minimum time period for survival. A short survival period might only cover a small part of the initial entrepreneurial phase and a long survival period might include established, developed companies instead of start-ups. Previous studies use a three to five year time frame when using survival as a parameter of entrepreneurial performance (Brüderl & Preisendörfer, 1998; Gartner, Starr, & Bhat, 1999). The third measurement of success is the growth rate of the company (Brüderl & Preisendörfer, 1998; Witt, 2004). The most commonly used growth rates are sales growth (Brüderl & Preisendörfer, 1998) and employment growth (Baum et al., 2000).

Studies of offline social networks have shown that entrepreneurs who are well connected are more successful (Baum et al., 2000; Raz & Gloor, 2007; Schilling & Phelps, 2005; Uzzi, 1997; Uzzi & Spiro, 2005). There is empirical evidence for the importance of social networks for entrepreneurial performance in offline settings. We aim to investigate whether the same holds true in the online realm by linking online social network structures to entrepreneurial survival. However, we need to take into consideration that measuring the performance construct will be difficult given its multidimensional nature (Cameron, 1978; Chakravarthy, 1986). Furthermore, in the context of entrepreneurial start-ups, general performance measures, such as profit, are somewhat misleading given initial (sunk) costs that need to be regained (Bosma et al., 2004).

In this chapter, we used non-financial entrepreneurial performance measures (Bosma et al., 2004; Bouchikhi, 1993; Gimeno, Folta, Cooper, & Woo, 1997; Lumpkin & Dess, 1996; Singh, 1997), namely 'survival' to represent the performance of a new venture. In the context of this study, survival refers to the hazard of business ownership. Information was available on the survival time of the start-ups in our study. On this basis, we constructed a variable measuring the number of years that a firm had been active.

Our data included a snapshot view at one particular point in time rather than longitudinal data, which would have supported the use of Compound Annual Growth Rate (CAGR) as a performance measure and allow the results to be compared between the ventures. In cases where revenue information over time is not available, indirect performance measures such as the percentage change in revenues and in the number of employees can be used. However, this study focuses solely on survival as a measurement of performance. In the following section we will present the results of our analysis of the effect of the entrepreneurial network structure on performance in terms of survival.

3.5 Results

All the entrepreneurs in our study use LinkedIn. In the first step in the analysis, we performed a one-way ANOVA for LinkedIn industry diversity and company age to test the similarities among different groups (Table 8). We grouped the industries into ten categories. The respondents belonged to six of these – industrial materials, service, health, financial, IT and telecommunication industries – though their networks were linked to nodes in all ten categories. We found that respondents in each of the categories had distinctively different levels of industry diversity ($F_{(5,183)} = 4.786$, $p < 0.001$). They were also are significantly different in terms of company age ($F_{(5,183)} = 3.968$, $p = 0.002$). Among the groups, those in the service industry had the lowest industry diversity in their online social networks, with the rest of the groups being at the same level. The health industry had the highest company age, with the rest of the groups being at the same level.

We propose that the size of an entrepreneur's network is related to performance. In Table 9 we present the results of the second step of our analysis, a regression analysis testing the correlation between online social network size and venture survival.

Table 8 ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Industry diversity	Between Groups	.228	5	.046	4.786	.000*
	Within Groups	1.698	178	.010		
	Total	1.926	183			
Company age	Between Groups	418.065	5	83.613	3.968	.002*
	Within Groups	3,750.668	178	21.071		
	Total	4,168.734	183			

Table 9 Regression coefficients with survival as the dependent variable

Predictors	P-value (Std. ß)
LinkedIn network size	.01 (0.28)*
Facebook network size	.83 (0.02)
Twitter network size	.03 (-0.20)*
The age of entrepreneurs	.00 (0.43)*
R_2 ($R_{2\ adj}$)	*38% (34%)*

The results suggest that the LinkedIn network size is significantly related to entrepreneurial performance in terms of survival (Hypothesis 1a). However, Facebook network size has no correlation with performance in terms of survival, while Twitter network size is negatively related to entrepreneurial performance in terms of survival. The results of this study suggest that the entrepreneurial survival rate will increase as the LinkedIn network size increases, while an entrepreneur's survival rate will decrease as their Twitter network increases. This model as a whole explained 34% of the variance in entrepreneurial performance in terms of survival and implies that LinkedIn network size has a positive relationship to entrepreneurial survival. A plausible explanation is that entrepreneurs might use Facebook for purposes other than business. Twitter, which is a directed network, has both friends and followers. Twitter, which had a negative effect on survival rate, may require more 'online time' and if this is indeed the case, it may impact on entrepreneurs performance. In this chapter, we did not include measurements for the time spent by entrepreneurs on each of their online social networks. This may be an interesting topic for future research.

These results indicate that an entrepreneur's use of LinkedIn, in terms of LinkedIn network size, is positively correlated to a venture's survival. However, there was no causality found between network size and venture survival in this study. A future study should address the question of whether online social network size is the cause or the consequence of new ventures.

No relationship was found between online social network diversity and entrepreneurial performance in terms of the number of employees and revenue growth. We conducted a regression analysis with regards to the diversity in the network and found that entrepreneurs' online network diversity has no relationship with performance in terms of survival (Hypothesis 2a-Hypothesis 2d). This could be due to the data on survival not being strong enough to explain entrepreneurs' performances in terms of survival.

In order to explore future steps for this research project, we carried out a correlation analysis on all of the study variables we used. We found that industry diversity is correlated with network size (Hypothesis 1b), while geographical diversity also demonstrates a significant correlation with network size. Similar to our result for Hypothesis 1a, there was no causality found between geographical diversity and online social network size. Due to the lack of longitudinal data, we aim to explore the causality between online social network size and entrepreneurs in the next phase of our study, which will take place in the future.

We examined the degree of centrality relative to the network map generated based on the entrepreneurs' LinkedIn accounts using Gephi (Figure 4) (Bastian et al., 2009). The dataset

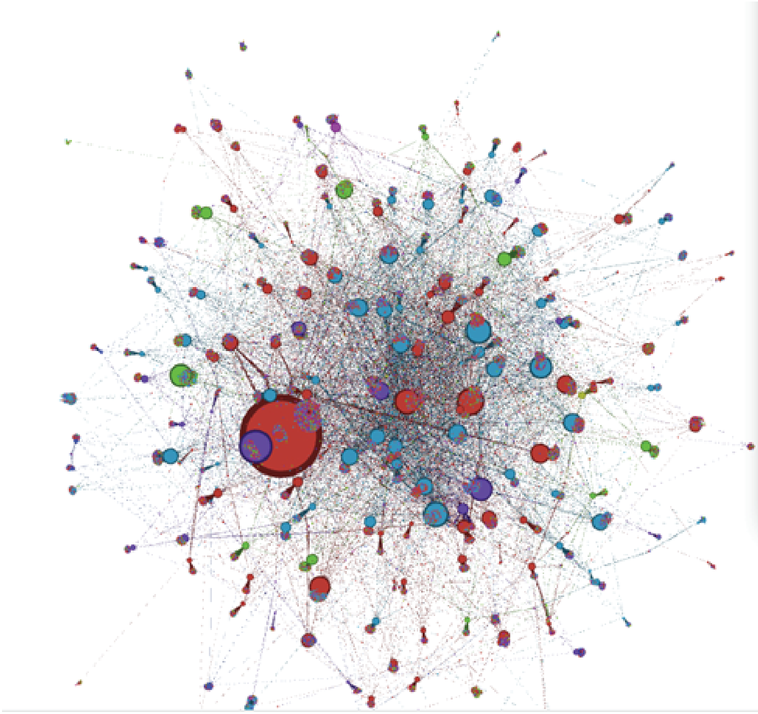

Figure 4 Entrepreneurs' LinkedIn network structure by degree of centrality.

includes 185 respondents and a network of more than 58,000 nodes. The circle size depicts an entrepreneur's importance in terms of degree of centrality and network size. The different colours of the nodes represent different industries. The industries in which entrepreneurs have networks showing a higher degree of centrality (larger networks) are business services, IT and the financial industries.

3.6 Discussions and conclusions

In this chapter we first explored and mapped the entrepreneurs' LinkedIn networks. We selected 63 entrepreneurs from the gaming industry from our database. We found that entrepreneurs tend to build a very diverse network when starting up their businesses. Based on our first analysis, we continued to test our hypotheses by analysing online social network data from LinkedIn, Facebook and Twitter. We included 185 entrepreneurs, of which 114 used LinkedIn and Facebook, and 78 used LinkedIn, Facebook and Twitter. Our dataset includes more than 58,000 nodes. Although our method was used in this chapter to generate a snapshot view of the networks, it can also be used for longitudinal studies, in which the dynamics of the networks can be explored over time. As mentioned in the previous chapter, our method improved the quality of the data in comparison to self-reported data used in previous studies of social networks.

We used the data to study the structural diversity of entrepreneurs' networks and conducted an analysis of the impact of the networks on entrepreneurial performance in terms of survival. We found that the LinkedIn network size is positively correlated with performance in terms of a venture's survival. In other words, entrepreneurs who survive longer have more online connections than other entrepreneurs. This result further confirms that entrepreneurs' online social networks are important (Nann et al., 2010). However, we did not find a clear causal link in this research. In other words, it was not clear whether the entrepreneurs survive because of the online social network degree, or whether the online social network degree results in a higher survival rate. This remains a question for future research.

Our research also found that network diversity is not related to a venture's survival. Previous studies have shown that the nature and effects of diversity remain uncertain (Harrison & Klein, 2007). Although previous studies have also shown that diversity in an individual's relationships is strongly correlated with the economic development of communities (Nathan Eagle et al., 2010), the effect of network diversity does not seem to be relevant in our study. One of the reasons for our result might be that entrepreneurs tend to use their online social networks for multiple reasons, as mentioned in Chapter 1, such as information exchange, social support, friendship, recreation, common interests and technical support (D'Andrea et al., 2010; Ridings & Gefen, 2004).

This chapter makes several important contributions. First, it demonstrates the feasibility of a novel approach to accessing and collecting online social network profiles and network information. The results suggest that the structure of online social networks in terms of network diversity differs from what had been expected. Entrepreneurs tend to have very diverse networks. However, not all of the networks are related to each other, which can be interpreted to mean that entrepreneurs do not use all of their online social networks for business purposes, or that the purposes for which entrepreneurs use online social networks differs.

Secondly, as a contribution to the literature on online social networks, which has primarily focused on private use, our study provides new insights into the use of online social networks by entrepreneurs and the effect of this on entrepreneurial survival. In relation to the literature on entrepreneurship, we thus provide some initial insights into aspects of online social network structures that positively influence performance and how this influence may differ from that of offline social networks. The literature shows that within the online communities, the similarities are extremely high (Bisgin et al., 2010), which means that network homophily theory (McPherson et al., 2001) holds true for online social networks. However, this conflicts with our dataset, with the study in this chapter revealing that the online social networks of entrepreneurs in the gaming industry are very diverse.

Thirdly, in this chapter we found that LinkedIn seems to be more relevant to entrepreneurship in terms of network size. However, this does not mean that we suggest that entrepreneurs use the LinkedIn network more than other social media. The Facebook network has a small-world effect and six degrees of separation, as confirmed on a truly global scale according to a previous study (Ugander et al., 2011). In other words, individuals on Facebook potentially have distant borders for their networks. Due to the large number of friends of friends, individuals might have more connections, but they are very weak ties. This may be an interesting aspect for entrepreneurs using Facebook networks in the future. The Twitter network did not appear important in our study, especially with respect to the Twitter network size. One of the reasons for this is that Twitter is used more for micro-blogging than social networking. Thus, the content of the networks might be interesting for future research.

However, we cannot overlook the importance of online connections for the formation of weak ties, since most of the entrepreneurs identify opportunities through their weak ties (Elfring & Hulsink, 2007). Even though this chapter could not explain the underlying causes of the conflicting results, the characteristics of the internet allow individuals, in particular entrepreneurs, to connect with people in distant places. Although online community users generally have a trusting attitude towards others in terms of fairness, trust and helpfulness, this attitude is not transferred to specific individuals they meet online, indicating that the online community lacks the capacity to create the deeper relationships or attachments between its members which are naturally formed in physical communities (Junghee Lee & Hyunjoo Lee, 2010). This difference between offline and online relationships suggests that trust among nodes in online social networks would be a worthwhile topic for future research.

Last but not least, empirical research on entrepreneurial network dynamics has been limited by a lack of longitudinal and process-oriented data. Consequently, the research addresses neither the emergence or dynamics of networks over time, nor provides links to venture performance. The study discussed in this chapter showed that it is possible to collect entrepreneurs' behavioural data automatically. It also implies that it is possible to collect online social network data longitudinally for a dynamic network analysis.

As mentioned above, in this chapter we studied entrepreneurs' online social networks from the perspective of network characteristics such as network size and network diversity. In order to further study the underlying mechanisms of online social networks, in the following chapter we will investigate the structure of entrepreneurs' online social networks and their distribution.

CHAPTER 4

Entrepreneurs' Online Social Networks: Networks of Networks[1]

Abstract

In view of the importance of networks for entrepreneurs, the study presented in this chapter is intended to fill a gap in the literature pertaining to the structure and entrepreneurial use of online social networks such as LinkedIn, Facebook and Twitter. We have suggested in the previous chapters that entrepreneurs use multiple online social networks as NoNs. In this chapter, we focus on the distribution of entrepreneurs' online social networks. Using the theory of weak ties, we explore the community overlaps among different online social networks by removing the edges with the highest betweenness values. In addition, we merge the data from the three online social networks to study the structure of the entrepreneurs' NoN. Finally, we also present a visualization of the entrepreneurs' online social networks as an NoN. Our analysis suggests that the entrepreneurs' NoN follows an exponential degree distribution, which implies that weak ties between individual networks play an important role in forming entrepreneurs' NoNs. Furthermore, we find overlaps between entrepreneurs' neighbours across the NoN, which suggests that entrepreneurs develop and use NoNs to support the entrepreneurial process.

1 A revised version of this chapter was submitted to Journal of Business Research on October 16,2012.

4.1 Introduction

Online social networks provide us with a powerful means of sharing, organizing and connecting with contacts. The benefits of online social networking sites have already been evaluated by various researchers (Ellison et al., 2007; Garton et al., 1997). It has been shown that successful entrepreneurs have more online connections and, in particular, more connections with peers from their alumni networks than less successful entrepreneurs (Nann et al., 2010).

The ubiquitous usage of the internet via computers and smart phones has increased human communication and interaction, and the emergence of online social sites such as LinkedIn, Facebook and Twitter offer an opportunity to study and further understand the structure of social networks. However, previous research has mainly focused on individual networks using a single online social networking site rather than the integration of multiple networks and sites. Different online social networking sites provide both profile and network data for different purposes. Moreover, immediately after joining one of the online social networking sites entrepreneurs tend to expand their network. By combining the network data available through different online social networks it is possible to study the entrepreneurs' NoNs (Craven & Wellman, 1973; De Jesús Cruz Guzmán & Oziewicz, 2004; Garton et al., 1997) and discern the potential of these networks.

Each online networking site provides us with network information, including an entrepreneur's profile information and connection information. As online social networking sites are free and open to all, it is more likely that any node of any online social networking site will be the same as a node on a different online social networking site. We can extract different network groups from online social networking sites. Consequently, an entrepreneur's online social network is in fact made up of all the network groups from different online social networking sites, which can be integrated into one large network, as mentioned in Chapter 2. We refer to the amalgamation of these networks as a 'Network of Networks' (NoN) (Craven & Wellman, 1973; De Jesús Cruz Guzmán & Oziewicz, 2004; Garton et al., 1997).

In this chapter, we investigate online social network data from the perspective of an NoN. The data was collected using the methodology introduced in Chapter 2. As we mentioned earlier in this dissertation, our data uses the online social network Application Programming Interface (API) to automatically extract the entrepreneurs' profile and network information. By analysing the NoN data, we aim to model and study the emergence, patterns, structures and dynamics of the entrepreneurial use of NoNs. We developed the following research questions:

- What structures and patterns of entrepreneurs' online social networks can be discerned?
- Do all of the entrepreneurs' online social networks share the same structure?
- What structure does our entrepreneurs' NoN have?

We will first present the theoretical background to the research in Section 2. In Section 3, we describe the characteristics of the data we will use in this chapter. In Section 4, we will analyse the pattern of the network and map the entrepreneurs' NoN. Our research allows us to identify the main variables and important relationships between the NoN and entrepreneurial performance. We conclude with a discussion of the limitations of this research and examine future research directions.

4.2 Theoretical framework

4.2.1 Network structures

Previous studies of network structures have identified random networks (Erdös & Rényi, 1960) and scale-free networks (Barabási, Albert & Jeong, 2000) as the dominant network structures. In random networks, every node has the same probability of being connected to other nodes in the network. Random graphs were first presented by Erdös and Rényi (1960). In their model, a probability space of graphs is denoted G(n, M), where n is the number of nodes in the graph and M is the number of edges in the graph. The model describes a probability distribution over all possible graphs with n nodes and M connections. Erdös & Rényi (1960) suggested that networks in communication studies and the life sciences could be effectively modelled by connecting their nodes with randomly placed links, and concluded that most nodes will have approximately the same number of links.

In a random network, the degree distribution in G follows a Poisson distribution (Erdös & Rényi, 1960). Nodes with a degree that deviates from what is expected are exceedingly rare. Thus, nodes with a very low degree, which are only connected to a few other nodes, only occur infrequently. Nodes with many more connections than the average are a veritable anomaly. Figure 5 shows the complementary cumulative distribution function (CCDF) of a random network on linear, semi-logarithmic and double-logarithmic scales.

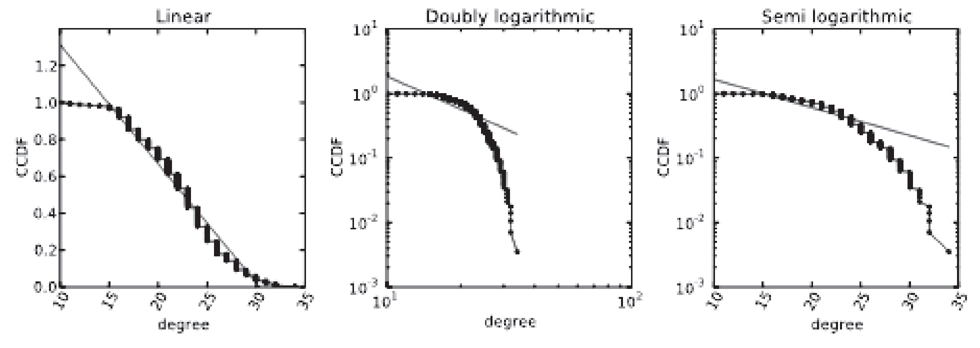

Figure 5 CCDF of a random network on different scales.

The other dominant network structure is the scale-free network, as developed by Barabási et al. (2000). In a scale-free network, the following relationship should (by approximation) hold:

$$P(k) \sim k^{-\gamma},$$

where P(k) is the rank of k. The relationship between P(k) and k appears as a straight line on a double-logarithmic plot. In scale-free networks, the degree distribution follows a power-law form (Barabási, 2002). In other words, a few nodes have the most connections and act as hubs within the network. These hubs connect a large number of people and therefore have an important position within the network. The characteristics of scale-free networks mean that they are robust when a *random actor* is removed from the network. However, as shown by the example of the internet router network, the removal of just a few *key hubs* from a scale-free network splinters the system into tiny groups of hopelessly isolated routers (Barabási et al., 2000; Barabási & Bonabeau, 2003). Figure 6 shows the degree-rank plot for a synthetic scale-free network generated by the Barabási-Albert method on linear, semi-logarithmic and double-logarithmic scales.

