The entrepreneurial process and online social networks : forecasting survival rate

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The Entrepreneurial Process and Online Social Networks: Forecasting Survival Rate

Abstract

To launch a new business, entrepreneurs search for information and resources through their networks. We are concerned with collaboration among entrepreneurs with a network, and with the impact this has on new venture survival. Using entrepreneurs' network data extracted from their respective online social networks, our paper develops a simulation model of the entrepreneurial process and its outcomes in terms of growth and survival. Findings from 273 entrepreneurs reveal that initial wealth at start-up, network density, and time to first collaboration have an impact on the probability of survival. We show that using numerical simulation, and based on one's social network, the survival time of a start-up can be forecasted.

Keywords: Entrepreneurial process, start-up, social capital, networks, simulation, survival rate

Introduction

Banerji & Reimer demonstrate that "several variables in LinkedIn profiles were positively correlated with the amount of funds raised by startup companies establishing a link between social networks and entrepreneurial success. The average number of followers that the founders of a company had according to their LinkedIn profile was the strongest predictor of the amount of funds raised by companies (2019, p. 46)." Once funded, plenty of new ventures are launched, but their impact on society varies with *survival* rate. In order to have a positive effect on society, a firm must survive. Can survival be accurately predicted and if so how?

Testing the relationship between human capital stocks and new firm survival, Acs et al. (2007) demonstrate that the positive relationship between human capital and survival is supported for the period 1993–1995, but is not as strong for a recession period. Survival rate is found to be positively related to all-industry intensity, but negatively related to service sector specialization, suggesting that city size and diversity may be important in determining survival.

Can networks predict survival? Business is embedded in networks of social relationships (Gedajlovic, et al. 2013; Gulati, 1998, 1999; Light, 1984; Uzzi, 1999; Zimmer & Aldrich, 1987). Networks are the building blocks of social and economic relationships that are used to select trustworthy partners, to create and enlarge a social network and to exert social control on cheaters (Bouchikhi, 1993). Aldrich (1999) claims that one tends to base decisions on social cues. Cook & Wills (1999) argue that insights of considerable value can be generated by observing to the ways in which entrepreneurs create social capital; such capital develops through changes in relations among persons who facilitate action and this is vital in resource-acquisition strategies required for new venture creation and success. Entrepreneurship is a social activity, in that customers and suppliers form part of the social web within which the economic elements of entrepreneurship are conducted; hence the presence, or absence, and the form of social capital is likely to influence the nature of the business (Anderson & Miller, 2003). One is more likely to adopt an innovation as the number of already adopting people becomes larger because of stronger expected evaluations (i.e., the theory of increasing returns); such influence may be modeled as a network externality in which entrepreneurship is assumed to exhibit increasing returns with respect to the size of the network (Choi et al., 2007).

Simangunsong (2016) shows that start-up companies have used social media to increase sales. One is usually a member of a number of diverse networks in parallel, each founded on different basis of relationships and aims leading to different communication approaches and platforms utilized (Song & Berger, 2017). Blazquez, Domenech, & Debón, (2018) show that a web page can *reflect* a firm's status, but without predictive value. Shu, Ren, & Zheng (2018) propose a model of entrepreneur network capability concerning the role of nascent entrepreneurs in developing and managing social networks, but there has not been a model to predict survival based on online networks. As observed by Smith, Smith & Shaw, there is a "growing gap between contemporary entrepreneurial practices and existing social capital theory and research in entrepreneurship (2017, p. 18)."

How do entrepreneurs collaborate with each other in a given network and how does this affect survival rate? Studies point to the centrality of networks during the process of innovation (Ibarra & Andrews, 1993; Reinholt, Pedersen, & Foss, 2011); however, the literature is lacking with regards to when and where the processes evolve and what the impact is (Brenner, 2001; Lane, 2002, Song & Berger, 2017). Cummings & Cross (2003) note that there has been relatively little research on the structural properties of natural work groups and their consequences for performance. Traditional social network analysis has generally been constrained in accuracy, breadth, and depth due to reliance on self-reported data (Eagle et al., 2009). The lacunae seem particularly critical in the current context, as start-ups are undergoing profound changes to face a new competitive landscape and lack of access to resources.

