Network of networks: Uncovering the secrets of entrepreneurs' networks

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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 & Antonicc, 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.

![Histogram of connection](image)

*Figure 21  Histogram of entrepreneurs’ connections.*
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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.

<table>
<thead>
<tr>
<th>Group</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of nodes for each component</td>
<td>139</td>
<td>5</td>
<td>4</td>
<td>3</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Frequency</td>
<td>139</td>
<td>10</td>
<td>8</td>
<td>3</td>
<td>24</td>
<td>89</td>
</tr>
<tr>
<td>The percentage of entrepreneurs</td>
<td>51%</td>
<td>4%</td>
<td>3%</td>
<td>1%</td>
<td>9%</td>
<td>33%</td>
</tr>
</tbody>
</table>

Figure 22 Entrepreneurs’ online social networks.
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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

<table>
<thead>
<tr>
<th>Table 13 Structural properties of the biggest network component</th>
</tr>
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<tbody>
<tr>
<td>Average path length</td>
</tr>
<tr>
<td>---------------------</td>
</tr>
<tr>
<td>Regular</td>
</tr>
<tr>
<td>Actual</td>
</tr>
<tr>
<td>Random</td>
</tr>
</tbody>
</table>
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.
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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:

\[
\text{Minimum survival time} = \frac{\text{initial wealth}}{\text{Searching cost}}
\]

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
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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.
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- **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:

$$p = \frac{1}{kn}$$

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 $S_t$ 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 $S_t$, $w_t$ represents the wealth of the entrepreneur $i$ at period $t$, $g_t$ 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. $a_t$ 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. $\phi_t$ refers to the phase of entrepreneur $i$. $c_t$ 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, $w_0^i > 0, a_0^i = 0, \phi_0^i = 1, c_0^i = 0$, thus the initial status of each entrepreneur $i$ is:

$$t = 0, S_t^i = (w_0^i, 0,1,0)$$

After this initial status, while $t \geq 0$, we assume an entrepreneur $i$ could find another entrepreneur $j$ with whom to collaborate, with $w_t^i$ and $w_t^j$ being the wealth of entrepreneur $i$ and entrepreneur $j$ for the next period. The value of $\phi_t^{i+1}$ and $\phi_t^{j+1}$ 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

$$\phi_t^i = 2; a_t^{i+1} = a_t^i + 1; \text{ we have: }$$

$$S_t^i = (w_t^i, a_t^i, \phi_t^i, c_t^i)$$

$$g_t^i = \alpha * a_t^i \left( \beta - a_t^i \right)$$
\[ w_i^t = w_i^{t-1} + \frac{w_i^{t-1}}{w_i^{t-1} + w_j^{t-1}} \ast g_i^t \]
\[ w_j^t = w_j^{t-1} + \frac{w_j^{t-1}}{w_i^{t-1} + w_j^{t-1}} \ast g_i^t \]
\[ a_i^t = t; \]
\[ q_i^{t+1} = \begin{cases} 1 & \text{if } w_i^t > 0; \ a_i^t = 0; \ c_i^t = 0 \\ 2 & \text{if } w_i^t > 0; \ a_i^t > 0; \ c_i^t > 0 \\ 3 & \text{if } w_i^t = \max \left( w_i^{t-1} - c \right) = 0; \ c_i^t = 0 \end{cases} \]
\[ q_j^{t+1} = \begin{cases} 1 & \text{if } w_j^t > 0; \ a_j^t = 0; \ c_j^t = 0 \\ 2 & \text{if } w_j^t > 0; \ a_j^t > 0; \ c_j^t > 0 \\ 3 & \text{if } w_j^t = \max \left( w_j^{t-1} - c \right) = 0; \ c_j^t = 0 \end{cases} \]

If an entrepreneur exits the market, it is not possible for them to return to any other phase, thus we have:
\[ q_i^t = 3 \]
\[ w_i^{t+1} = w_i^t \]
\[ a_i^{t+1} = 0 \]
\[ c_i^t = 0 \]