A less common network structure is the exponential network. Exponential networks have been identified in physical infrastructure networks, such as the North American Power Grid network (Albert, Albert, & Nakarado, 2004) and the email network (Guimerà, Danon, Díaz-Guilera, Giralt, & Arenas, 2003). An exponential network is described by the following function:

$$P(k) \sim e^{-\lambda k}$$

In networks exhibiting an exponential degree distribution, each node that is added to the network means the addition of the node's network and not only the particular node.

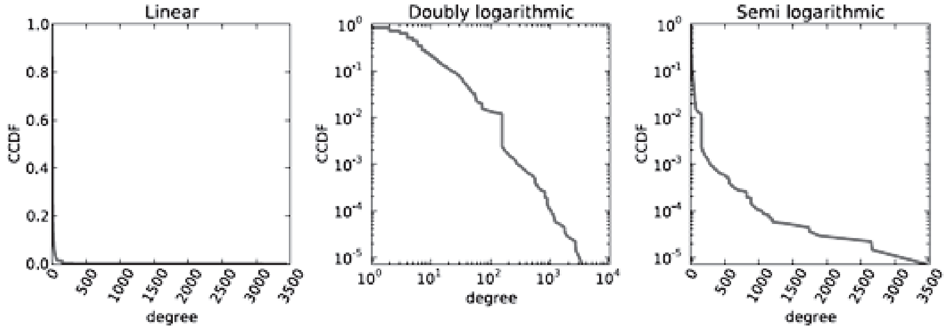

Figure 6 CCDF of a scale-free network on different scales.[2]

Furthermore, it follows a random *non-preferential attachment* process (Dorogovtsev & Mendes, 2005). A *preferential attachment* connection mechanism plays a central role in generating a scale-free network: new nodes prefer to attach to nodes with high degrees of edges. In contrast, an exponential network is generated through a *non-preferential attachment* process: each existing node has an equal probability of connecting to the newly created node. The mechanism of creating an exponential network is as follows: create an initial network, then at each step, attach a new node with *m* random connections until the desired network size is reached. Thus, the main difference between generating a scale-free network and an exponential network lies in the selection of new connections to which new nodes are added.

4.2.2 Multiple networks

As mentioned in Chapter 2, the concept of an NoN can be used to study entrepreneurs' online social networks. As a research approach to the study of social networks, the concept of an NoN implies that ties between individuals and ties between network clusters need to be included in the analysis of social networks (Craven & Wellman, 1973; Garton et al., 1997). In an entrepreneurs' NoN, we suppose the nodes are entrepreneurs.

In this study, we draw upon previous work on NoNs and extend it to cover entrepreneurial networks. We propose that a network of entrepreneurs is in fact an NoN. In such networks, each node hosts and participates in one or more networks that are hosted by other nodes. We propose that none of these networks are independent, and that the NoN constitutes the

2 Data adapted from Barabási et al. (2000).

entrepreneurs' network rather than the individual network. We believe that analysing the structure of NoNs can make a relevant contribution to research into human behaviour, and especially entrepreneurial behaviour and the study of entrepreneurs' NoNs.

4.2.3 The role of weak ties

To discern the communities making up entrepreneurs' online social networks, we will use graph partitioning to determine the online network structures, and apply the theory of strong and weak ties. However, rather than using node betweenness centrality, which is a measure of a node's influence over the spread of information through a network (Linton, 1977; Newman, 2005), we use a more recent network measurement called 'edge betweenness', which was suggested by Girvan and Newman (2002). Edge betweenness is a measure of a particular edge's importance in keeping a network connected, these edges are most 'between' communities (Girvan & Newman, 2002). We can intuitively understand the concept if we think of a network as a form of flow, such as traffic flow. If each node were a town and the edges roads, and there was traffic between all of the towns, then edge betweenness would be the amount of traffic on each 'road'.

Edge betweenness can be used to calculate the strength of a tie in a network, which reflects the connections between nodes in a network in terms of 'the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie' (Granovetter, 1973). While in typical graph theory, the existence of an edge is binary, Granovetter (1973) also identifies two types: strong and weak ties.

In a network graph, a tie with a person from another community is called a 'local bridge'. A local bridge is by definition a weak tie, as it is hard for two people from different communities to devote the necessary resources to strengthening their relationship. However, bridges to other communities prove to be a very valuable information source. While weak ties provide access to a large and diverse pool of information and resources, strong ties are built on the basis of trust. The more intimate relationship between people connected by strong ties makes them more likely to help each other. Krackhardt (1992) has shown that strong ties are especially valuable in turbulent environments, where change and uncertainty reign. Nodes in the same group or community in a network are tightly connected through strong ties. The members of such a group have many mutual connections, and we call such a group a community. Different communities are connected to each other through weak ties.

Researchers have shown that strong and weak ties have different advantages in different contexts (M. T. Hansen, 1999; Krackhardt, 1992; Podolny & Baron, 1997). According to Burt

(1992), an entrepreneur's social contacts are often informal and non-work related. These informal contacts, such as family and close friends, can be seen as 'strong assets', and are mainly used for assistance, requests for confidential information and obtaining resources (Krackhardt, 1992). Family support can be a crucial resource in the context of entrepreneurship and small-business formation (Brüderl & Preisendörfer, 1998; Barry Wellman & Wortley, 1990). Strong ties are described as enhancing firm performance directly through the building of trust, information transfer and joint problem-solving arrangements (Uzzi, 1997). Entrepreneurs use their other contacts – the 'weak ties', in other words – to obtain information that they cannot obtain from 'strong assets' (M. Granovetter, 1985; M. S. Granovetter, 1973).

In a network, the shortest paths between nodes run through the weak ties among communities. For example, if two communities are only connected through one weak tie, all of the shortest paths between members of the first group and members of the second group must include this edge. Therefore, edges with highest betweenness values are the weak ties of a network and the bridge between two communities. In order to discover the structure of the network and the communities in the network, the edges with the highest betweenness values can be removed until no edges are left (Freeman, 1977; Girvan & Newman, 2002). The components remaining are the different communities of the network.

4.3 Data

In this section, we will discuss the data we collected. We will then undertake a simple data matching process before dealing with missing data.

4.3.1 Data description

The data was collected through the method mentioned in Chapter 2. As shown in Chapter 2, Table 5, 345 respondents in total, including both entrepreneurs and non-entrepreneurs, participated in our survey. We filtered out the non-entrepreneurs, leaving 286 participants for our analysis. The online social networks analysed in our study consisted of LinkedIn, Facebook and Twitter, with 95,076, 59,365 and 114,907 links respectively. The links among users on LinkedIn and Facebook are undirected; in other words, the connections among entrepreneurs on these two networks are mutual. However, the connections on Twitter are different: the user information is accessible to everyone by default and the connections among users are directed.

Of the 286 entrepreneurs, 261 participants shared their LinkedIn data with us. We collected both the entrepreneurs' LinkedIn profile data and that of their connections, while 188 participants shared their Facebook data with us. In addition, we stored each entrepreneur's profile data and friend profile data from Facebook. Only 174 participants shared their Twitter network data with us. The Twitter connections are directed, with, on average, each entrepreneur following 396 others and being followed by 628. The data we extracted for our dataset was summarized in Table 5 (Chapter 2).

4.3.2 Data matching

As we knew which LinkedIn, Facebook and Twitter accounts corresponded to each of the entrepreneurs before beginning the profile matching process, shown in Figure 7 below, we were already aware that the entrepreneurs were using multiple online social networks. Entrepreneurs tend to gather information and resources from all of their online social networks. However, whereas non-entrepreneurs tend to use each network separately, entrepreneurs use their online social networks as an NoN, as shown in Figures 7 and 8. The vast majority of entrepreneurs (73%) have an account on two of the three networks, while almost half (45%) have an account on all three. Only one entrepreneur did not fill in any social network account information in the survey.

However, for most of the profiles in our database, the match between individuals and their social network profiles was not explicit. There was no information in the social media profiles that allowed us to uniquely identify an individual. Matching profiles across different social media to find which belonged to the same natural person was a challenging task. To do this, we drew on research that is being done in the area of duplicate record detection (Elmagarmid,

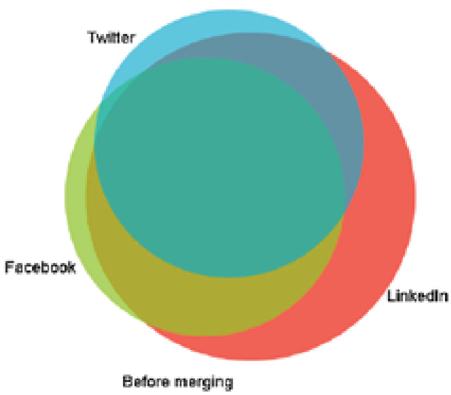

Figure 7 Venn diagram of entrepreneurs' profiles before merging process.

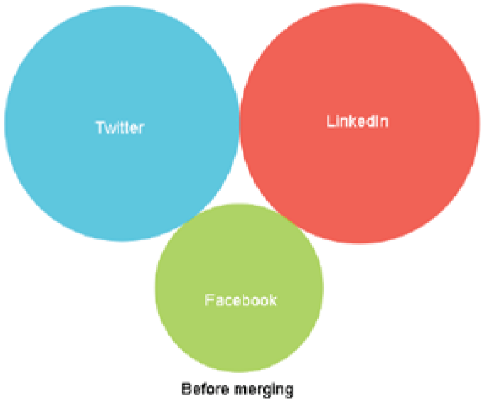

Figure 8 Venn diagram of non-entrepreneurs' profiles before merging process.

Ipeirotis, & Verykios, 2007; Winkler, 2007). As we will see below, this further supported our hypothesis that online social networks are used as an NoN by entrepreneurs, compared to the isolated use of individual networks by non-entrepreneurs.

In order to identify whether two nodes are the same person in different online social networks, we first compared the full names for each profile. If two names were identical, we utilized the graph of relationships between them and compared the profiles for the same names. Assuming that social networks overlap significantly for each entrepreneur, their connections on LinkedIn and Facebook should overlap significantly. Thus, to check if two profiles with the same names belonged to the same person, we could check the overlap in the networks for the two profiles.

Assume we found three profiles with the same name, Yang. We marked them as Yang _1, Yang_2 and Yang_3 to distinguish them. As shown in Figure 9, assume Yang_1 is a

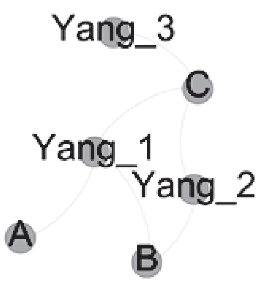

Figure 9 Matching names across online social networks.

Facebook profile, and that Yang_2 and Yang_3 are LinkedIn profiles. Nodes A, B and C are the connections of Yang_1.

Yang_1 and Yang_2 have two shared connections in common, while Yang_1 and Yang_3 only share one connection. We identified Yang_1 and Yang_2 as the same person, since they have the same name and share connections from different online social networks. However, Yang_2 and Yang_3 cannot be the same person, since they are both from LinkedIn. We assumed that a person would only have one account on a social networking site. Because the Yang_1 and Yang_2 profiles have the most connections in common, they most probably belong to the same person, and we matched the profiles and integrated the network into the picture in Figure 10.

Figure 10 Result after merging names.

Before the merging procedure, the database contained 294,144 social network profiles, that is, 294,144 nodes in total. There were 623 nodes from different social networks belonging to entrepreneurs. We performed the cross-matching process described above, examining the network nodes in the whole dataset before conducting the profile matching for our dataset.

After the merging process, as shown in Figure 11 and Figure 12, we found that there was only a slight change in entrepreneurs' networks; the number of entrepreneurs using multiple online social networks remained at the same level. By contrast, after the merging process for non-entrepreneurs we found that they were using more multiple online social networks, but in fact appeared less connected with each other.

As Table 10 shows, there were 261 entrepreneurs on LinkedIn, 188 entrepreneurs on Facebook and 174 entrepreneurs on Twitter respectively. One hundred and seventy-six entrepreneurs had both LinkedIn and Facebook accounts, and 129 entrepreneurs were on all three online social networks. Before the matching process, different social media profiles belonging to

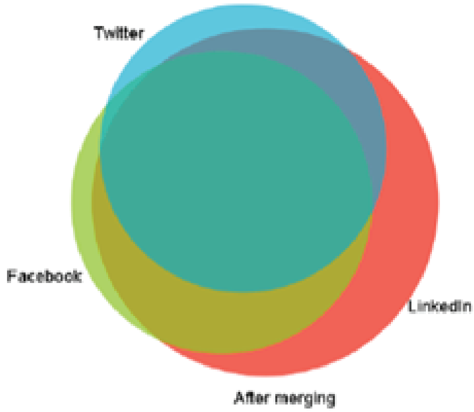

Figure 11 Venn diagram of entrepreneurs' profiles after merging process.

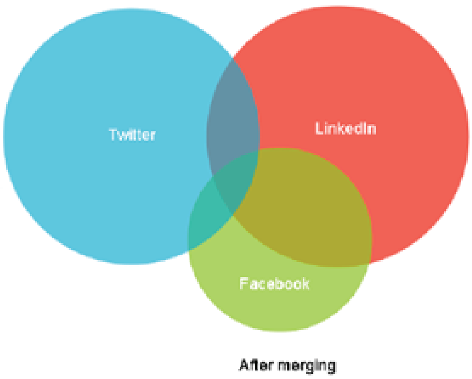

Figure 12 Venn diagram of non-entrepreneurs' profiles after merging process.

one person were counted as distinct people. After the matching process, profiles belonging to the same person were marked as such.

There are 119,625 LinkedIn profiles, 59,145 Facebook profiles and 114,725 Twitter profiles in the full dataset. All of these profiles have first-degree links with at least one entrepreneur. After matching, 14,605 LinkedIn and Facebook profiles were known to belong to the same person, as well as 5,564 LinkedIn and Twitter profiles, and 3,320 Facebook and Twitter profiles. Across all three networks, 2,438 accounts were matched.

Table 10 Merging process

	Entrepreneurs		Non-entrepreneurs	
	Before	After	Before	After
LinkedIn	261	261	119,364	119,364
Facebook	188	197	58,957	58,948
Twitter	174	179	114,551	114,546
LinkedIn and Facebook	176	185	39	14,605
LinkedIn and Twitter	158	163	20	5,564
Facebook and Twitter	133	138	17	3,324
LinkedIn, Facebook and Twitter	129	142	17	2,434

4.3.3 Missing data

In the survey, nine entrepreneurs indicated that they did not use Facebook and thus did not share Facebook network data with us. However, during the matching process, we found their Facebook profiles from their connections with other entrepreneurs who participated in our survey. We linked their profile information with their survey data. We also found five extra Twitter profiles in the same way. One explanation for this might be that as the survey was conducted over nine months, some entrepreneurs who were not on Facebook when they filled out the survey created an account later. The adoption of LinkedIn in our target group is over 90%, while the adoption rates for Facebook and Twitter are 65% and 60%, respectively. Additional LinkedIn profiles were not found because almost all of the entrepreneurs already had LinkedIn profiles when we began the survey.

We found 30 extra Twitter profiles belonging to entrepreneurs who had participated in our survey in addition to the profiles they had used for our survey. This is because they had two Twitter accounts, one for personal use, and the other for their company. While the survey asked entrepreneurs to share one set of Twitter network information with us, their network data also included information relating to their other Twitter account. This may indicate that entrepreneurs tend to separate their personal networks from their business networks.

4.4 Data analysis

In this section, we present the results of the entrepreneurs' online social network degree distribution for each respective network. Following this, we discuss the structure of the NoN that we identified in our research.

4.4.1 LinkedIn degree distribution

Figure 13 shows the degree-rank linear, double-logarithmic and semi-logarithmic plot for the LinkedIn network. Contrary to expectations, the distribution of the number of connections in the LinkedIn network is not scale free. The best (least-squared error) scaling function is plotted as a red line. As shown in the semi-logarithmic plot of the same data, with the best least squares exponential function describing the data again plotted in red. Except for a few outliers (one person with more than 3,000 friends), the exponential function fits the data rather well.

4.4.2 Facebook degree distribution

Figure 14 shows degree-rank plots for Facebook on log-log and logarithmic scales, respectively. The results are very similar to those for the LinkedIn network. The Facebook network degree distribution does not follow a power-law distribution. Similarly, Ugander et al. (2011) also found that the Facebook network is not scale free.

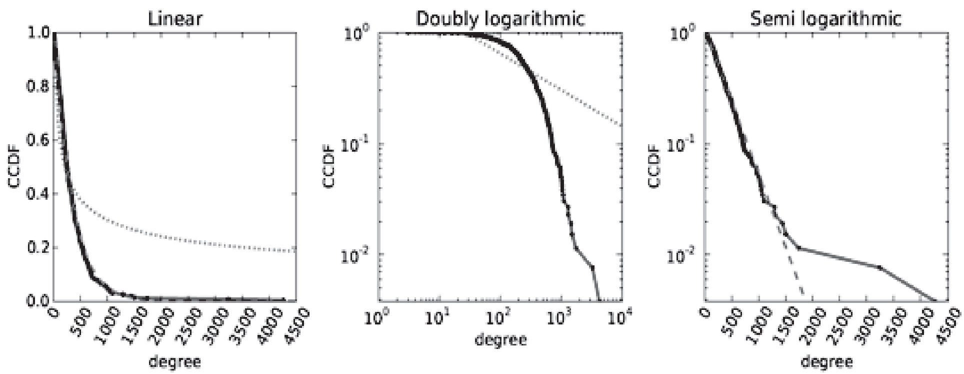

Figure 13 CCDF of LinkedIn degree rank network.

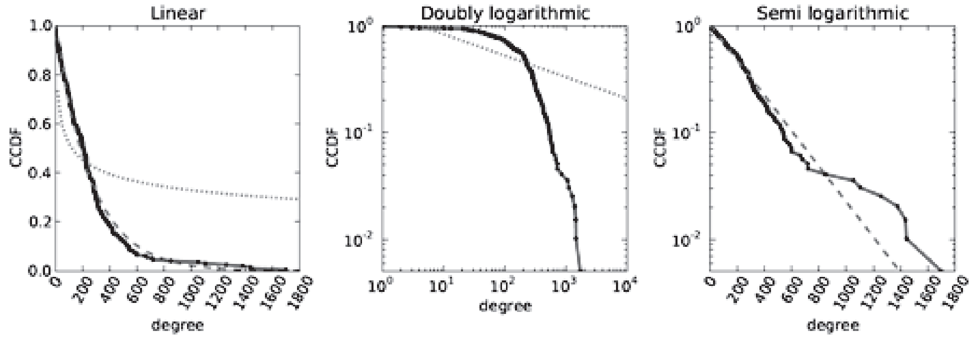

Figure 14 CCDF of Facebook degree rank on different scales.

4.4.3 Twitter degree distribution

Since the edges in the Twitter network are directed, the network has a different in-degree and out-degree. For this reason, we examined the in-degree and out-degree network distribution separately. In Figures 15 and 16, the degree-rank plots of the in- and out-degree are plotted on double-logarithmic and logarithmic scales, respectively. As shown in the figures, the exponential function fits better than the scaling function in both cases.

As discussed above, we have seen that the degree distribution of the nodes in the social network does not follow a scale-free distribution. Our results suggest that LinkedIn, Facebook and Twitter network distributions do not follow power-law distribution, meaning that they are not scale-free networks. Instead, our results indicate that an exponential distribution fits online social networks better than a power-law distribution.