As entrepreneurs are surrounded by different networks, determining the value of a network and estimating the optimal configuration of a network would contribute greatly to both theory of entrepreneurship formation and that of social networks in general (Greve & Salaff, 2003; Hoang & Antoncic, 2003). In order to understand the effect of social networking on entrepreneurship, we focus on the relationship between network collaboration and new venture survival rate. We view the simulation model approach as an effective tool to evaluate the effect of entrepreneurs' network collaboration on the entrepreneurial survival rate over time; therefore, we develop a simulation model to forecast entrepreneurial survival rate in a given network. We model our simulation by focusing on social links among entrepreneurs and on their rich social structure and we use network degree, network constructs, network position for the simulation. In our model, entrepreneurs find resources and collaborators from an online social network. Together with these collaborators they start up new businesses that can grow or fail depending on the growth and time variables. The paper further examines the effect of one's position in the network and survival rate after a certain period of time in comparison to those who failed. We contribute to the theory of entrepreneurship by increasing understanding of the relationship between one's social network and survival.

The paper is structured as follows. Following a literature review, we discuss methodology and justify the use of simulation for this study. We then present the source of our simulation data, simulation model, simulation procedure, simulation algorithm and simulation model parameters. This is followed by the result of our simulation data and the result of data analysis separately. Finally, we illustrate the implications of our network simulation modeling and discuss future research.

The literature

A century ago, the word capital implied money and property, as these were the hoards of value deemed necessary for production and/or trade. Access to these explained access to entrepreneurship. This was so until Becker (1963) invented the concept of human capital – competence from investment in formal education and on-the-job training – and for this he earned the Nobel Prize in economics. Bourdieu (2002) subsequently introduced three other forms of capital: (i) social capital; (ii) cultural capital; and (iii) symbolic capital.

Coleman pointed out that social capital "comes about through changes in the relations among persons that facilitate action (1988, p. S100)." Fukuyama qualified, "social capital is an instantiated informal norm that promotes co-operation between individuals (2001, p. 7)." Putnam (1995) proposed that social capital provides information that could become an inclusive bridging lubricant. Knack & Keefer (1997) observed that the notion of social capital was gaining increasing attention. Adler & Kwon (2002) suggested that social capital could enhance trust, by means of the bonding of individuals. Davidson & Honig (2003) found that social capital was a robust predictor of *who* became an entrepreneur. Baron & Markman (2003) confirmed the view that a high level of social capital assisted entrepreneurs in gaining *access* to important persons, but once such access is attained outcome was influenced by social competence.

Social capital was recognized as being vital to the entrepreneurial process because its ability to provide an entrepreneur with access to additional financial, human and additional social capital leading to success; those entrepreneurs with a larger stock of these capital resources would be better able to sustain and grow their businesses, because greater capital resource assets can act as a buffer against ambiguities and random environmental shocks to which new firms are especially susceptible. Aldrich & Zimmer (1986) showed that participation in social networks is a crucial element for entrepreneurs to lower ambiguity. Saxenian (1990) argued that much of the accomplishment of Silicon Valley is to be credited to its social environment; the larger the number of entrepreneurs one observes, the lower the ambiguity one experiences (Minniti, 2005). Before starting a venture, people are influenced by others (Anderson & Miller 2003); by observing, a potential entrepreneur acquires information and skills and meets others who have similar or complementary expertise and can assist in lowering ambiguity (Obschonke et al., 2015).

Dubini & Aldrich (1991) noted that to be useful, networks need a critical mass; entrepreneurial networks should be sufficiently large to ensure access to a diversity of information resources because information is more likely to be spread across a number of individuals rather than concentrated in few resources. Many agreed that entrepreneurs with social capital across a large and diverse network could receive more support from their connections thus, become more successful than others (Aldrich & Zimmer, 1986; Brüderl & Preisendörfer, 1998; Greve & Salaff, 2003; Hoang & Yi, 2015, Leyden et al., 2014).

The evolutionary perspective of entrepreneurship in concerned with: the creation of new organizational structures (variation); the way in which entrepreneurs modify their ventures (adaptation); the conditions under which organizational arrangements lead to success and survival (selection); and the way in which successful arrangements tend to be imitated and perpetuated by other entrepreneurs (retention) (Aldrich & Martínez, 2001). To compensate for a firm's small size, external resources and network arrangements could sustain innovation and *secure survival* (Bougrain & Haudeville, 2002). Using data spanning 41 years, Makarevich (2018) investigated how network ties interacted with a firm's level of specialization and found an inverted J-shaped relationship between the degree of VC firms' specialization and the risk of failure; that study also revealed that firms in the sample depended on their network ties in avoiding failure, with this effect stronger for generalist VC firms than specialist firms, and that ties to specialist VC firms reduce the risk of failure of generalist firms with heterogeneous portfolios the most. Those findings advanced understanding of the joint effects of specialization and network connections on firm survival.