### 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.
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:

\[
\text{Relative survival time} = \frac{\text{Actual Survival time}}{\text{Minimum survival time}}.
\]

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
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 $g^i$, 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).
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

<table>
<thead>
<tr>
<th>Degree/wealth</th>
<th>Group 1</th>
<th>Group 2</th>
<th>Group 3</th>
<th>Group 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low/low</td>
<td>25.93%</td>
<td>50%</td>
<td>96.15%</td>
<td>49.02%</td>
</tr>
</tbody>
</table>

Figure 29  Time to first collaboration by groups.
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:

\[
\ln (\ln (t_{ms})) = \beta_0 + \beta_1 \cdot t_s
\]

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, \( \text{Adj-}R^2 = 0.87, F(1,127) = 1432, p < 0.001 \). 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 \( \text{Adj-}R^2 \) 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.
Chapter 5  A Simulation Approach

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 $\ln \left( \ln \left( t_{max} \right) \right)$.
Figure 33  Continued.
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

<table>
<thead>
<tr>
<th>Table 15  Regression table</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept $\beta_0$</td>
</tr>
<tr>
<td>Slope $\beta_1$</td>
</tr>
<tr>
<td>Degree 1</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Degree 2</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Degree 3</td>
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<tr>
<td></td>
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<tr>
<td>Degree 4</td>
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<td>Degree 5</td>
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<td>Degree 6</td>
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<td>Degree 7</td>
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<td>Degree 8</td>
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<td>Degree 9</td>
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<tr>
<td>Degree 10</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Degree 15</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>All degree</td>
</tr>
</tbody>
</table>
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

<table>
<thead>
<tr>
<th>Start-up time interval</th>
<th>False</th>
<th>Pro_False</th>
<th>True</th>
<th>Pro_True</th>
<th>Survival time T2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>10</td>
<td>4666</td>
<td>0.841630592</td>
<td>878</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>20</td>
<td>1565</td>
<td>0.830679406</td>
<td>319</td>
</tr>
<tr>
<td>3</td>
<td>20</td>
<td>30</td>
<td>950</td>
<td>0.829694323</td>
<td>195</td>
</tr>
<tr>
<td>4</td>
<td>30</td>
<td>40</td>
<td>609</td>
<td>0.807692308</td>
<td>145</td>
</tr>
<tr>
<td>5</td>
<td>40</td>
<td>50</td>
<td>350</td>
<td>0.808314088</td>
<td>83</td>
</tr>
<tr>
<td>6</td>
<td>50</td>
<td>60</td>
<td>222</td>
<td>0.773519164</td>
<td>65</td>
</tr>
<tr>
<td>7</td>
<td>60</td>
<td>70</td>
<td>131</td>
<td>0.779761905</td>
<td>37</td>
</tr>
<tr>
<td>8</td>
<td>70</td>
<td>80</td>
<td>66</td>
<td>0.694736842</td>
<td>29</td>
</tr>
<tr>
<td>9</td>
<td>80</td>
<td>90</td>
<td>38</td>
<td>0.703703704</td>
<td>16</td>
</tr>
<tr>
<td>10</td>
<td>90</td>
<td>100</td>
<td>17</td>
<td>0.53125</td>
<td>15</td>
</tr>
<tr>
<td>11</td>
<td>100</td>
<td>110</td>
<td>14</td>
<td>0.518518519</td>
<td>13</td>
</tr>
<tr>
<td>12</td>
<td>110</td>
<td>120</td>
<td>6</td>
<td>0.461538462</td>
<td>7</td>
</tr>
<tr>
<td>13</td>
<td>120</td>
<td>130</td>
<td>6</td>
<td>0.666666667</td>
<td>3</td>
</tr>
<tr>
<td>14</td>
<td>130</td>
<td>140</td>
<td>2</td>
<td>0.4</td>
<td>3</td>
</tr>
<tr>
<td>15</td>
<td>140</td>
<td>150</td>
<td>0</td>
<td>0</td>
<td>2</td>
</tr>
</tbody>
</table>
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.