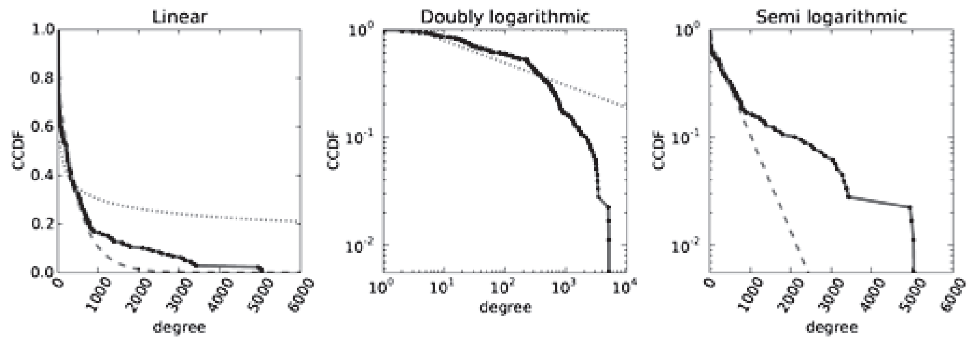

Figure 15 CCDF of Facebook degree rank on different scales.

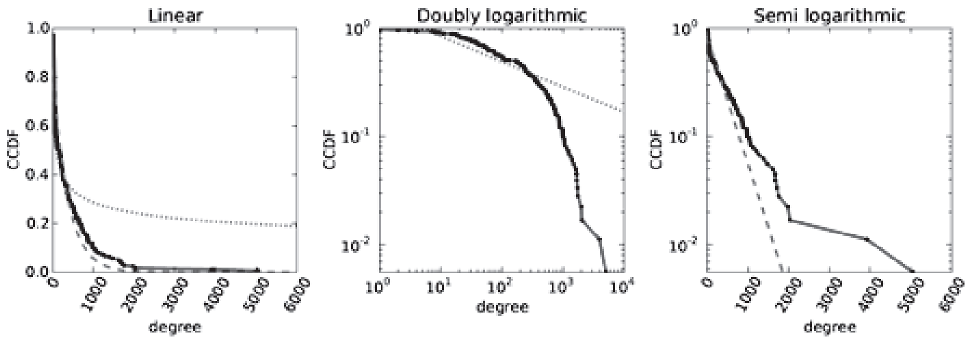

Figure 16 CCDF of Twitter out-degree rank on different scales.

4.4.4 The NoN

Entrepreneurs use social networks for both business and personal purposes. Table 11 shows the number of entrepreneurs who indicated in the survey that they used a particular network for personal and/or business purposes.

As shown in Table 11, entrepreneurs use LinkedIn and Twitter for both business and personal purposes, while entrepreneurs mainly use Facebook for personal purposes. We have seen that many entrepreneurs use more than one social network, and almost half have accounts on all three networks. The table above shows that many also use these networks for the same purposes: LinkedIn and Twitter for business, and Facebook and Twitter for personal purposes. Thus, we would expect to see a large overlap of connections between LinkedIn and Twitter, and between Facebook and Twitter. Because LinkedIn and Facebook are used for such different purposes, we would expect to find fewer common connections over these two networks.

Figure 17 shows the NoNs of the three different networks within the entrepreneur community. The overlap between the networks is calculated by dividing the number of connections in

Table 11 Purposes of social networks per entrepreneur

Network	Business	Personal	Both	Neither
LinkedIn	231	80	74	49
Facebok	90	169	77	104
Twitter	164	104	97	115

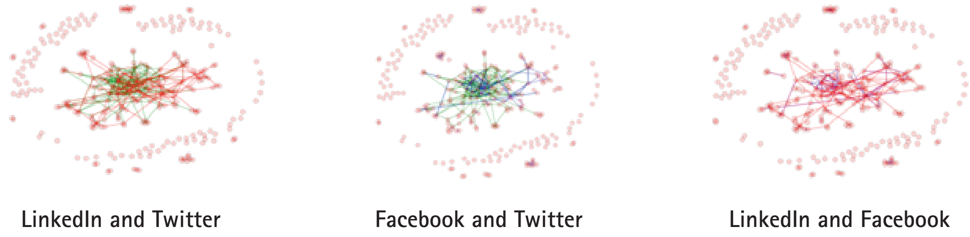

Figure 17 The overlaps of NoNs.

both networks by the number of connections in either network. The set of edges A is taken to be the connections in one network, and B is taken to be the set of edges in the other.

$$F(A,B) = \frac{|A \cap B|}{|A \cup B|}$$

The overlap of connections between entrepreneurs on LinkedIn and Twitter is 21%; on Facebook and Twitter, 19%; and on Facebook and LinkedIn, 29%. Over the whole dataset, not limited to connections between the entrepreneurs alone, the overlap is 2.5% on LinkedIn and Twitter, 2% on Facebook and Twitter, and 8.4% on Facebook and LinkedIn. This is because many profiles matched for LinkedIn and Facebook names, while fewer matched for LinkedIn and Twitter or for Facebook and Twitter names. Another reason is that both LinkedIn and Facebook are used to make strong links, meaning that there are strong ties on both networks. Moreover, the people that entrepreneurs follow on Twitter are always their strong ties. Figure 17 shows us that certain entrepreneurs are connected with each other, while others remain isolated from other entrepreneurs in the networks in our dataset. The latter are connected through non-entrepreneurs, rather than entrepreneurs. The exponential degree distribution and the visualization suggest a random exponential graph topology for entrepreneurs' online social networks.

4.5 The communities in the NoNs

Previous studies have found that individuals benefit from having social ties that form a bridge between communities (Nathan Eagle et al., 2010). We assumed that entrepreneurs' online social networks share similar structures, and thus that they are part of the same communities on different online social networks. In order to detect the different communities in the different networks, we adopted Girvan and Newman's (2002) method: the edge with the highest betweenness centrality was removed for graph partitioning purposes. Examining the overlapping connections within the NoN, this process quickly disconnected the well-connected communities in the graph. We calculated the edge betweenness for all ties after we had removed the ties with the highest betweenness values.

We adopted the following algorithm to test the overlapping nodes among networks: first, we set the betweenness of each tie to 0; second, we found k shortest paths between ties for each pair of nodes in the network; third, we took the value of '1/k' to be the betweenness value for each tie on the shortest path. The basic Girvan and Newman (2002) method works according to the following: while there are edges in the graph, compute the betweenness of all edges and remove the edges with highest betweenness values.

This method starts out with the graph and then iteratively removes edges. The process splits up existing communities into smaller sub-communities until there are no edges in the graph. The end state of the graph is not particularly interesting, as it is always a graph without edges. However, the process can be stopped, for example, when a certain criterion is reached. The ties that were removed during our process were always the weakest ties. Well-connected cliques stayed connected the longest, while bridges between different groups of people were eliminated.

As we can see from Figure 18, the graph describes the process of removal of the edges with highest betweenness from the Twitter NoN. The edges that survive in the graph have a

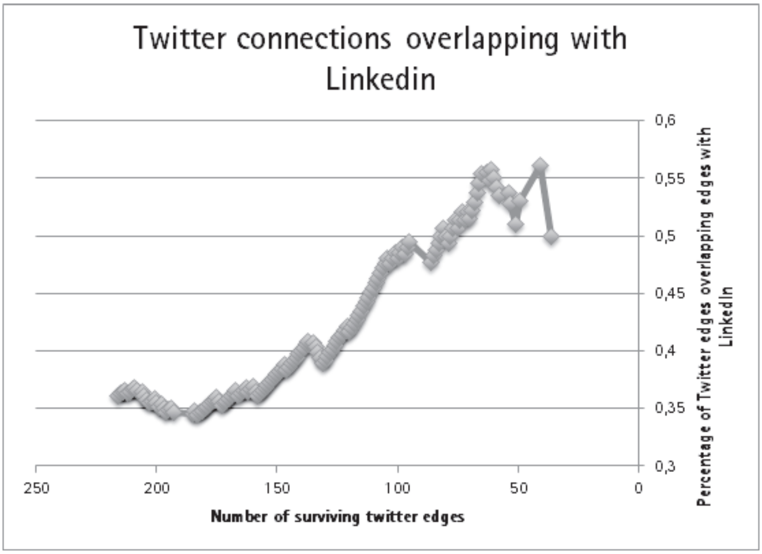

Figure 18 Twitter connections overlapping with LinkedIn.

higher chance of being in both LinkedIn and Twitter networks. Our removal process showed that 33% of the edges in the Twitter graph corresponded with edges in the LinkedIn graph. Removing Twitter edges using the betweenness centrality method raises the percentage of overlap with the LinkedIn network over the remaining edges.

Similarly, we used the same methodology between Twitter and Facebook. As shown in Figure 19, the graph shows the process of removal of the edges with highest betweenness from Twitter. The edges that survive in the graph have a higher chance of being in both Facebook and Twitter networks. Our results showed that 23% of the edges on Twitter overlapped with Facebook edges. Iterative removal of edges with the highest betweenness centrality raises the percentage of Twitter edges that overlap with Facebook.

This study focused on the use and structure of entrepreneurs' online social networks. Our findings suggest that entrepreneurs' networks are in fact networks of networks (NoNs), rather than single networks. Entrepreneurs use all three online social networks – LinkedIn, Facebook and Twitter. Entrepreneurs' networks overlap at a range of between 19% (Twitter-Facebook), 21% (LinkedIn-Twitter) and 29% (Facebook-LinkedIn). The overlapping parts link groups of entrepreneurs' online social networks together and establish an NoN for entrepreneurs. By contrast, non-entrepreneurs use these networks separately, with limited overlapping among the three networks, at 2%, 2% and 8.4% respectively.

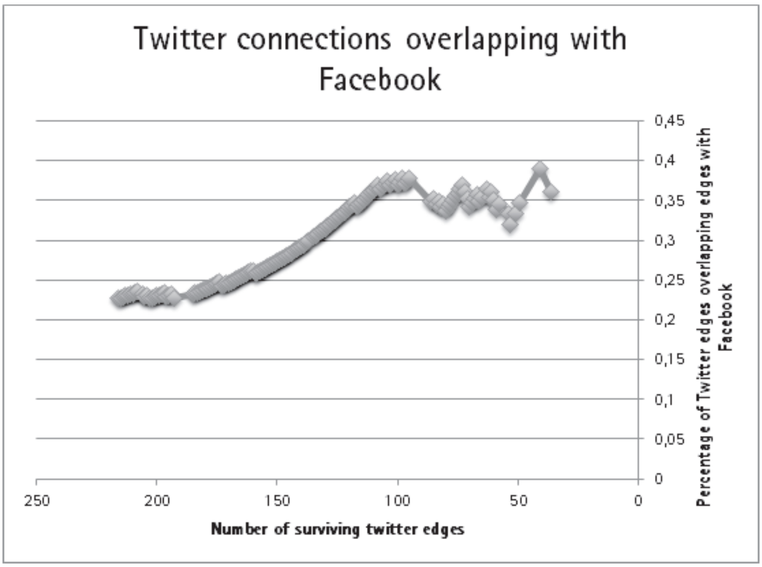

Figure 19 Twitter connections overlapping with Facebook.

The entrepreneurs' NoN follows an exponential degree distribution, showing it to be a form of random network. This finding suggests a high connectedness between entrepreneurs' online networks and the existence of weak ties in the entrepreneurs' NoN. Seminal work by Granovetter has demonstrated the importance of weak ties for providing access to a large and diverse pool of resources across networks and communities (M. S. Granovetter, 1973). The role played by weak ties in the entrepreneurs' NoN is twofold: on the one hand, they serve as links between the different networks and facilitate the flow of information within and between the networks; on the other, the algorithm for the removal of weak ties helps us to uncover the network communities within the entrepreneurs' NoN. By comparing whether entrepreneurs share similar communities among networks, we were able to test whether entrepreneurs' online social networks overlapped with each other. In other words, we confirmed that entrepreneurs are actually using a NoN to support their businesses. Even if they appear to be multiple networks, all the networks are in fact part of the NoN.

Figure 20 visualizes the entrepreneurs' NoN formed by the three online social networks of LinkedIn, Facebook and Twitter using Gephi (Bastian et al., 2009). As shown in the graph, the entrepreneurs are using multiple networks. We highlighted the nodes that belong to a giant component with colours. The isolated nodes or the leaves of the networks are ignored.

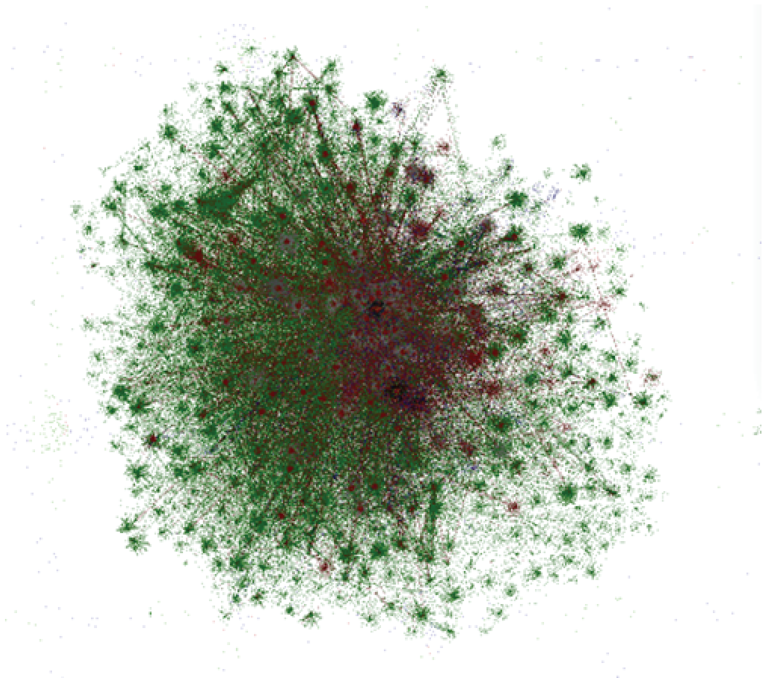

Figure 20 Entrepreneurs' NoN.

4.6 Discussions and conclusions

Drawing on the literature on networks, this study explored the use and structure of entrepreneurs' online social networks (LinkedIn, Facebook and Twitter). We suggested that the networks used by entrepreneurs formed an NoN, rather than being individual networks. This entrepreneurial NoN formed as a random network with exponential degree distribution, and feature a high degree of overlap between the individual networks.

In order to explore the structure of an NoN, we used a method to identify which profiles belonged to the same person across different online social networks based on overlapping neighbourhoods. This method was employed on a dataset consisting of LinkedIn, Facebook and Twitter profiles. Our manual check of the profile data showed that many entrepreneurs use the same profile image across different networks. While the images differ in terms of size, quality and (in the case of LinkedIn) watermarking, they are generated from the same base image. Relatively simple image comparison software should be able to find identical images. Image-based comparison might be a more reliable method of identifying the same entrepreneur across different networks than our overlapping neighbourhoods method.

Another improvement might be to allow variation in the spelling of names. For example, Jonathan Doe may use his full name on LinkedIn, while being known as 'John Doe' on Twitter. Many Chinese and other non-Western names are written with the family name first, but reversed for use in international contexts. These names might occur in different orders on different social networks. We found a significant overlap for entrepreneurs between the LinkedIn, Facebook and Twitter networks, and we were able to identify people across the three networks. We found that entrepreneurs tend to use multiple Twitter accounts, usually one with a personal title and one that represents their company. Many personal Twitter accounts refer to these company accounts in their 'description' attribute. Future research could explore patterns in entrepreneurs' corporate and personal Twitter accounts. In addition, we also found that entrepreneurs are more connected than non-entrepreneurs from our dataset.

Online social networks can provide us with large amounts of data that shed light on entrepreneurs' behaviour in real-life situations. The data extracted from online social networks can thus help us study and predict interactions among individuals who constitute a particular group, such as entrepreneurs. Due to the multiple communication purposes and functions that can be fulfilled by computers and mobile phones, we find that entrepreneurs keep in touch with their contacts through different online networking sites, such as LinkedIn, Facebook and Twitter. People tend to connect to other people at random across different networks; for example, when they receive an invitation from another person.

Our method shows how entrepreneurs' online social networks can be studied by extracting profile and network information, and by identifying the same entrepreneurs across multiple networks. Using this method makes it possible to build a large dataset of entrepreneurs' online networks in order to study the network structure, dynamics and its impact on the entrepreneurial process.

Although we found that the entrepreneurs' online social network followed an exponential degree distribution, more empirical research is needed to test this structure. Furthermore, future studies should look at how this particular network structure can be used to acquire information and resources.

Our research contributes to the fields of entrepreneurship and social network analysis in the following ways. First, we can infer how entrepreneurs use their networks by focusing on NoN data. Second, by removing edges with highest betweenness, we are able to identify the communities of networks, which are normally connected through weak ties. Third, understanding the emergence of entrepreneurial networks can help us to understand how new ventures, industries and, in fact, economies are interlinked. However, a deeper level of analysis is needed to uncover the structure and dynamics of entrepreneurship networks through NoN data. We believe NoN can lead to new ways of designing entrepreneurial business strategies and new ways of propagating new ventures, products, services and technologies.

Finally, the study also offers a novel method for the quantitative study of entrepreneurs' networks, creating a large-scale dataset relating to entrepreneurs' online networks. According to Jack (2010), more innovative data collection methods and analysis may be a way forward in the study of networks in entrepreneurship. Most studies use self-reporting data collection methods, such as interviews, questionnaires and case studies. Our method supports the collection of actual network data and the development of a large-scale dataset on entrepreneurs' networks from their online networks, enabling quantitative analysis and visualization.

While this chapter discussed the structure of the entrepreneurs' NoN, to further understand whether such networks can affect the entrepreneurial process, the next chapter will move beyond the mere data study to a simulation process.

CHAPTER 5

Simulation of the Entrepreneurial Process Based on the Online Social Network Structure

Abstract

In this chapter, we investigate the growth of entrepreneurs' businesses in a given network and the impact of the network on the entrepreneurial process. We assume entrepreneurs are interested in starting up new businesses with other people in a given network. They attempt to obtain information and resources through interaction with the other entrepreneurs in their network and decide whether to collaborate on projects. We developed a simulation model of the entrepreneurial process in terms of venture growth. In general, the simulation models the cooperation between two entrepreneurs in a given network, and identifies the survival rate of entrepreneurs in the network after a certain period. Our results imply that both the extent of networking and start-up wealth positively influence entrepreneurial growth. With our simulation model, we can infer the survival time of a venture based on a given start-up time frame.

5.1 Introduction

Entrepreneurs' are connected with other people, such as friends, colleagues and collaborators, through social networks. These enable entrepreneurs to gather information and resources, solve problems and boost their own reputation. The network that entrepreneurs' are embedded in plays a very critical role in the entrepreneurial process (Aldrich & Zimmer, 1986). The social network can be seen as part of entrepreneurs' social capital, according to Burt (1992), 'friends, colleagues, and more general contacts through whom you receive opportunities to use your financial and human capital. Online social networks enable people to connect with friends, family, and colleagues through the internet in a non-intrusive way' (Ellison et al., 2007).

Traditional network research only allows us to obtain self-reported data rather than behavioural data and cannot present the big picture in relation to entrepreneurs' networks (Eagle et al., 2009). Online social networking sites supply part of their data to the public depending on the settings chosen by users. In addition, the online social network allows us to collect entrepreneurs' network data automatically through an Application Programming Interface (API) (Kwak, Lee, Park, & Moon, 2010).