Several network theories have been developed, including the strength of weak ties theory (Granovetter, 1973) and the structural hole theory (Burt, 1992). Granovetter (1973) posits that successful entrepreneurs are more likely to be found in networks where their centrality is high and in which they are connected to an array of "weak ties". Granovetter (1973, 1982) explains the differences between strong and weak ties. The first is the frequency of contracts. The second is the reciprocal commitments between the actors involved and the third is the degree of intimacy. Strong ties are frequent contacts that almost invariably have affective, often friendly, overtones and may include reciprocal favors. Weak ties are infrequent contacts that, because they are episodic, do not necessarily have affective content (Nelson, 1989). Weak ties are beneficial as they provide access to novel information since they offer linkages to divergent network regimes (Granovetter, 1982); in contrast, strong ties relate to the exchange of fine-grained information and tacit knowledge, trust-based governance, and resource cooperation (Rowley et al., 2000; Starr & MacMillan, 1990). Granovetter maintains that the pool of information available to an entrepreneur could be more easily accessed through ones weak ties, as "those to whom we are weakly tied are more likely to move in circles different from our own and thus will have access to information different from that which we receive" (1973, p. 1365). The strength of weak ties theory is based on two premises: The first is that the stronger the tie between two people, the more likely their social worlds will overlap and as thus, they will have ties with the same third parties. This can be explained by Freeman's (1979) g-transitivity concept. Publics tend to have robust ties with publics who are similar to them (McPherson et al., 2001). The second premise is that bridging ties are a potential source of novel ideas. The notion is that, through a bridging tie, an individual can hear news that was not previously circulating among his/her close friends (Borgatti & Halgin, 2011). Burt's (1992) structural holes theory is concerned with ego networks. This theory contends that the benefits from social capital curtail from the brokerage prospects created by disperse ties – i.e., the lack of network closure (Gargiulo & Benassi, 1998).

According to Elfring & Hulsink (2003), networks are among the most powerful assets of firms; networks and networking provide access to power, information, knowledge and capital. Borgatti et al. (2009) noted that among the most compelling notions in the social sciences is that beings are embedded in dense webs of social relations and interactions. Since the wide-spread use of the Internet, social networks today are no longer limited to physical connections; *online social networks* are a reality and the Internet does provide weak ties. These networks enable one to connect with others through the Internet in a non-intrusive way (Ellison et al., 2007), allowing entrepreneurs to gather information and resources solve problems and promote their ventures, *leading to the formation of social capital* (Bruderl & Preisendorfer, 1988; Burt, 1992).

The networks, in which entrepreneurs are embedded, play a critical role in their probability of success (Aldrich & Zimmer, 1986). Entrepreneurs interact and communicate with others using diverse networks for diverse purposes. The network may be a family, friendship, or a business based network. We refer to the amalgamation of these networks as a Network of Networks (NoN) (Garton et al., 1997; Guzmán and Oziewicz, 2004). The NoN allows entrepreneurs to more easily obtain the information and resources that they need for their business from a wide array of sources. The prevalent use of the Internet makes it possible for entrepreneurs to integrate their connections from diverse online social networks and to associate with other entrepreneurs when considering starting up a new business. This type of communication is dubbed Computer Meditated Communication (CMC), defined as any human communication that occurs through the use of two or more electronic devices (Goyette et al., 2010). They are involved in the elusive shaping of communication in virtually every relational context. Perception of a medium's synchronicity and the communication process is a key element of shared understanding. The platform's processing capabilities influence the way individuals can transmit and process information. Social information processing theory suggests that users of CMC may be able to adapt to the channel by transforming affective intentions into text-based cues (Giardini et al., 2008).

Shu, Ren, & Zheng (2018) emphasize that social networking is increasingly important – but can they forecast survival? With regards to firm survival, Esteve-Pérez & Mañez-Castillejo (2008) confirmed that firms that develop firm-specific assets through advertising and making R&D (independently of the technological intensity of the industry) enjoy better survival prospects. Using Global Entrepreneurship Monitor data, Hipango & Dana (2012) revealed that race and gender are important explanatory variables of firm survival in New Zealand; Māori face a distinct disadvantage in terms of firm survival, when compared to others in New Zealand. Using data from the Kauffman Firm Survey, Coleman et al. (2013) revealed that the fundamental resources that contribute to survival are education, work and life experience and adequate levels of startup financial capital; that study found a link between human capital, industry and exit route for this sample of new firms. Pe'er & Keil (2013) argued that while local levels of skilled labor, suppliers, and purchasers have a beneficial influence and local competition has a detrimental influence on startup survival, these relationships are moderated by heterogeneity in firms' resources and capabilities.