In order to understand the effect of social networking on the entrepreneurial process, it would be useful for a study to link the network structure to entrepreneurial performance. Moreover, as entrepreneurs are surrounded by many different kinds of networks, determining the value of a network to the entrepreneurial process and estimating the best configuration of a network would contribute greatly to both the theory of entrepreneurship and that of social networks. A simulation approach may be an effective tool to evaluate the effect of entrepreneurs' network structures on the entrepreneurial process over time. This evaluative approach is also useful because despite some work being done on entrepreneurial network dynamics and evolution (Arent Greve, 1995; Arent Greve & Salaff, 2003; Larson, 1992; Minguzzi & Passaro, 2001; O'Donnell, Gilmore, Cummins, & Carson, 2001), most of the research on entrepreneurship has adopted a longitudinal network-based approach and tends to be descriptive (Arent Greve & Salaff, 2003; Hoang & Antoncic, 2003) rather than explanatory.

Entrepreneurs may interact and communicate with other people using different networks for different purposes. The network may be a family network, a friendship network, or various business networks. As we have argued in previous chapters, considered together, the networks comprise a Network of Networks (NoN), which allows entrepreneurs to more easily obtain the information and resources that they need for their business. The widespread use of the internet makes it possible for entrepreneurs to integrate all their connections from different online social network services and to connect with other entrepreneurs when consider starting up a new business. However, due to the privacy and sensitivity of entrepreneurial information, we are unable to study the real evolution of entrepreneurial behaviour due to their network.

According to the literature, the founding of a business can be divided into three phases: 1) idea development, 2) organizing the founding of a firm, and 3) running a newly established firm (Arent Greve, 1995; Wilken, 1979). At the beginning of the start-up phase, entrepreneurs need to find business ideas through their networks. During the second phase, entrepreneurs always experience the problems associated with limited capacity and resources, and new technologies. While the network may supply entrepreneurs with the connections which could solve these problems, opportunities for start-ups are always limited and transient. Entrepreneurs might even waste their opportunities if they spend too much time searching for the collaborators in the network. While, there is always a particular date on which an entrepreneur starts a business, however, the boundary between the first and the second phase may thus be blurred (Arent Greve, 1995). Moreover, the mechanisms and processes by which particular ties play a role in the development of an emerging firm remain unclear (Elfring & Hulsink, 2003).

In order to uncover the potential influences of entrepreneurs' online social networks on the entrepreneurial process, in this chapter we designed a simulation model of this process. We assume that when entrepreneurs start businesses, the network plays a vital role during the first and second phases. We combined the first and second phases mentioned above (Arent Greve, 1995; Wilken, 1979) into the 'searching phase' for our simulation model, meaning that in this phase entrepreneurs generate business ideas and search for collaborators. We assume that the length associated with start-up can be related to the survival at a given time or the ultimate success of the business. The task of determining the optimum start-up time frame for entrepreneurial survival appears to be a very valid subject for research (Gartner, Starr, & Bhat, 1999; Raz & Gloor, 2007; Strotmann, 2007).

After the 'searching phase', entrepreneurs become engaged in organizing and maintaining the business, and the company may succeed or fail. If they are successful and their business makes money, they will continue to run the newly founded business; if the business loses too much money it will fail and the entrepreneur will exit the market. In order to fulfil our task and discover the influence of the network structure on the entrepreneurial process, we developed a simulation model to infer entrepreneurial survival rate in a given network. In our study, the second phase is known as the 'growth phase', which means that an entrepreneur has already started a business in collaboration with others from the network. The third phase, the 'exit phase', entails exiting the market. In this phase, the entrepreneurs neither search for collaborators nor organize and maintain their business. Entrepreneurs engaged in this phase have failed to start up a business, and having used up the wealth allocated to the venture, will exit the market.

In our model, entrepreneurs find resources and collaborators from the given network, in other words, the online social network. Together with these collaborators they start up new businesses which can grow or fail depending on our growth function, which is based on certain conditions. We compared the entrepreneurs who survive with those who failed during our entrepreneurial simulation process. In addition, we provide more evidence on the time threshold for entrepreneurs to start up their business during the searching process. Furthermore, we examine the effect of the network position of the entrepreneurs who survived in the market after a certain period.

In this chapter, Section 2 will first describe the source of our simulation data and the characteristics of the data. In Section 3 we will present a simulation model, including the simulation procedure, a simulation algorithm and the simulation model parameters. In Section 4 we will present our simulation data and the results of the data analysis separately. In the final section we will illustrate the implications of our network simulation models and outline directions for future research.

5.2 Data description

As mentioned in previous chapters, we have already saved all the online social network data in our database. We built the simulation on the basis of data collected through LinkedIn, which is one of the major business-related social networking sites in the world. In the LinkedIn network nodes represent people, while edges represent the connections among people. The LinkedIn graph is undirected. Edges between individuals are called ‘connections’ and are formed using the mutual consent model. Nodes that have been part of LinkedIn longer have a higher number of connections. This is not only because they joined LinkedIn earlier but also because, for users of LinkedIn, activity generally slowly increases over time (Leskovec et al., 2008).

In this research, 273 entrepreneurs completed our online survey. Of the 273 entrepreneurs, we have information about the number of connections on LinkedIn for 138. For the entrepreneurs who completed our survey, we were able to extract their connection information automatically through the LinkedIn API. However, due to the privacy setting options of the LinkedIn API, we were not able to access the connection numbers for every user.

Figure 21 depicts the histogram of the connection number for all the entrepreneurs from the online social network. The highest connection number for an entrepreneur from the LinkedIn online social network is 1,451, while the lowest connection number is 10. The average connection number is 277.9, excluding the entrepreneurs with no connection number.

To determine the structure of the entrepreneurs' LinkedIn network, we divided the 273 entrepreneurs into six groups (Group 1 to Group 6) according to the number of nodes for each connected component. Each group belongs to a connected component in the network. As shown in Table 12, the number of nodes for the connected component in each group is 139, 5, 4, 3, 2 and 1 respectively. We take all isolated nodes as Group 6. We found that 51% of entrepreneurs belong to a connected component which contains 139 nodes, while 33% are isolated from the network.

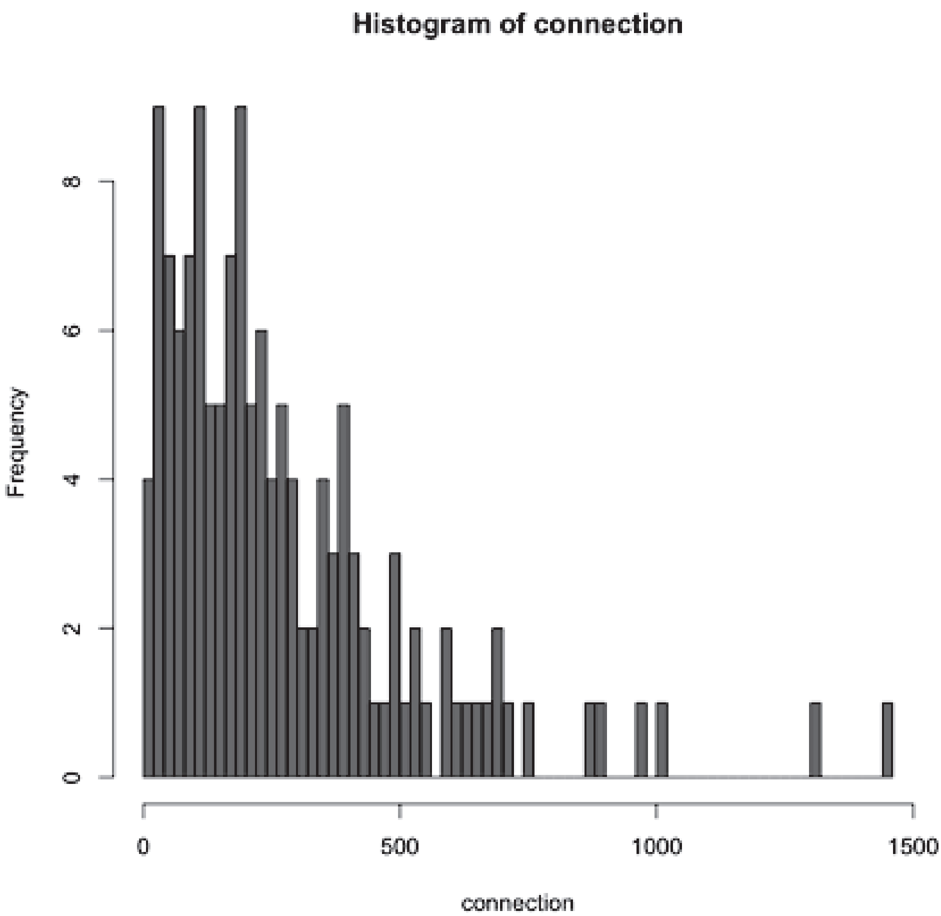

Figure 21 Histogram of entrepreneurs' connections.

Table 12 Connected components of the network

	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
Number of nodes for each component	139	5	4	3	2	1
Frequency	139	10	8	3	24	89
The percentage of entrepreneurs	51%	4%	3%	1%	9%	33%

Figure 22 visualizes the entrepreneurs' initial LinkedIn network. We used condor software to map the entrepreneurs' initial network (Gloor, Krauss, Nann, Fischbach, & Schoder, 2009). This was not only because of the convenience of the software for visualization but also because of its focus on social media and network dynamics analysis. As shown in Figure 22, the largest component is highlighted in red. We have removed the isolated nodes. In other words, the nodes remaining are the entrepreneurs' with more than one connection with other entrepreneurs.

Before we moved to the next step of this study, we first examined the data characteristics of our online social network to test its structural properties. We adopted the model of Watts and Strogatz (1998) to test whether our data had small-world network characteristics, examining the average path length and the clustering coefficient to evaluate the structural properties of the network. The average path length refers to the typical separation between two nodes in the graph, while the clustering coefficient measures the cliquishness of a typical neighbourhood (a local property) (Watts & Strogatz, 1998). Table 13 depicts the structural properties of our online social network.

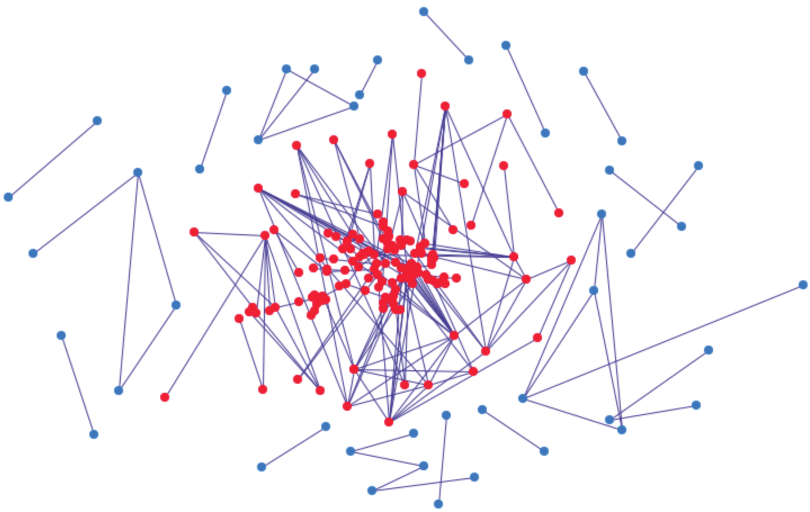

Figure 22 Entrepreneurs' online social networks.

Table 13 Structural properties of the biggest network component

	Average path length	Clustering coefficient
Regular	25.15	0.75
Actual	6.241	0.216
Random	4.855	0.020

The average degree of our initial network is 1.648, while the average degree of the biggest component, which involves 139 nodes in the given network, is 2.763. According to the measurement we adopted, the clustering coefficient is 0.216, while the average path length is 6.241. The results imply that our network dataset has the characteristics of a small-world network (Watts & Strogatz, 1998), with a structure of highly clustered or locally ordered graphs and necessarily short path lengths (Watts, 1999).

In addition to these small-world characteristics, we also found that our network exhibits an exponential degree distribution. Exponential networks are usually associated with physical networks (e.g. the North American Power Grid (Albert et al., 2004) or the email network (Guimerà et al., 2003)). Networks that exhibit an exponential degree distribution can be explained by non-preferential growth (Dorogovtsev & Mendes, 2005).

In order to study whether this particular online network structure has any impact on entrepreneurial behaviour, we designed a simulation model for the entrepreneurial process. As mentioned above, for some of the nodes in our dataset, we have their connection number from LinkedIn, while others were not available to us. In our simulation model, we first entered the existing data using a gamma distribution and then generated random numbers according to the fitted distribution, thus assigning connection numbers to entrepreneurs for whom we did not have this information. The nodes use the wealth they have to start up a business. We aim to predict to what extent the network influences entrepreneurial growth in terms of survival time. In the following section we will introduce our simulation model based on the given network.

5.3 The network simulation model

This section introduces our simulation model involving 273 entrepreneurs. We determined each entrepreneur would undergo the entrepreneurial process over 200 simulation periods. For each period, we assumed the entrepreneurs would be in one of the following three phases: searching, collaborating/growth, or exiting the market. The entrepreneurs could only collaborate with one person in any single simulation period. Each entrepreneur had some wealth which could be used to start up a business if they met a collaborator. The whole simulation process was run 100 times. Below we will introduce the details of the simulation parameters, the simulation process and the simulation algorithm.

5.3.1 Simulation parameters

Wealth: Wealth refers to the information and resources that an entrepreneur requires to start up a business. In our model, we assume that when two entrepreneurs meet, the combined wealth includes all the necessary items for them to start a business. Before the simulation process, every entrepreneur has an initial wealth. However, one entrepreneur is not allowed to start up business alone, no matter how great their initial wealth. During the entire entrepreneurial process, if entrepreneurs are in collaboration, they will gain extra wealth from the growth of the business. The cumulative wealth is the final wealth value for an entrepreneur.

Degree: The degree refers to the number of connections that an entrepreneur has with other entrepreneurs in a network.

Searching cost: Searching cost is the wealth that an entrepreneur requires to search for a collaborator in the searching phase. In order to simplify our simulation model, we set the searching cost as a constant.

Actual survival time: Previous research has identified entrepreneurial performance measures (Bosma et al., 2004; Bouchikhi, 1993; Gimeno et al., 1997; Lumpkin & Dess, 1996; Singh, 1997), namely, the hazards of business ownership.

We use survival time to measure entrepreneurial performance. Based on the model of our simulation, we define survival time as the number of survival simulation periods in a simulation run, which is the actual survival time for an entrepreneur in a simulation run. The maximum survival time is the total number of simulation periods for each entrepreneur.

In this model, any entrepreneur will survive until the first period in which their wealth is equal to or less than 0. There are two ways for entrepreneurs to survive longer: one is by having a relatively high initial wealth, and the other is by collaborating with other entrepreneurs repeatedly. In order to take this distinction into account, we also consider minimum survival time in addition to the actual survival time.

Minimum survival time: Minimum survival time refers to the actual survival time in which an entrepreneur could not find any collaborators during the simulation period. In this case, an entrepreneur can still use their initial wealth to search for collaborators. However, entrepreneurs incur a certain cost in searching for collaborators, thus their total wealth decreases during this phase. Since the cost for searching is a constant, we can divide initial wealth by cost to determine an entrepreneur's minimum survival time:

Minimum survival time = initial wealth/Searching cost

If an entrepreneur can find a collaborator, we assume they will make a profit together in their business. Thus, the total wealth will increase for both of them. In other words, the minimum survival time is always shorter than the actual survival time.

Entrepreneurs obtain the ideas they need and start their businesses, sometimes succeeding but mostly failing. In our project, we focus on those who succeed in starting up a business. However, it is not easy to define success in a business venture given the dynamic nature of the venture process. Success is not a stable state but a moving reality (Bouchikhi, 1993). Therefore, rather than evaluating entrepreneurial success, we will focus on survival time. Small and/or new businesses are not usually expected to be profitable during their first years of existence and changes may not emerge in the number of salaried employees or in annual sales growth during those early years (Kariv, Menzies, Brenner, & Filion, 2009).

Number of simulation runs: we repeated the whole simulation process for n times until we were satisfied with it.

5.3.2 Simulation procedure

Entrepreneurs are embedded in their social networks, within which they can contact other entrepreneurs. We can assume that when entrepreneurs start up their businesses, they need entrepreneurial ideas, information and resources, as well as network support from non-entrepreneurs. We will examine a network of entrepreneurs in which each entrepreneur has a certain wealth but not enough to start the business in question. Every entrepreneur is interested in starting up a company. However, due to their lack of resources they need to collaborate with another entrepreneur in the network.

Based on the premise of starting up business, we define a discrete time simulation model to discern the entrepreneurial process. Adapting previous research on the founding of businesses we designed three phases of the entrepreneurial process (Wilken, 1979). Figure

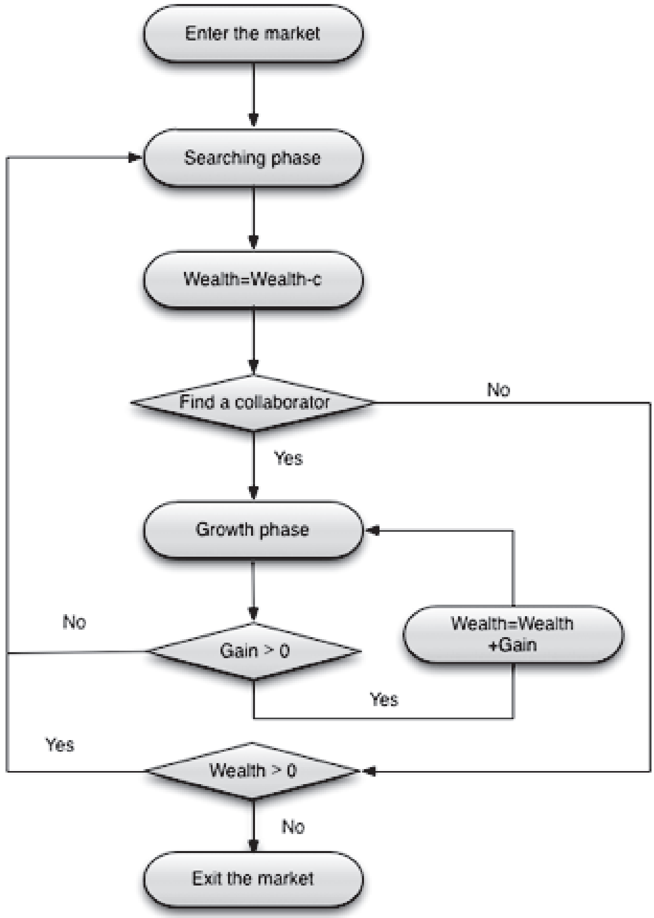

Figure 23 The flowchart of entrepreneurial process.

23 depicts the entire entrepreneurial process for an individual entrepreneur. Below we describe each phase:

- *Searching phase:* entrepreneurs search for another entrepreneur in the network. When entrepreneurs are engaged in the searching process they need to budget a certain amount of their wealth for every simulation period. The wealth can be time, money, resources, etc. The function of these costs decreases linearly. We use c to present the cost per period and assume the costs for entrepreneurs searching for opportunities are constant in the searching phase.

- *Growth phase:* during this phase, an entrepreneur collaborates with another entrepreneur in the network. In this phase, the entrepreneurs make a profit. The profit created during each entrepreneurial simulation period is added to their wealth.
- *Exit phase:* when entrepreneurs run out of wealth, they exit the market.