Fischer & Reuber (2014) identified that narratives and symbolic actions produced by some firms could help reduce audience uncertainty about quality and differentiate these firms from rivals. Using qualitative methods, that study compared the communications enacted by eight firms using Twitter in order to pursue growth.

Blazquez, Domenech, & Debón, (2018) used multi-period logistic regressions and a duration model to study the relationship between a firm's status and its website. The study tracked changes in the corporate websites of a panel of Spanish firms and found that a web page can reflect a firm's status.

As evident from the above, social capital and network-related topics including online networks are among research subjects in the limelight. Although Banerji & Reimer (2019) showed that a LinkedIn profile could predict funds raised by companies, it is not yet evident how networks can forecast survival. Our mission was to show how the survival time of a start-up can be forecasted, with numerical simulation, and based on one's social network.

Methodology

User-generated Internet and social media content are forms of big data, which is differentiated from "small data" by its volume, real-time or near-real-time velocity, and the variety of sources from which it is generated. User data was found to be promising because it represents untapped sources of information that could help us understand our rapidly evolving world. A growing body of work has highlighted their analytical utility. For instance, big data from Twitter and LinkedIn was shown to be valuable (Ellison et al., 2007). Prior work has highlighted that the process of conceiving of and starting an entrepreneurial venture is a fundamentally networked activity where weak ties from a diverse and large group of actors can improve access to information. More recent work also highlights that social media can improve access to information for entrepreneurs.

In order to uncover the potential influences of entrepreneurs' online social networks on the entrepreneurial process and success, we designed a simulation model. We assumed that the length of a start-up's survival rate is associated with its ability to network with others (Gartner et al., 1999; Strotmann, 2007; Raz & Gloor, 2007; de Jong & Marsili, 2015). The task of determining the optimum start-up time frame for survival appears to be an important subject for research and our focus.

With regards to the complexity science approach, simulation models are considered as complex adaptive systems (CASs), consisting in an evolving network of heterogeneous, localized and functionally integrated interacting agents (Chandler & Hanks, 1993). An agent-based simulation model is characterized by the existence of many agents who interact with each other with little or no central direction. The main goal of agent-based simulation is to enrich our understanding of social processes through mutual interaction (Axelrod, 1997). It is seen as a valuable tool to build new theories, concepts, and knowledge about business processes (Carley & Gasser, 1999). Agent-based simulation is a methodology appropriate to study entrepreneurship network modeling (Lane, 2002). Scholars have adopted this approach to analyze the processes of formation, development, and coordination (Albino et al., 2003). Thus, we utilize an agent-based simulation model in this paper to explain how entrepreneurs collaborate with each other.

Entrepreneurs' network collaboration can be complex. By using simulation, we are able to investigate the collaboration results according to our model. In this study, we use survey data to collect entrepreneurs' online social network. For their further behavior, we designed a collaborating model and simulated how they collaborate with each other. Our hypotheses are as follows:

H1a: *Entrepreneurs with low network degree and low wealth have low survival rate.*

H1b: *Entrepreneurs with high network degree and low wealth have low survival rate.*

H1c: *Entrepreneurs with high network degree and high wealth have high survival rate.*

H1d: *Entrepreneurs with low network degree and high wealth have high survival rate.*

H2: *Entrepreneurs' survival time is significantly related to entrepreneurs' start-up time.*

H3: *Entrepreneurs' survival probability is significantly related to entrepreneurs' start-up time.*

In Figure 1, we described our conceptual model.