Phase changes:

- ***Searching phase to growth phase:*** If an entrepreneur can find a collaborator during the searching phase, the entrepreneurial process for this entrepreneur moves to the growth phase.
- ***Searching phase to exit phase:*** If an entrepreneur runs out of wealth during the searching phase and still cannot find a collaborator, the entrepreneur will exit the market.
- ***Growth phase to searching phase:*** If an entrepreneur is in the growth phase, the wealth function increases very quickly at the beginning then stops growing when it reaches the maximum value. Entrepreneurs stop collaborating with each other and use their wealth to search for new collaborators. The entrepreneurial process returns to the searching phase.
- ***Growth phase to exit phase:*** the entrepreneur will exit the market if they fail during the start-up process.

5.3.3 Simulation algorithm

In this simulation model, we assume that all the nodes in our network are entrepreneurs; however, only two entrepreneurs can collaborate at the same time. All the entrepreneurs hold a certain wealth, which includes ideas, information and resources as well as connections with non-entrepreneurs. The combined wealth of any two entrepreneurs includes all the items necessary for starting up a new business. All kinds of start-up wealth can be transformed into a monetary value, which can be represented as a number in this research. In this simulation model, entrepreneurs can collaborate with anyone in the network, depending on the network path and collaboration probability.

The probability of collaboration between two entrepreneurs depends on the distance between them in the network. Entrepreneurs search for a collaborator in a simulation period and decide whether to collaborate with each other. In order to simplify our simulation model, for entrepreneur i, we take $N(i, k)$ as the set of all the nodes at a fixed distance k, where the whole number of $N(i, k)$ is n. The probability p that node i can find node $j \in N(i, k)$ is in inverse proportion to k and n, in other words:

$$p = 1 / kn$$

We take q as the probability that one entrepreneur would like to collaborate with another entrepreneur. In the following, we will explain the parameters that we used for this simulation.

We created the simulation algorithm for our model based on the entrepreneurial process discussed above. For any entrepreneur i and any time epoch t, we defined a vector S_i^t to identify each entrepreneur's status in order to track their behaviour during the entrepreneurial process, for example, whether they collaborate with other people in the network or quit the market at a particular time.

In the elements of S_i^t, w_i^t represents the wealth of the entrepreneur i at period t. g_i^t represents the net profit of the entrepreneur's business, in other words, the profit entrepreneur i gains during collaboration with entrepreneur j; In this function, we set $\alpha = 1$, $\beta = 10$ to control for the profit of an entrepreneur during each simulation period. a_i^t represents the age of entrepreneur i's business at simulation period t, that is, the time elapsed since the moment they started the current collaboration. φ_i^t refers to the phase of entrepreneur i. c_i^t refers to the collaborator of entrepreneur i in period t.

At the beginning of our simulation, the entrepreneurs in the network are searching for information and resources, $w_i^0 > 0$; $a_i^0 = 0$; $\varphi_i^0 = 1$; $c_i^0 = 0$, thus the initial status of each entrepreneur i is:

$$t = 0, S_i^0 = (w_i^0, 0,1,0)$$

After this initial status, while $t \geq 0$, we assume an entrepreneur i could find another entrepreneur j with whom to collaborate, with w_i^t and w_j^t being the wealth of entrepreneur i and entrepreneur j for the next period. The value of φ_i^{t+1} and φ_j^{t+1} defines the next phase for entrepreneur i and entrepreneur j. Their business continues to grow until it stops at a certain point. When the entrepreneurial process moves to the growth phase, thus

$\varphi_i^t = 2$; $a_i^{t+1} = a_i^t + 1$; we have:

$$S_i^t = (w_i^t, a_i^t, \varphi_i^t, c_i^t)$$

$$g_i^t = \alpha * a_i^t (\beta - a_i^t)$$

$$w_i^t = w_i^{t-1} + \frac{w_i^{t-1}}{w_i^{t-1} + w_j^{t-1}} * g_i^t$$

$$w_j^t = w_j^{t-1} + \frac{w_j^{t-1}}{w_i^{t-1} + w_j^{t-1}} * g_i^t$$

$$a_i^t = t;$$

$$\varphi_i^{t+1} = \begin{cases} 1 \text{ } if \; w_i^t > 0; a_i^t = 0; c_i^t = 0 \\ 2 \text{ } if \; w_i^t > 0; a_i^t > 0; c_i^t > 0 \\ 3 \text{ } if \; w_i^t = max\,(w_i^{t-1} - c) = 0; c_i^t = 0 \end{cases}$$

$$\varphi_j^{t+1} = \begin{cases} 1 \text{ } if \; w_j^t > 0; a_j^t = 0; c_j^t = 0 \\ 2 \text{ } if \; w_j^t > 0; a_j^t > 0; c_j^t > 0 \\ 3 \text{ } if \; w_j^t = max\,(w_j^{t-1} - c) = 0; c_j^t = 0 \end{cases}$$

If an entrepreneur exits the market, it is not possible for them to return to any other phase, thus we have:

$$\varphi_i^t = 3$$

$$w_i^{t+1} = w_i^t$$

$$a_i^{t+1} = 0$$

$$c_i^t = 0$$

5.4 Simulation result

In this section, we will first present the measurements for the simulation process. We will then present our regression analysis based on a given start-up time interval. Finally, we will conclude our observations of the entrepreneurial process.

5.4.1 Measurements

We assigned an initial wealth value to every entrepreneur. This value was based on their online network connections, which included their connections with both entrepreneurs and non-entrepreneurs. As mentioned above, since not all of the entrepreneurs had a connection number, we first entered the existing connection data using a gamma distribution and then generated random numbers for the other entrepreneurs according to the fitted distribution. Thus we assigned a connection number to all of the entrepreneurs in our dataset. Figure 24 shows the entrepreneurs' initial wealth for each of the 100 simulations with a fitted distribution.

An entrepreneur might collaborate with many people in the course of their business life. They might collaborate with the same people repeatedly or find different collaborators.

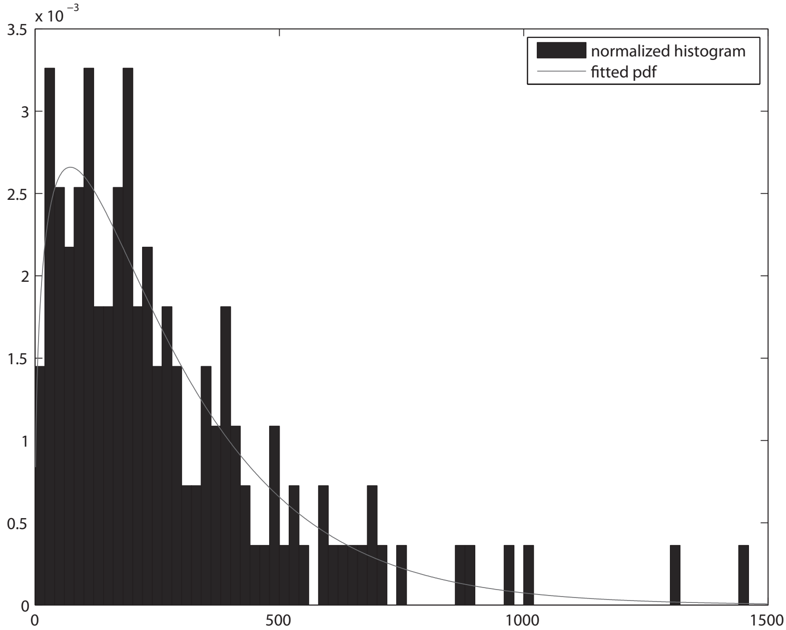

Figure 24 Distribution of entrepreneurs' wealth.

However, starting another collaboration with the same person immediately after a previous collaboration is somewhat unrealistic because of a lack of incentive or new technology, for example. We avoided this chance by deleting the last collaborator from the set of possible entrepreneurs for a certain period.

Entrepreneurs search for information and ideas all the time. Providing access to resources is an important contribution of networks to the venture process. Entrepreneurs rarely possess all the resources required to seize an opportunity (Elfring & Hulsink, 2003). While it is not always the case that they can start up immediately once they have an idea, there are always some who take action as soon as possible. In our model, we take the time to first collaboration as the start-up time. We define survival time in terms of the number of simulation periods that an entrepreneur can survive during one simulation run. In this model, any entrepreneur will survive until the period that their wealth is equal to or less than 0.

As mentioned in Chapter 3.4.2, there are three kinds of possible measurements to evaluate the success of an entrepreneurial endeavour (Witt, 2004). The first is based on self-evaluations of entrepreneurs' about the success of their business. However, as different entrepreneurs are not equally satisfied about their performance, this measure is not suitable to study the success of start-ups (Chandler & Hanks, 1993). The second measure is the number of survival years of new start-ups. The difficulty of using firm survival as a measure of success is determining a minimum time period for survival. A short survival period might only cover a small part of the initial entrepreneurial phase and a long survival period might include well-established or developed companies instead of start-ups. Previous studies use three to five years as a measure of survival as a parameter of entrepreneurial performance (Brüderl & Preisendörfer, 1998; Gartner et al., 1999). The last measurement of success is the growth rate of the company (Brüderl & Preisendörfer, 1998; Witt, 2004). The most commonly used growth rates are sales growth (Brüderl & Preisendörfer, 1998) and employment growth (Baum et al., 2000).

In our analysis we define a relative survival time and consider it to represent entrepreneurial growth. As mentioned above, as long as an entrepreneur's wealth is greater than 0, the entrepreneur is able to survive for a minimum time in the market. There are two ways for entrepreneurs to survive. One is by collaborating repeatedly, while the other is by having a great amount of initial wealth. If an entrepreneur has an extremely high wealth value but cannot find a collaborator, s/he will still survive longer because of the initial wealth. In addition, the initial wealth can also influence entrepreneurs' minimum survival time. In order to remove the influence of wealth, we normalized entrepreneurs' growth into a scale, which is relative survival time. The relative survival time is the actual survival time divided by minimum survival time:

Relative survival time = Actual Survival time/Minimum survival time.

Rather than the actual survival time, the relative survival time represents the real survival of an entrepreneur in our model irrespective of their initial wealth.

In general, the simulation can be stopped at a predetermined time or when all of the entrepreneurs exit the simulation process. Since there is a positive probability that some entrepreneurs will never fail, we fixed the terminal time in our simulation, and as most of the entrepreneurs will exit the market within 100 simulation periods, set 200 periods for the whole entrepreneurial simulation process. In total, we ran the whole simulation 100 times. The maximum actual survival time for an entrepreneur in a simulation run is 200.

5.4.2 The magic of simulations

As shown in Figure 25, we simulated all the entrepreneurs' collaborations and growth over time. Figure 25 shows the entrepreneurs' wealth-growth graph for all the entrepreneurs over 200 simulation periods; in other words, all the collaborations. We then selected three

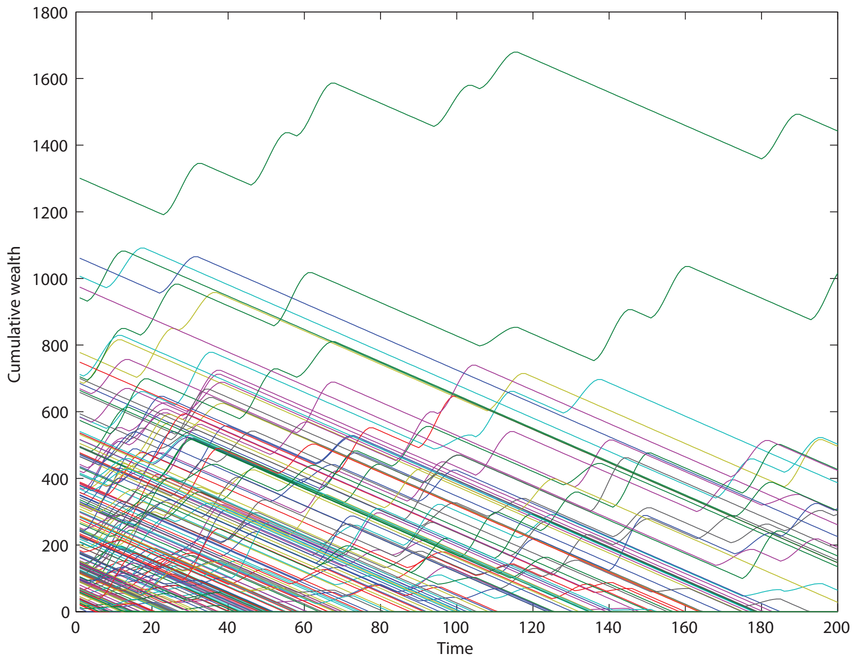

Figure 25 Simulation of entrepreneurial process over time.

entrepreneurs, presented in Figure 26, which thus shows three examples of entrepreneurs' wealth-growth over 200 simulation periods. The red line shows that this entrepreneur did not find a collaborator during the whole simulation period. Thus, the wealth of this entrepreneur continuously decreases until they exit the market. The actual survival time of this entrepreneur is equivalent to minimum survival time. The green line and the blue line show that the entrepreneurs found three collaborators and four collaborators respectively, over the whole simulation run. The actual survival time of the green line and the blue line is longer than their minimum survival time.

In our simulation model, we only allow two entrepreneurs to collaborate with each other in every simulation period. Once they meet and collaborate with each other, they will start up a business using the total wealth they have. The wealth of these entrepreneurs will increase; however, if they start searching for collaborators again, this wealth will decrease. The changes in their wealth are depicted in the wave of Figure 26. Our profit function g_i^t , considers that entrepreneurs can only collaborate for ten periods and will then stop collaborating and start searching for new opportunities. At such a point they will split the profit and gain a new wealth value, with which they continue searching for new opportunities to collaborate.

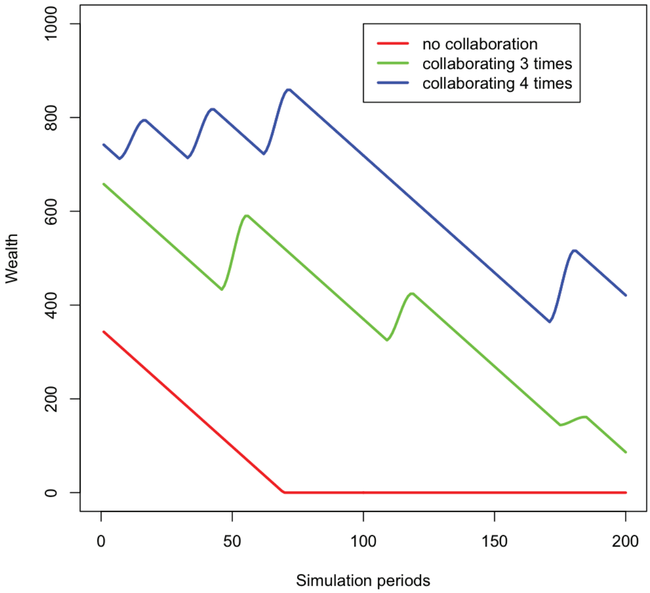

Figure 26 Example of simulations for 3 entrepreneurs over time.

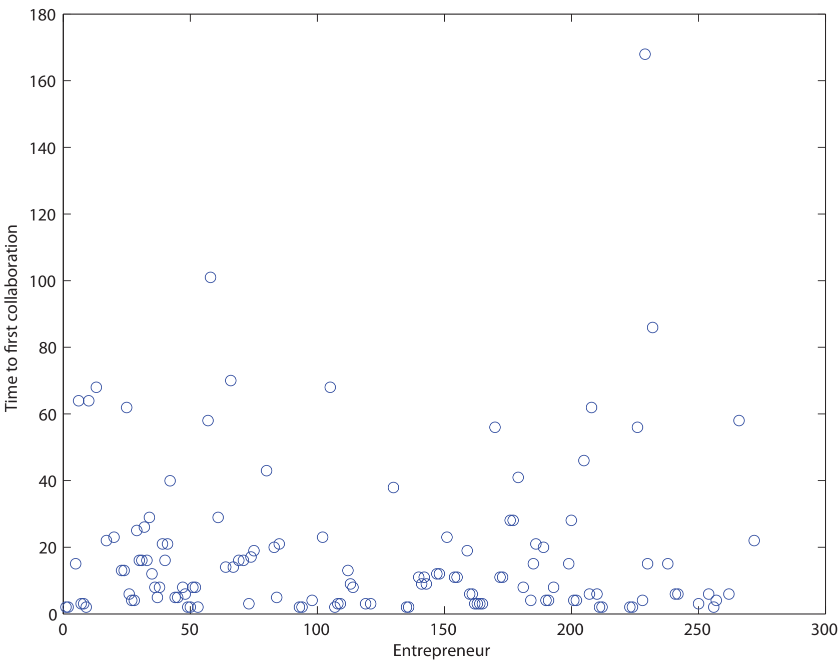

Figure 27 Time to first collaboration.

We found that some entrepreneurs' wealth continued growing until we finished the simulation process, while others could not find any partners. In addition, we found that certain entrepreneurs never had the chance to collaborate with others. Thus, we removed entrepreneurs with 0 degree. However, we still found that some entrepreneurs could not find opportunities to start up a business with other entrepreneurs. We assume this might be caused by the lack of initial wealth or the degree difference, and on this basis did a further analysis based on the differences of network degree and initial wealth.

Figure 27 presents the time to first collaboration during the whole entrepreneurial simulation process. According to the plot, most of the entrepreneurs find collaborators after the first or second simulation periods. We divided entrepreneurs into four groups according to their network degree and their initial wealth. As shown in Figure 28, the wealth separation and degree separation are 350 and 3, respectively. We retrieved the entrepreneurs who survived during our simulation. As shown in Table 14, we examined their network position and found that around 96% of entrepreneurs with a higher network degree and wealth would survive until the end of our simulation. However, entrepreneurs with higher network degree but low wealth or the reverse had only a 50% survival rate in our simulation procedure. Nevertheless, the results showed that entrepreneurs with either higher degree or higher start-up wealth have a higher survival rate (see Table 14).

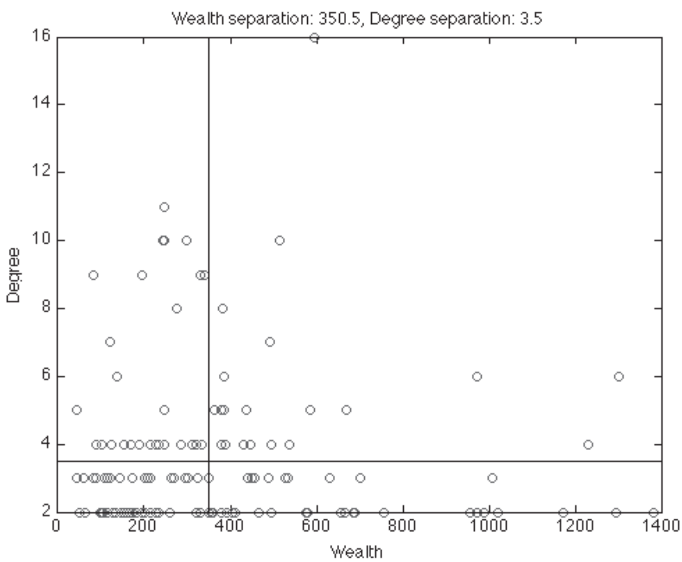

Figure 28 Simulation of entrepreneurial process over time.

Table 14 Survival rate by degree and wealth

	Group 1	Group 2	Group 3	Group 4
Degree/wealth	Low/low	High/low	High/high	Low/high
Survival rate	25.93%	50%	96.15%	49.02%

We double-checked the histogram by groups (Figure 29). Both Table 14 and Figure 29 show that network degree and initial wealth influence simulation results. In the following we will discuss the influence of initial wealth, network degree, and start-up time on the entrepreneurial process. Figure 30 maps the entrepreneurs' networks by their degree of connection and separation, visualizing the entrepreneurs' network based on wealth and degree of separation.

Entrepreneurs search for collaborators randomly in the given network. The collaborator may be the same person throughout the entire simulation. In order to avoid this problem, we assume that when two entrepreneurs start collaborating with each other, the number of collaboration periods is probably more than one depending on both their initial wealth

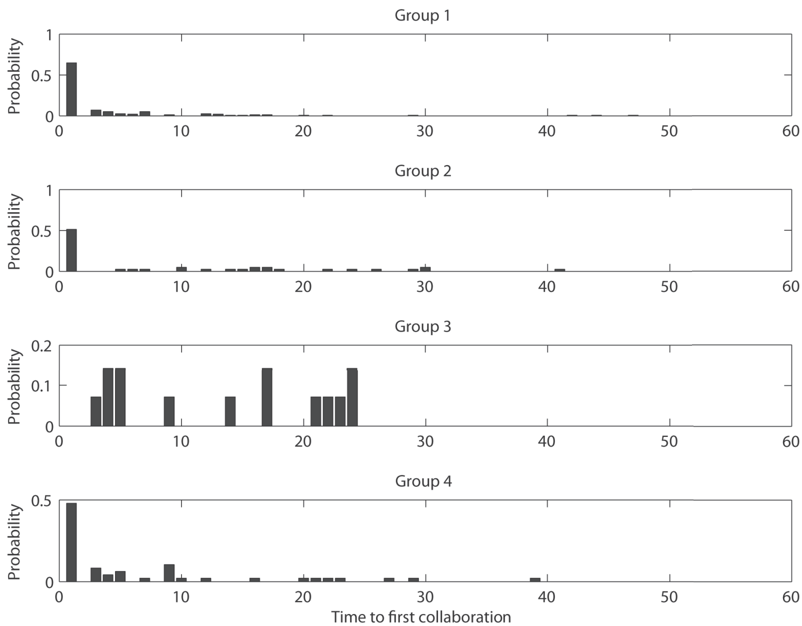

Figure 29 Time to first collaboration by groups.

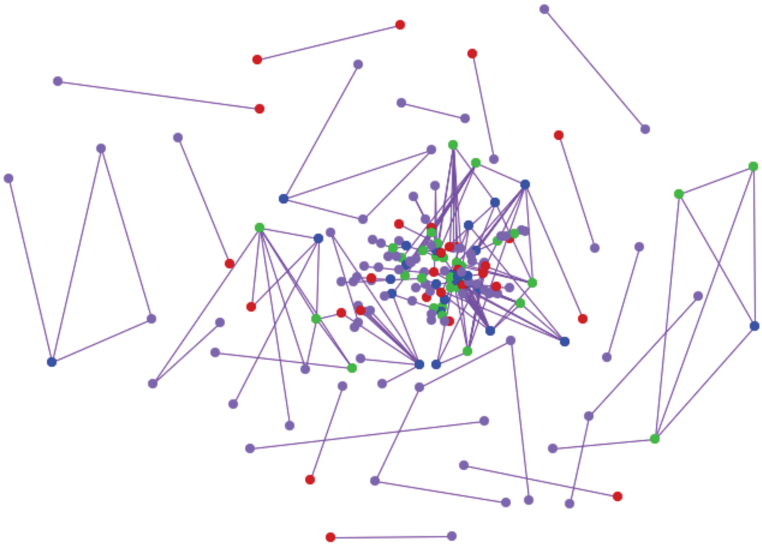

Figure 30 Entrepreneurs' network by degree and wealth separation.

and their profit. They stop collaborating with each other when no more profit can be made and start searching for a new collaborator. The previous collaborator will not be included in this search.

Based on the above and the characteristics of our data, we propose that (i) entrepreneurial growth is strongly related to entrepreneurial start-up wealth, (ii) first-time collaboration is related to initial wealth, (iii) entrepreneurs with a shorter start-up time will survive longer, and (iv) entrepreneurs with shorter start-up time will have a higher probability of surviving at time T. In the following subsection we will present our results.

5.4.3 Results

In total we have 273 entrepreneurs in the whole network. By repeating the simulation process 100 times, the whole simulation dataset resulted in 27,300 nodes. Without regard to the simulation time, all of the entrepreneurs whose initial wealth was equal to or higher than 1000 had a minimum survival time that was equal to or higher than 200 simulation periods and thus survived the entire simulation process.

As we were more interested in the survival rates during the 200 simulation periods, we removed the 480 entrepreneurs (nodes) whose initial wealth was equal to or higher than 1000, and thus still alive after 200 simulation periods. We also removed the entrepreneurs who failed to collaborate with another entrepreneur. Figure 31 plots the remaining entrepreneurs' start-up times and survival times. The horizontal bar above each figure represents entrepreneurs who survived more than 200 simulation periods. The vertical bar on the right of each figure represents entrepreneurs who did not collaborate during the entire simulation process and exited immediately. As shown in Figure 31, we plotted entrepreneurs' start-up time and growth by network degree after 200 simulation periods.

The plot in Figure 31 reveals no obvious relationship between start-up time and survival time. There are also no obvious differences between entrepreneurs based on their network degree. However, Figure 31, does imply that for a given start-up time, we can predict the maximum survival time.

For a given start-up time we selected those entrepreneurs who had the longest survival time, which we plotted in Figure 32 and did a regression analysis for entrepreneurs' start-up time and maximum survival time in Figure 33.

The relationship between maximum survival time t_{ms} and start-up time t_s is presented as:

$$\ln(\ln(t_{ms})) = \beta_0 + \beta_1 * t_s$$

As shown in Table 15, entrepreneurs' start-up time significantly predicted maximum survival time, b = -0.022, t = -37.85, $p < 0.001$. The start-up time explained a significant proportion of variance in the longest survival time, Adj-R^2 = 0.87, F (1,127) = 1432, $p < 0.001$. In order to further understand our result, we grouped entrepreneurs by their network degrees. We found that entrepreneurs with a network degree from 1 to 10 significantly predicted the maximum survival time; however, the Adj-R^2 decreases from network degree 1 to 10. Entrepreneurs with a network degree of 15 negatively predicted the optimal survival time. As we had only one entrepreneur at a network degree of 15, we argue that entrepreneurs' maximum survival time is significantly related to entrepreneurs' start-up time. Based on our simulation formula, we can predict entrepreneurs' optimal survival time on the basis of a given start-up time.

Our regression analysis also shows that entrepreneurs with a lower network degree are better predictors than entrepreneurs with a higher network degree. In other words, this means that a greater network degree might be detrimental to an entrepreneur's success. This was also suggested by Nann et al. (2010). Based on our simulation formula, we can predict

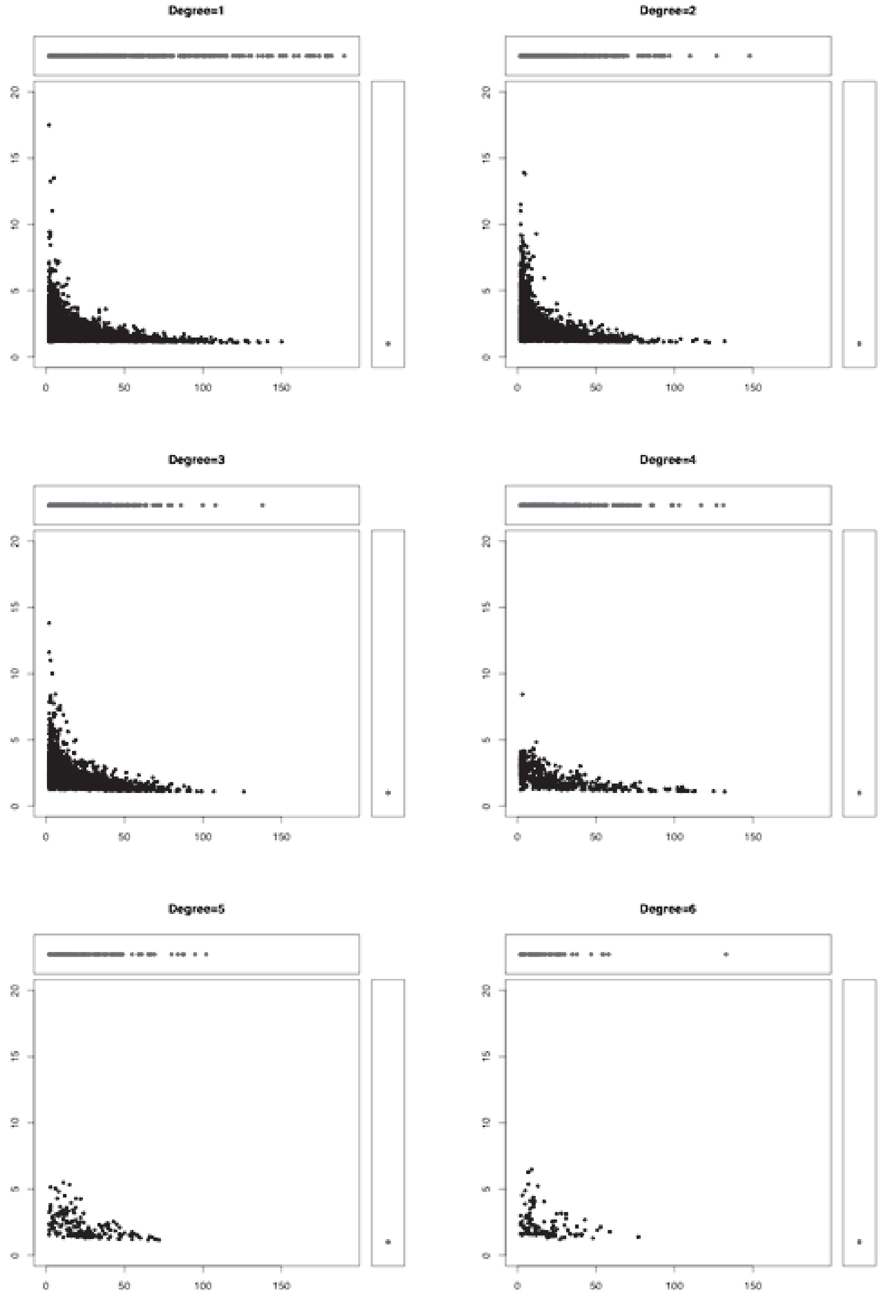

Figure 31 Entrepreneurs' start-up time and growth by degree. x stands for start-up time, y stands for survival time.

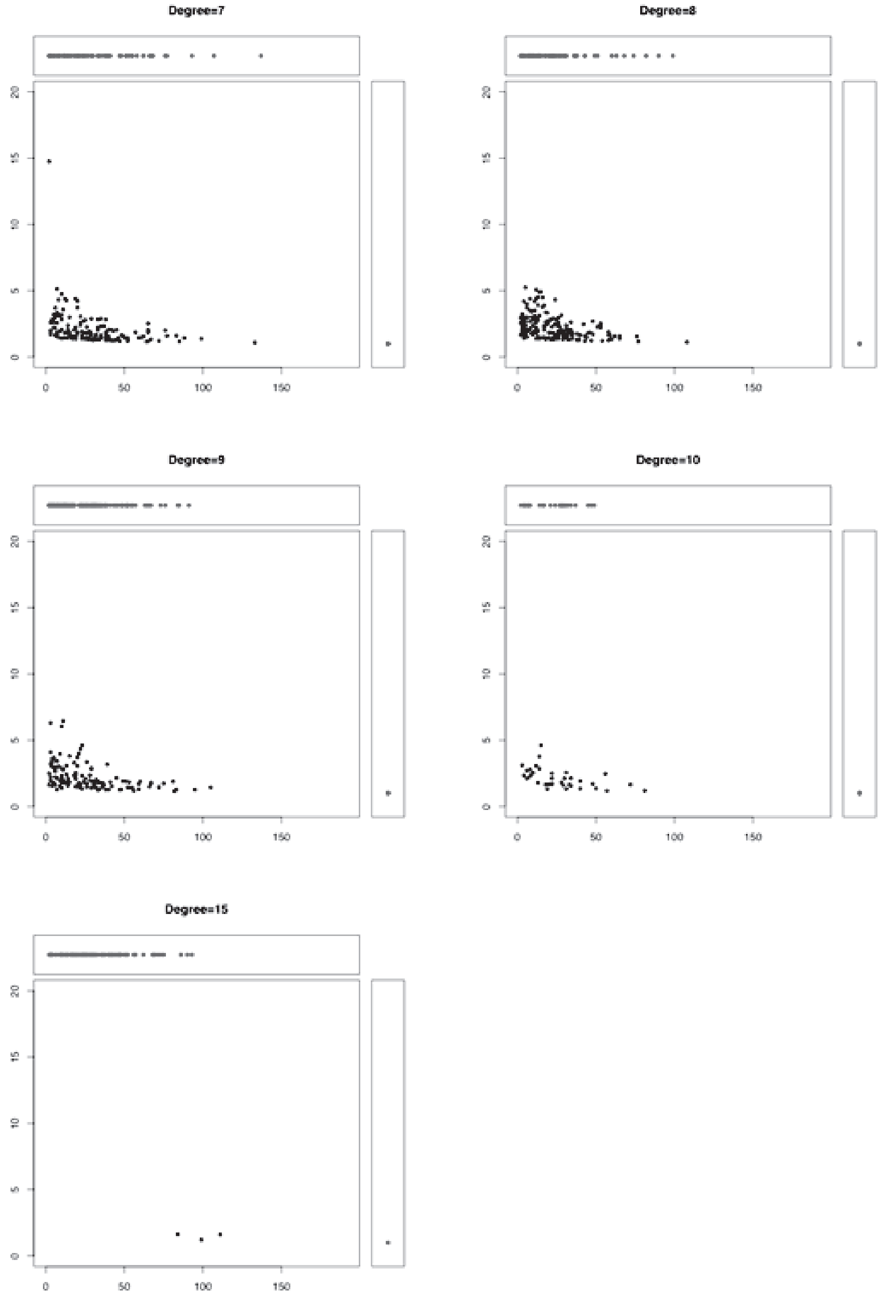

Figure 31 *Continued.*

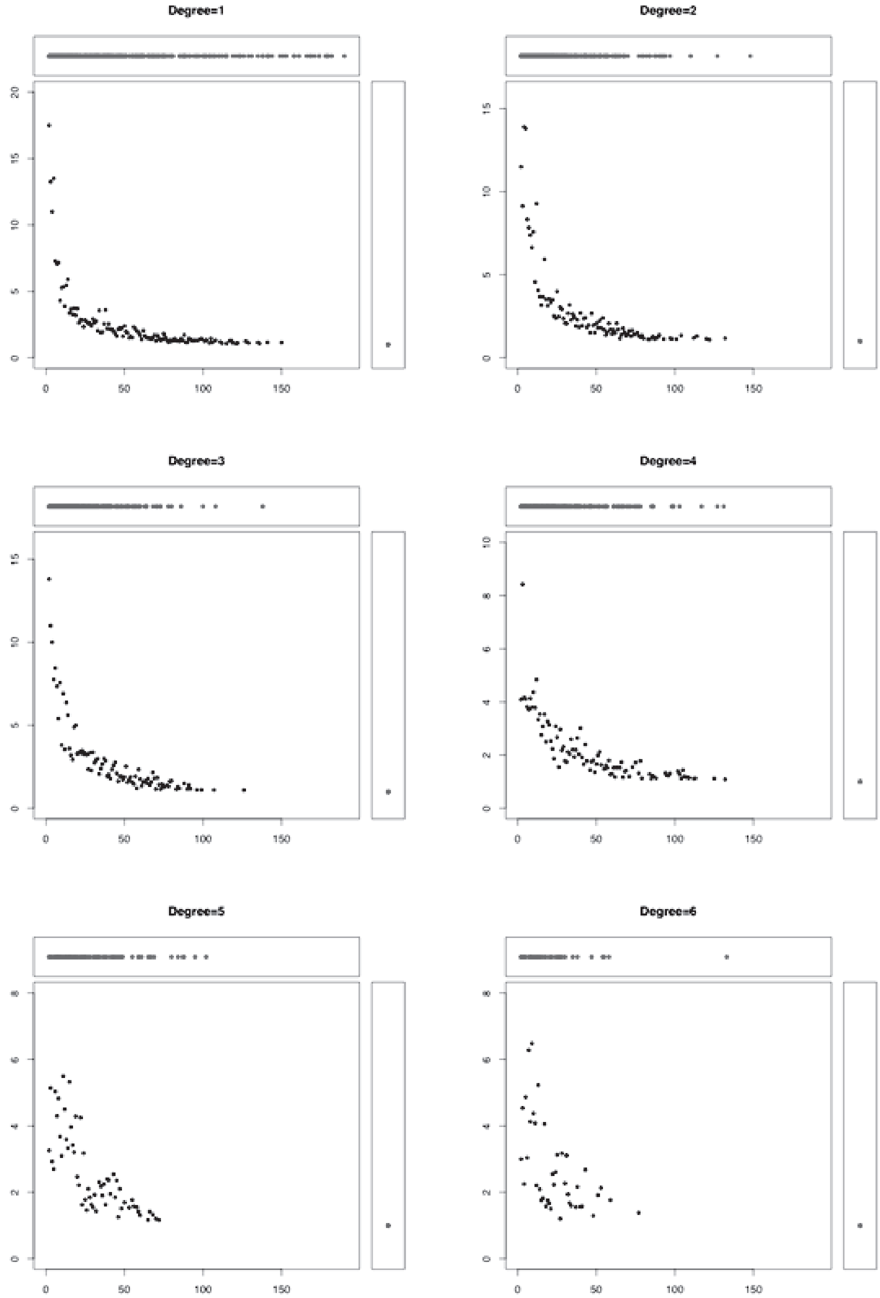

Figure 32 Plot of entrepreneurs' start-up time and maximum survival time. x stands for start up time, y stands for survival time.