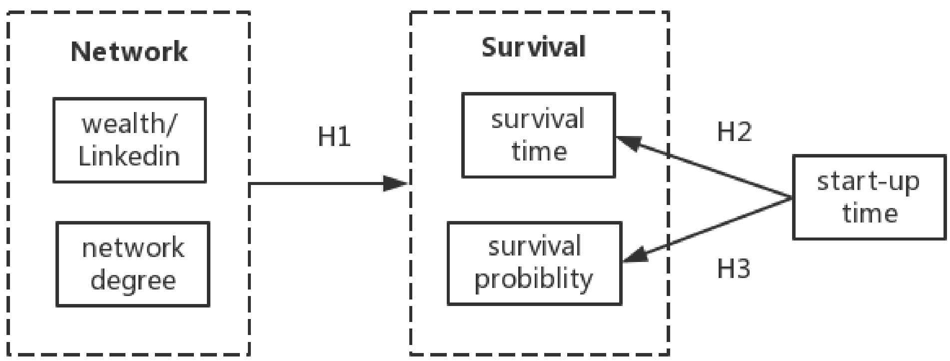


Figure 1 Conceptual model

The data, simulation parameters, procedure and algorithm are presented in Appendix.

Simulation results

In the simulation model we assigned an initial wealth value to every entrepreneur. This value was a function of their online network connections. Since not all 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. Figure 2 illustrates the entrepreneurs' initial wealth for each of the 100 simulations with a fitted distribution.

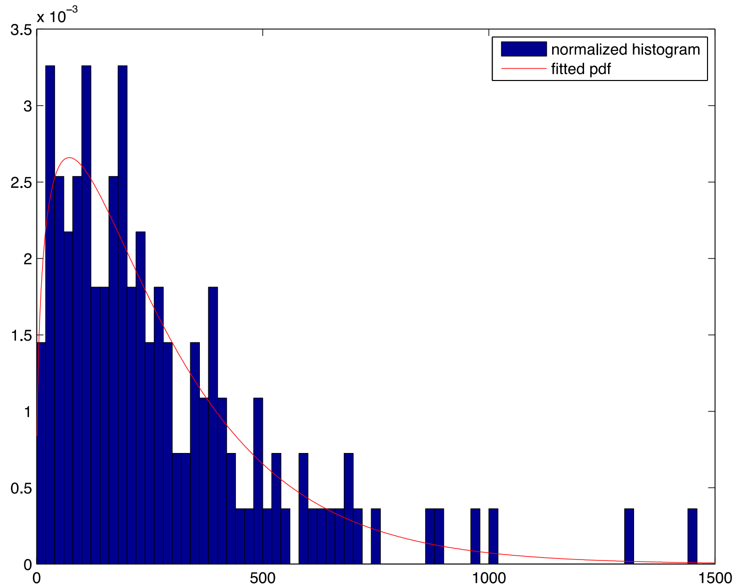


Figure 2 Distribution of entrepreneurs' wealth

We presumed that an entrepreneur could collaborate with many, with the same people repeatedly or not. However, starting collaboration with the same person immediately after a previous collaboration is somewhat unrealistic because of a lack of incentive. We deleted the last collaborator from the set of possible entrepreneurs for the first period in-order to avoid this occurrence.

We presumed that entrepreneurs search for information and ideas all the time and access to resources through business networks is seen as key. We defined 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.

There are three kinds of measurements to evaluate the success of an entrepreneurial endeavor as defined by 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 and Hanks, 1993). The second is the number of survival years of new start-ups. The difficulty of using firm survival as a measure of success is determining the 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 and Preisendörfer, 1998; Gartner et al., 1999). The last measurement of success is the growth rate. The most commonly used are sales growth (Brüderl and Preisendörfer, 1998) and employment growth (Bellandi, 1989).

We define a relative survival time and consider it to represent entrepreneurial growth as this was found to be a good indicator and data was available through LinkedIn. 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, he will still survive longer because of the initial wealth. In other words, entrepreneurs use their wealth when searching for collaborators in every simulation period. In order to remove the influence of initial wealth, we divided the survival time by the length of time an entrepreneur can survive without collaboration, which is the relative survival time in this model. Since cost is a constant value, we can determine the absolute survival time: ***Relative survival time = Survival time / (initial wealth / cost).***

The simulation can be stopped at a predetermined time or when all of the entrepreneurs exit the simulation process. Since there is a probability that some entrepreneurs will never fail, we fixed the terminal time of our simulation to 100 simulations. As most of the entrepreneurs exited the market within 100 simulation periods, the system became stable and was found to be at the correct length. We set 200 periods for the whole entrepreneurial simulation process to better view its progression dynamics. In total, we ran the whole simulation 100 times with 200 periods.

Discussion

We simulated all the entrepreneurs' collaborations and growth over time. Figure 3 illustrates the entrepreneurs' wealth-growth graph for all the entrepreneurs in 200 simulation periods, in other words, all the collaborations possible. In the model, we only allowed 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. 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 entrepreneurs to collaborate with.