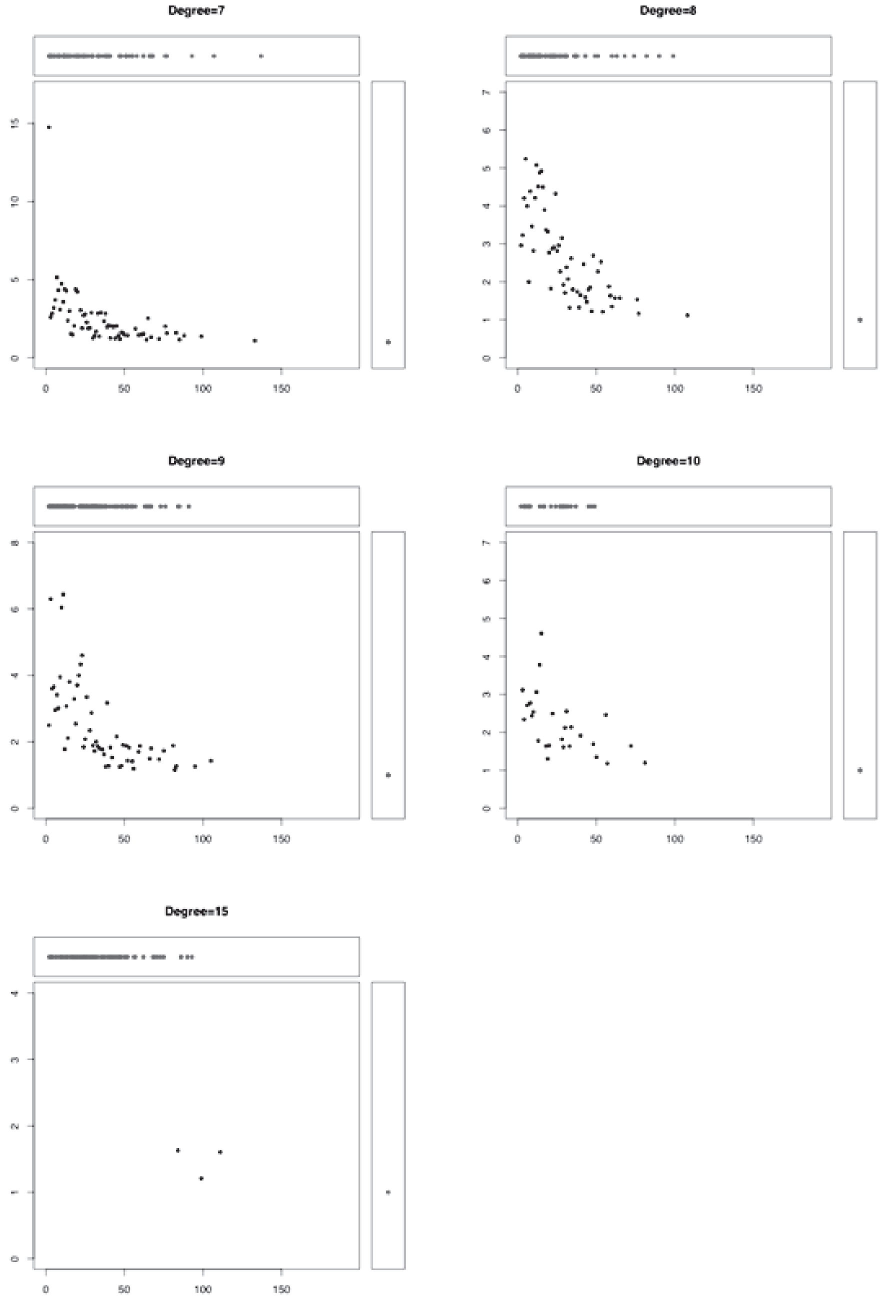

Figure 32 *Continued.*

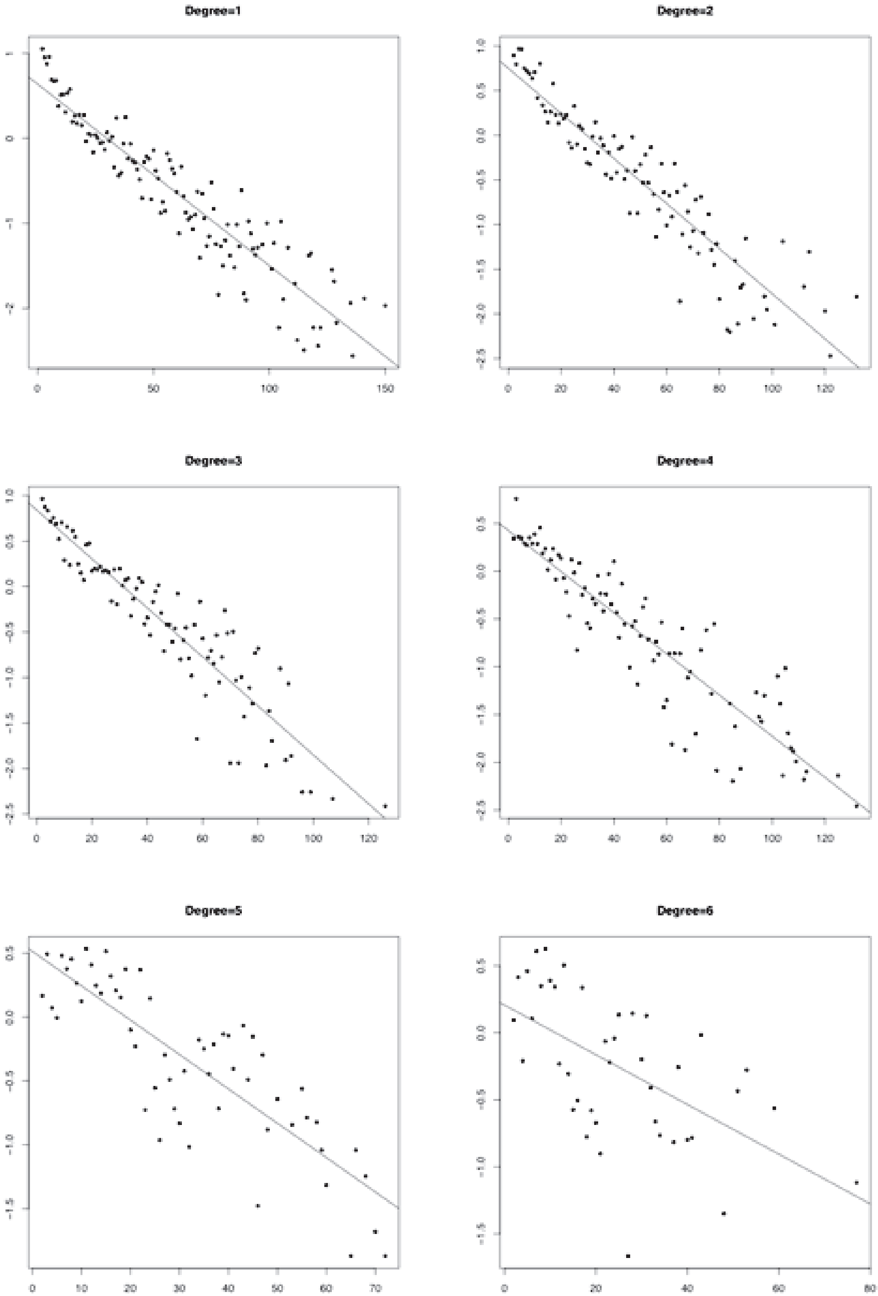

Figure 33 Regression analysis of start-up time and maximum survival time. x stands for start up time t_s, y stands for $\ln(\ln(t_{ms}))$.

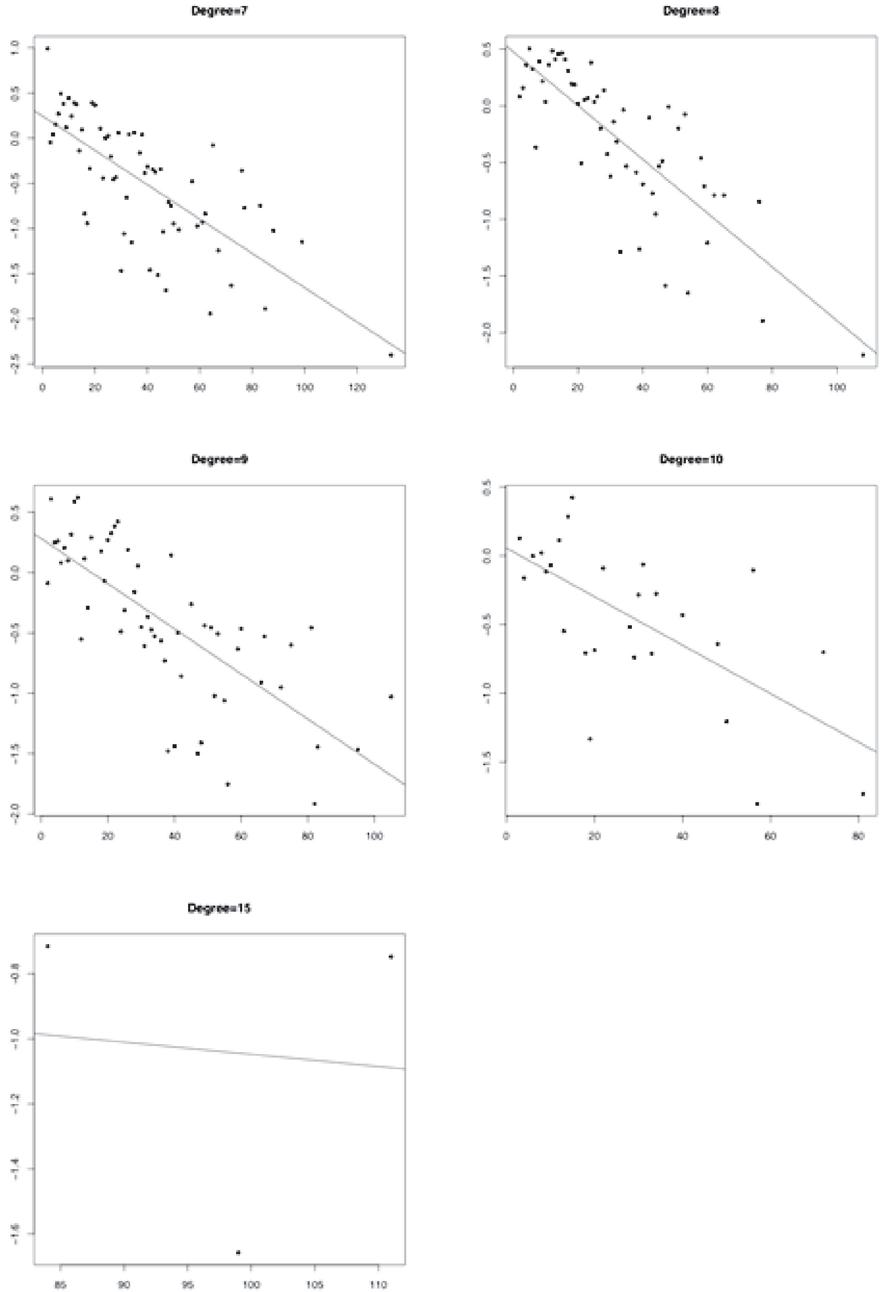

Figure 33 *Continued.*

Table 15 Regression table

	Intercept β_0 Slope β_1	Estimate	Std. Error	T value	Pr(>|t|)	Mul-R^2	Adj-R^2
Degree 1	Intercept	0.6361365	0.0555994	11.44	<2e-16 ***		
	Slope	-0.0213558	0.0007696	-27.75	<2e-16 ***	0.871	0.8699
Degree 2	Intercept	0.749595	0.063476	11.81	<2e-16 ***		
	Slope	-0.025247	0.001058	-23.86	<2e-16 ***	0.8596	0.8581
Degree 3	Intercept	0.841751	0.065942	12.77	<2e-16 ***		
	Slope	-0.026934	0.001201	-22.42	<2e-16 ***	0.8525	0.8508
Degree 4	Intercept	0.42621	0.06517	6.54	3.77e-09 ***		
	Slope	-0.02153	0.00105	-20.51	< 2e-16 ***	0.8253	0.8234
Degree 5	Intercept	0.513212	0.088395	5.806	3.30e-07 ***		
	Slope	-0.026909	0.002354	-11.431	3.74e-16 ***	0.7038	0.6984
Degree 6	Intercept	0.20599	0.12656	1.628	0.112		
	Slope	-0.01854	0.0042	-4.414	7.8e-05 ***	0.3331	0.316
Degree 7	Intercept	0.243237	0.107838	2.256	0.0277 *		
	Slope	-0.019006	0.002311	-8.226	1.8e-11 ***	0.5259	0.5181
Degree 8	Intercept	0.477225	0.095099	5.018	6.23e-06 ***		
	Slope	-0.023726	0.002435	-9.744	2.07e-13 ***	0.6417	0.635
Degree 9	Intercept	0.281863	0.104153	2.706	0.00904 **		
	Slope	-0.018707	0.002337	-8.006	8.51e-11 ***	0.5382	0.5298
Degree 10	Intercept	0.055175	0.144062	0.383	0.704962		
	Slope	-0.017651	0.004129	-4.275	0.000244 ***	0.4223	0.3992
Degree 15	Intercept	-0.675648	3.87766	-0.174	0.89		
	Slope	-0.003723	0.039319	-0.095	0.94	0.008884	-0.9822
All degree	Intercept						
	Slope	-0.0227053	0.0005999	-37.85	<2e-16 ***	0.9186	0.9179

entrepreneurs' maximum survival time on the basis of a given start-up time. However, similar to our results in Chapter 3, this correlation does not address the question of causality.

In addition, we found that some entrepreneurs never have a chance to collaborate with others. However, they can still survive based on their initial wealth. The start-up wealth allows entrepreneurs to survive even when they do not have a collaborator. Thus, there is always a minimum survival time for an entrepreneur, which is calculated by the initial wealth divided by searching costs. Initial wealth will definitely influence minimum survival time.

We examined initial wealth and the length of entrepreneurs' start-up time more closely, and found that we cannot predict whether the start-up wealth is related to the length of start-up time. However, it does guarantee that an entrepreneur will start a venture, as the initial wealth can guarantee a minimum survival period. Thus, we can say that initial wealth may also contribute to entrepreneurial growth.

We divided the entrepreneurs' start-up times into 15 time intervals, aiming to determine which interval will have the longest survival time after simulation period 150. As shown in Table 16, the survival probability at 150 increasingly grows as start-up time increases.

Moreover, we examined entrepreneurs whose network degree was 1 and the number of collaborations during their entrepreneurial process. We found the maximum number of collaborations is 6. In other words, entrepreneurs collaborated with the connections of their connections when searching for partners during start-up time.

Table 16 Survival probability more than 150 based on different start-up times

	Start-up time interval	False	Pro_False	True	Pro_True	Survival time T2
1	0 <start up time <= 10	4666	0.841630592	878	0.158369408	survival time>= 150
2	10 <start up time <= 20	1565	0.830679406	319	0.169320594	survival time>= 150
3	20 <start up time <= 30	950	0.829694323	195	0.170305677	survival time>= 150
4	30 <start up time <= 40	609	0.807692308	145	0.192307692	survival time>= 150
5	40 <start up time <= 50	350	0.808314088	83	0.191685912	survival time>= 150
6	50 <start up time <= 60	222	0.773519164	65	0.226480836	survival time>= 150
7	60 <start up time <= 70	131	0.779761905	37	0.220238095	survival time>= 150
8	70 <start up time <= 80	66	0.694736842	29	0.305263158	survival time>= 150
9	80 <start up time <= 90	38	0.703703704	16	0.296296296	survival time>= 150
10	90 <start up time <= 100	17	0.53125	15	0.46875	survival time>= 150
11	100 <start up time <= 110	14	0.518518519	13	0.481481481	survival time>= 150
12	110 <start up time <= 120	6	0.461538462	7	0.538461538	survival time>= 150
13	120 <start up time <= 130	6	0.666666667	3	0.333333333	survival time>= 150
14	130 <start up time <= 140	2	0.4	3	0.6	survival time>= 150
15	140 <start up time <= 150	0	0	2	1	survival time>= 150

We further looked at entrepreneurs' network degree and collaboration with a histogram by network degree. We found that entrepreneurs with a lower degree tend to collaborate more times than entrepreneurs with a higher network degree. This result occurred because our model assumed that each entrepreneur can only collaborate with one person in each simulation period, and therefore the entrepreneurs with a higher network degree will appear to have a lower probability of collaborating with other people in the network.

For entrepreneurs with a network degree of 1, we examined the histogram of collaboration times at different collaboration probabilities. We found that the higher collaboration probability we set, the greater the possibility that they collaborate with the same people during their business life. In other words, the entrepreneurs will tend to collaborate with fewer people during the simulation process.

5.5 Conclusions

This chapter presented a network simulation model to describe the entrepreneurial process depending on the position of an entrepreneur in a given network. The network structure was extracted from the LinkedIn network. This simulation model can predict entrepreneurs' maximum survival time based on a given start-up time.

In our model, we found that entrepreneurial growth is not only related to wealth but also to their network degree. An entrepreneur's start-up wealth can guarantee survival even without a collaborator. Although we were not able to determine the threshold for entrepreneurs to survive at a given time, we could still infer the survival probability from the start-up time frame.

We expected that entrepreneurs with a higher network degree would collaborate more with other people. However, our simulation model only allowed entrepreneurs to collaborate with one entrepreneur at a time. In other words, the probability that an entrepreneur would collaborate with someone in the network became lower when their network degree was high. In fact, entrepreneurs with fewer connections may collaborate more and survive longer than those with a higher network degree.

The initial network was collected from entrepreneurs' online social network. Based on different research questions, different network structures can be applied in our simulation model in real life. We are intending to develop an approach to further explore the entrepreneurial process in a given network. Furthermore, we will include network dynamics in our simulation model.

Our research not only contributes to the field of entrepreneurship but also to a further understanding of online social networks and the benefits of social media arising from the ubiquitous use of the internet. Our simulation model provides a novel approach to understanding the entrepreneurial process in a fixed network. However, in real life, the network is dynamic across the whole entrepreneurial simulation process. There is still much to be done in relation to future research on dynamic network data using the simulation process.

CHAPTER 6

Implications and Discussion

In this dissertation, we studied an entrepreneurial NoN from different perspectives. In brief, the dissertation included a methodology chapter and three chapters discussing empirical studies. Chapter 2 presented a novel methodology for collecting online social network data. Chapter 3 analysed the relationship of entrepreneurs' online social network diversity to their survival. Chapter 4 analysed the distribution of entrepreneurs' online social networks, while Chapter 5 used a simulation model to explore the potential influences of an NoN on the entrepreneurial process. The strengths of this dissertation lie in the methodology for collecting NoN network data and the simulation of the entrepreneurial process in a given network structure. In this chapter, we will summarize the contributions and limitations of this dissertation and suggest directions for future research.

6.1 Summary of methodology

In Chapter 2 we developed a methodology to explore entrepreneurs' social networks, which we found to be an NoN and on this basis used NoN theory to study the online social networks of entrepreneurs. The method of collecting NoN data was made possible due to the dramatic increase in the use of online social networking sites. Entrepreneurs in particular are interested in using multiple online social network sites. Rather than analysing entrepreneurs' online social networks individually, we examined their networks as a whole to determine the influence on entrepreneurship.

The central idea is that entrepreneurs are embedded in a network of networks (NoN). It is the NoN rather than the individual networks that contributes to the entrepreneurial process. We developed a method of collecting NoN data through online social networks and concluded that sufficient NoN data is available through online social networking sites. Our research project involved 384 participants. We suggest that this methodology can be applied in other fields to explain phenomena caused by social networks.

6.2 Summary of network diversity

We studied the size and structure of entrepreneurial social networks by analysing the online network industry and location diversity. Our findings suggest that entrepreneurs use multiple online social networks that form their network of networks (NoN). We examined the entrepreneurs' network size and diversity to gauge their impact on performance in terms of survival. Our findings suggest that the entrepreneurs' LinkedIn network size has a positive relationship with entrepreneurial survival, the size of the entrepreneurs' Facebook network is not related to their survival, while the size of their Twitter network had a negative relationship with survival. We visualized the entrepreneurs' LinkedIn network in terms of industry diversity. Finally, we reflected on the implications for future research on the structure of entrepreneurial online social networks.

6.3 Data secrets

In view of the importance of networks for entrepreneurs, the study presented here is intended to fill a gap in the literature pertaining to the structure and entrepreneurial use of online social networks such as LinkedIn, Facebook and Twitter. Drawing on the literature on social network analysis, we found that entrepreneurs use multiple online social networks as a network of networks (NoN). We merged the data from these three online social networks to study the structure of the entrepreneurs' NoN. We explored the communities within the NoN by removing the edges with the highest betweenness values. Our analysis suggested that the entrepreneurs' NoN follows an exponential degree distribution, which implies that weak ties between individual networks play an important role in forming an entrepreneurial NoN. Furthermore, we found overlaps between entrepreneurs' neighbours across the NoN, which suggests that entrepreneurs develop and use NoNs to support the entrepreneurial process.

6.4 The simulation of the entrepreneurial process in a given network

In our simulation model, we found that entrepreneurial growth is not only related to wealth but also to the network degree. The entrepreneurs' start-up wealth can guarantee they will survive when they do not have a collaborator. Although we were not able to find the threshold for entrepreneurs to survive at a given time, we could still infer the survival probability from the start-up time frame.

We expected that entrepreneurs with a higher network degree would collaborate more with others. However, our simulation model only allowed entrepreneurs to collaborate with one entrepreneur at a time. In other words, the probability that an entrepreneur could collaborate with someone in the network became lower when entrepreneurs' network degree was higher. In fact, entrepreneurs with fewer connections may collaborate more and survive longer than those with a higher network degree.

The initial network was part of the online social network, thus the whole analysis may be biased. However, we are intending to develop an approach to further explore the entrepreneurial process in a given network. Due to the limitations of our simulation model, it seems that entrepreneurs with a higher network degree had lower collaboration rates. We will solve this problem in the next simulation model. In addition, the empirical research was limited by a lack of longitudinal and process-oriented data. Therefore, it neither addressed the emergence and dynamics of networks over time nor the link to venture performance. Thus, future research should address entrepreneurial network dynamics from both the NoN and simulation perspectives. In order to understand network dynamics and evolution and their effect on entrepreneurial performance we must move beyond mere descriptive accounts of network structures in future research and develop in-depth explanations of the structural dynamics of entrepreneurial networks.

6.5 An additional note on methodology – future perspectives

In addition to the findings presented here, we also believe that mobile phones, especially smart phones which carry large amounts of information, could be used as an alternative for collecting information on entrepreneurs' NoNs. The information found on smart phones can help us further understand the nature of the interaction and communication between human beings. For example, mobile phones allow us to observe the geographical position of their carriers, to analyse the call logs or text messages to determine the frequency of communications between two carriers and to study the use of the internet through mobile phones. Jointly, this kind of information can provide us with large amounts of data that sheds light on human behaviour in real-life situations and can help us predict interactions among individuals constituting a particular group, such as entrepreneurs.

The recent literature on mobile phone networks has mainly adopted one of two perspectives: either the physical patterns of mobile phone networks have been analysed or a social perspective has been used to understand mobile phone networks. The physical perspective focuses on complex networks and analyses the network structure (graph) by looking at those non-trivial topological features that do not occur in simple networks, such as lattices or random graphs. The social perspective primarily reflects on how people communicate and interact with each other through mobile phones.

As we know, mobile phone data itself can provide interesting insights, for instance, the way mobile phone viruses spread (Wang, Gonzalez, Hidalgo, & Barabasi, 2009), and human mobility patterns that can be traced from a mobile phone user's position (Gonzalez, Hidalgo, & Barabasi, 2008). Moreover, this data reflects the interaction and communication between human beings, such as heterogeneous calling activities (Candia et al., 2008) and mobile communication networks (Onnela et al., 2007). In short, these studies make it clear that mobile phone data can provide relevant insights for research.

In addition to making phone calls and sending text messages, recent developments in mobile phone technology allow people to use the internet on the mobile phone, as well as small applications which allow them to communicate with each other in new ways. Adopting a qualitative view on mobile phone networks, Chen and Katz (2009) observed the pattern of mobile phone usage between college students and their families in order to analyse how mobile phones affect university students' lives. The research was conducted through focus-group interviews and focused on how college students use mobile phones to communicate with their parents. Furthermore, text messages can be used to collect and provide feedback when experiments are conducted in larger classes (Cheung & Lee, 2010).

Despite the relevant qualitative insights into mobile phone usage, these studies did not quantitatively analyse the structure or the dynamics of mobile phone networks. However, it is particularly these aspects of mobile phone networks that can provide us with novel insights into the dynamics and patterns of social networks – NoNs – over time, given the overwhelming number of mobile phone users. For example, inferring real networks from mobile phone network data (Palla, Barabasi, & Vicsek, 2007), researchers have studied scientists' collaborative networks and mobile phone network users. Eagle et al. (2009) inferred a friendship network structure by using mobile phone data and compared it with the real friendship network by correlation analysis, in which three types of information were collected to map networks – communication (via call logs), location (via mobile phone towers) and proximity to others (via repeated Bluetooth scans).

As we suggested, smart phones can be used as a tool to collect NoN data. With smart phone data collection, we can observe when a node is added or broken off from an existing network. The findings of such a study will be twofold. On the one hand, we will explore the different purposes for which entrepreneurial start-ups make use of SNSs. Equally important is exploring why they do not use certain SNSs (Boyd and Ellison, 2007). We will use these insights to understand why particular SNSs are more important for entrepreneurial start-ups than others. In addition, these insights will be used to assess the relationship between the use of SNSs and entrepreneurial performance.

Depending on the results, such a study could make several contributions. First, mapping and visualizing the closed network of entrepreneurial start-ups shows how SNSs support the building and maintaining of the social networks of entrepreneurs involved in starting up ventures. Second, exploring the different purposes for which such entrepreneurs use SNSs can help us understand how SNSs are used in organizational contexts and why certain SNSs are considered less significant from a business perspective. Third, analysing the relationship between the use of SNSs and entrepreneurial performance provides insights into the benefits of SNSs for venture start-ups. Therefore, such a study would contribute an understanding of how SNSs are used in organizational contexts and more specifically in the context of entrepreneurial start-ups, and provide insights into the benefits of online social networks for entrepreneurial start-ups.

Based on existing research on mobile phone networks, we can draw two conclusions. First, most of these studies focus on the physical patterns of the mobile phone networks using a complex network approach. Second, very little work emphasizes the social elements of the mobile phone network or has analysed human interaction and communication in detail. In other words, the majority of mobile phone network studies neglect the social aspect of mobile phone networks, given their focus on physical characteristics. This is due to practical problems associated with telecommunication companies collecting mobile phone data, such as privacy laws.

We believe that analysing entrepreneurs' mobile phone networks can provide relevant contributions to research on human behaviour such as that related to entrepreneurship and to the study of entrepreneurs' NoNs. As the mobile phone network is an NoN, it has all the characteristics of social networks, allowing us to use the same measures as we use in relation to social networks. Individual entrepreneurs will be the unit of analysis for this study. We also suggest that the structure and dynamics of entrepreneurs' social networks can also be studied using smart phone network data. The network data can be extracted from mobile phone call logs and mobile phone internet usage by gaining access to online social networking sites.

6.6 Limitations and conclusions

One of the limitations of this dissertation is the lack of data on entrepreneurial performance. Due to the limitations of our data collection method, we need more extensive performance data to support the whole design of this study. Nevertheless, we managed to collect a large amount of network data by sending our survey link randomly to entrepreneurs in the Netherlands. The boundary for this network is very broad, in other words, we do not have a lot of edges in the graph of our network.

Alternatively, we might also adopt methods similar to those we designed for extracting data from online social networks using smart phones which access the internet. We would only gain access to the entrepreneurs' online social network if they accessed the survey via smart phones. Applying the survey used here and improving it for use on smart phones would allow us to conduct our future research in another way. In order to collect mobile phone network data, both from the mobile network and the LinkedIn online network, several practical issues need to be given special attention. For example, entrepreneurs are generally reluctant to provide detailed calling records, because this is private or sensitive information. An alternative would be to provide entrepreneurs with smart phones which are already programmed to store and transfer the data. Our future study will provide entrepreneurs with IPhones as this will offer an additional incentive for engaging in the study.

In this thesis, we mainly focused on entrepreneurs' online social networks. The idea of this research project was to address the influence of online social networks, due to the ubiquitous use of the internet and smart phones. The thesis did not link entrepreneurs' online social networks to their offline networks; however, our simulation model could be used as an approach to study entrepreneurs' offline networks. The connection between online social networks and offline networks should be addressed in future research.

During the entrepreneurial process, the network can be used to search for information and resources. In addition, the interaction and communication between entrepreneurs can also influence their business decisions. The complex nature of this interaction remains a question for the future.

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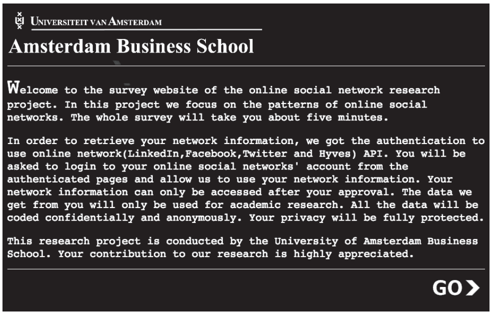
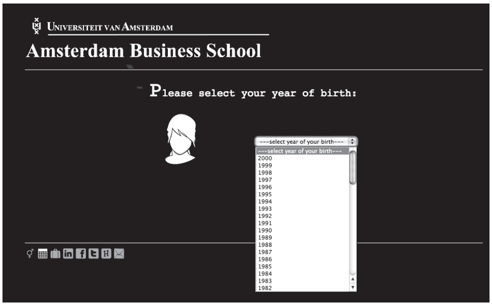
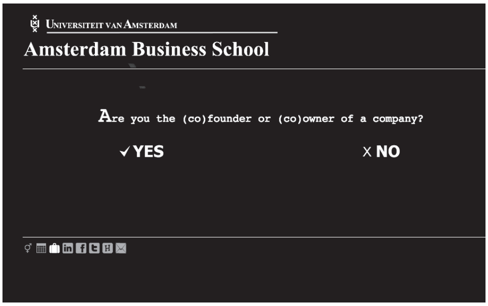
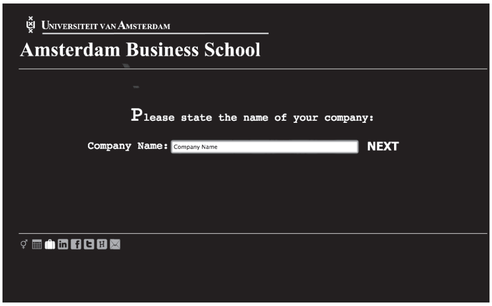
APPENDIX

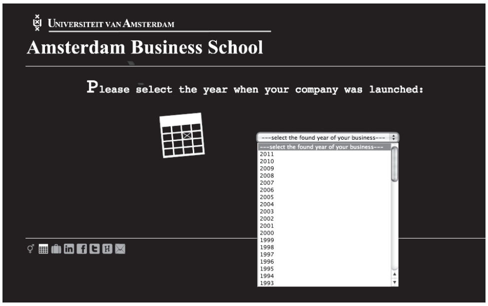
Online social network survey screen shots[1]

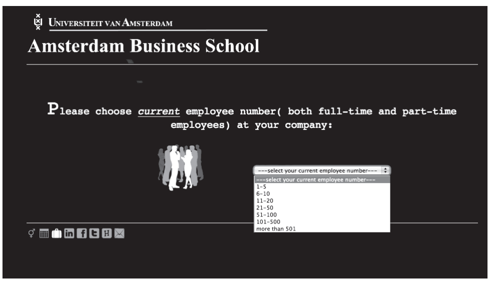




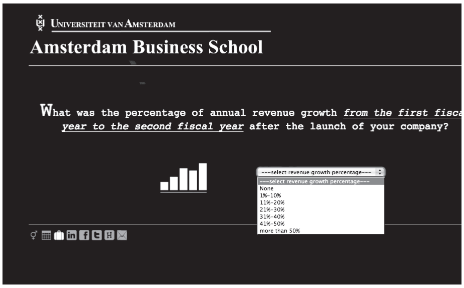




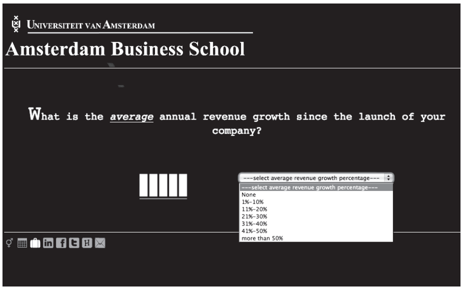


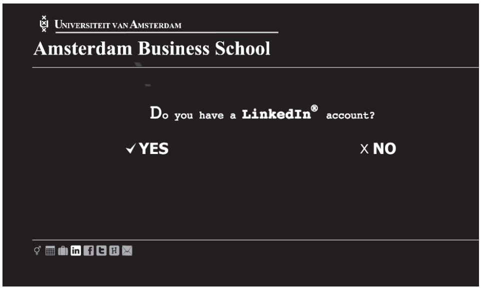


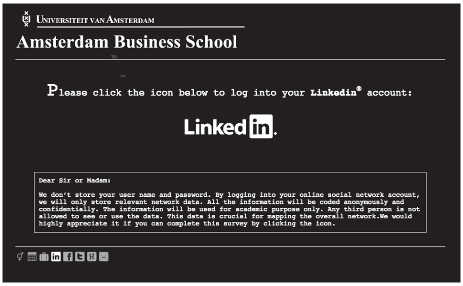
[1] The data was collected automatically and saved anonymously after the participants logged into their online social networks through the online social network logo (LinkedIn, Facebook and Twitter) in the survey.

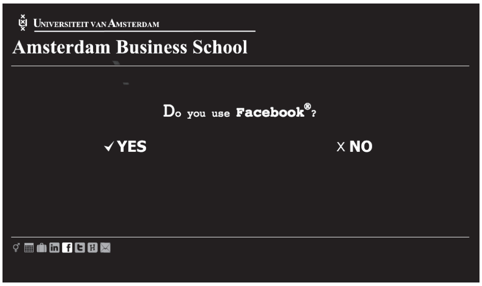

Universiteit van Amsterdam
Amsterdam Business School
What was the percentage of annual revenue growth from the first fisca
year to the second fiscal year after the launch of your company?
---select revenue growth percentage---
None
1%-10%
11%-20%
21%-30%
31%-40%
41%-50%
more than 50%


Universiteit van Amsterdam
Amsterdam Business School
Please choose the annual revenue growth of your company in the last fiscal year:
---select current revenuegrowth percentage---
None
1%-10%
11%-20%
21%-30%
31%-40%
41%-50%
more than 50%

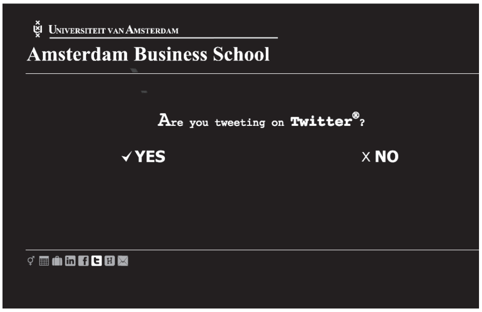

Universiteit van Amsterdam
Amsterdam Business School
What is the average annual revenue growth since the launch of your company?
---select average revenue growth percentage---
None
1%-10%
11%-20%
21%-30%
31%-40%
41%-50%
more than 50%

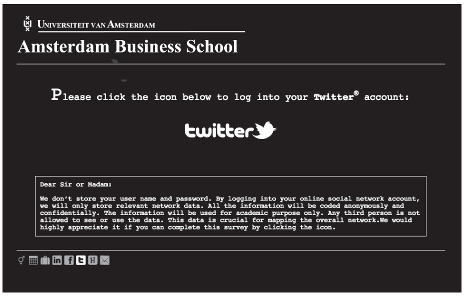

Universiteit van Amsterdam
Amsterdam Business School
Do you have a LinkedIn® account?
✓YES
X NO

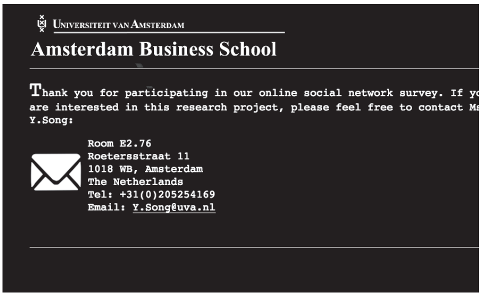

Universiteit van Amsterdam
Amsterdam Business School
Please click the icon below to log into your Linkedin® account:
Linkedin
Dear Sir or Madam:
We don't store your user name and password. By logging into your online social network account, we will only store relevant network data. All the information will be coded anonymously and confidentially. The information will be used for academic purpose only. Any third person is not allowed to see or use the data. This data is crucial for mapping the overall network.We would highly appreciate it if you can complete this survey by clicking the icon.


Universiteit van Amsterdam
Amsterdam Business School
Do you use Facebook®?
✓YES
X NO


Universiteit van Amsterdam
Amsterdam Business School
Please click the icon below to log into your Facebook® account:
facebook
Dear Sir or Madam:
We don't store your user name and password. By logging into your online social network account, we will only store relevant network data. All the information will be coded anonymously and confidentially. The information will be used for academic purpose only. Any third person is not allowed to see or use the data. This data is crucial for mapping the overall network.We would highly appreciate it if you can complete this survey by clicking the icon.


Universiteit van Amsterdam
Amsterdam Business School
Are you tweeting on Twitter®?
✓YES
X NO


Universiteit van Amsterdam
Amsterdam Business School
Please click the icon below to log into your Twitter® account:
twitter
Dear Sir or Madam:
We don't store your user name and password. By logging into your online social network account, we will only store relevant network data. All the information will be coded anonymously and confidentially. The information will be used for academic purpose only. Any third person is not allowed to see or use the data. This data is crucial for mapping the overall network.We would highly appreciate it if you can complete this survey by clicking the icon.


Universiteit van Amsterdam
Amsterdam Business School
Thank you for participating in our online social network survey. If y
are interested in this research project, please feel free to contact M
Y.Song:
Room E2.76
Roetersstraat 11
1018 WB, Amsterdam
The Netherlands
Tel: +31(0)205254169
Email: Y.Song@uva.nl

ABOUT THE AUTHOR

Curriculum vitae

Yang Song was born in Jilin, China on 9 February 1983. In 2005 she received her Bachelor's degree in Computer Science and Technology at Jilin University, China. In 2006 she started her Master's of Business Management at the School of Economics, Jilin University, completing it in July 2008.

In October 2008 she received a scholarship from the Chinese Scholarship Council (CSC) and entered the PhD programme in entrepreneurship at Amsterdam Business School, University of Amsterdam (UvABS). Her research on entrepreneurship takes a network approach and is based on online social network data. While she was a PhD candidate she attended many academic conferences, including the Interdisciplinary European Conference on Entrepreneurship Research (IECER 2009), the Babson College Entrepreneurship Research Conference (Babson 2010), the International Sunbelt Social Network Conference (Sunbelt 2010), the International Conference of Graduate Entrepreneurship: Research, Practices and Policies (ICEG2010) and Collaborative Innovation Networks: Thinking the Swarm (COINs11). She has a lively research interest in collecting and analysing large amounts of network data.

This thesis summarizes the main output of her PhD research over the past four years and presents the results. This research contributes to both entrepreneurship and social network theory, and the methodology developed in her thesis can also be used in other disciplines. She is currently working as a researcher at UvABS.

Papers

Song, Y., & Vinig, T. (2012). Entrepreneur Online Social Networks – Structure, Diversity and Impact on Start-up Survival. International Journal of Organisational Design and Engineering, 2(2), 189-203.

This paper was selected as the paper for journal press release, for more information please visit: http://www.alphagalileo.org/ViewItem.aspx?ItemId=122088&CultureCode=en

Song, Y., & Vinig, T. (2012). Entrepreneurs' Online Social Networks: Network of Networks (NoN). *Journal of Business Research, under review, submitted on October 16, 2012.*

Song, Y., Huang, J., & Vinig, T. (2012). Online Network Simulation on Entrepreneurial Process. Working-in-progress.

Conferences

Song, Y., & Vinig, T. (2010). Entrepreneurs' network of networks: studying entrepreneurs' social network structure using smart-phone data. Babson College Entrepreneurship Research Conference (BCERC 2010), 9–12 June 2010, Lausanne, Switzerland.

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