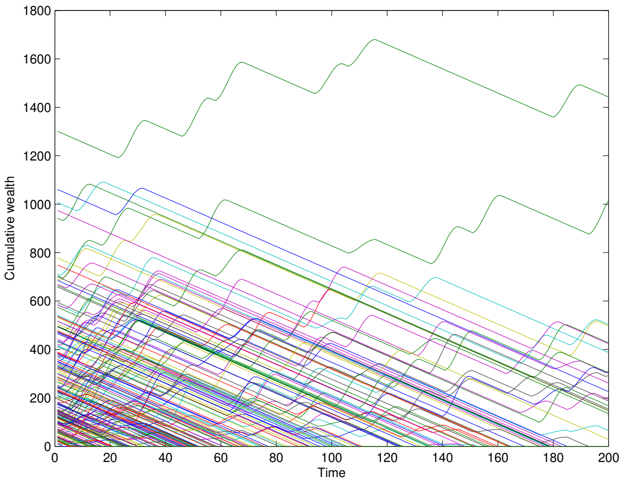


Figure 3: Simulation of entrepreneurial process over time

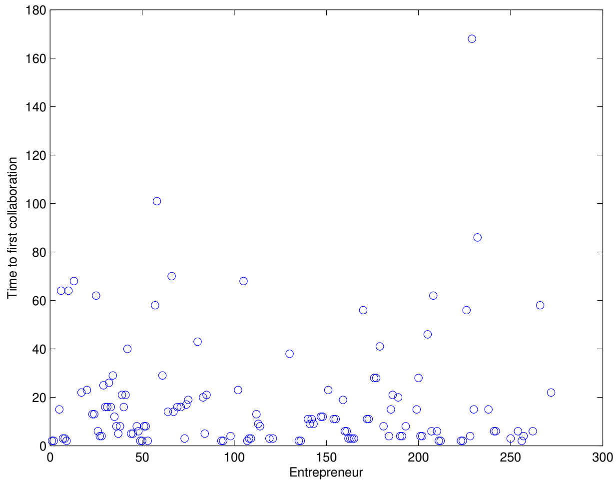


Figure 4: Time to first collaboration

We found that some entrepreneurs' wealth continued growing during the simulation process, while others could not find any partners. We found that certain entrepreneurs never had the chance to collaborate with others and exited the market in early stages of the simulation. Thus, we removed entrepreneurs with 0 degree, and let the simulation run. However, we still found that some entrepreneurs could not find opportunities to start up a business with other entrepreneurs. We assumed this might be caused by the lack of initial wealth or the degree difference between the entrepreneurs. On this basis we ran a further analysis based on the differences of network degree and initial wealth. Figure 4 illustrates 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 5, the wealth separation and degree separation are 350 and 3, respectively. We retrieved data on the entrepreneurs who survived during our simulation to better understand the reasons for their survival. In Table 1, 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. Therefore, we accept H1a and H1c. However, entrepreneurs with higher network degree but low wealth or the reverse had only a 50% survival rate in our simulation procedure, we reject H1b and H1d. Nevertheless, the results showed that entrepreneurs with either higher degree or higher start-up wealth have a higher survival rate. We double-checked the histogram by groups; Table 1 and Figure 6 show that network degree and initial wealth influence simulation results.

Table 1: 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%

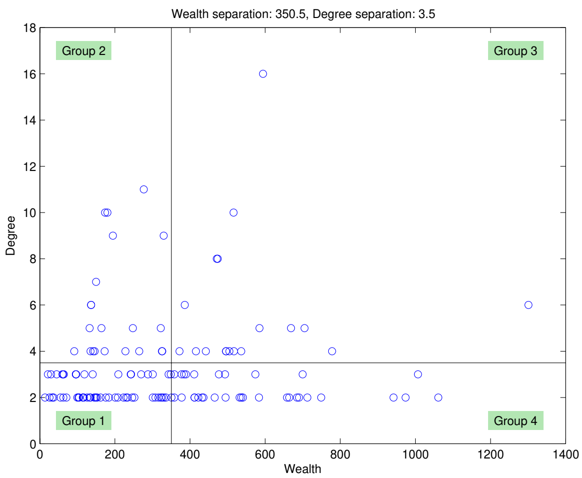


Figure 5: Simulation of entrepreneurial process over time

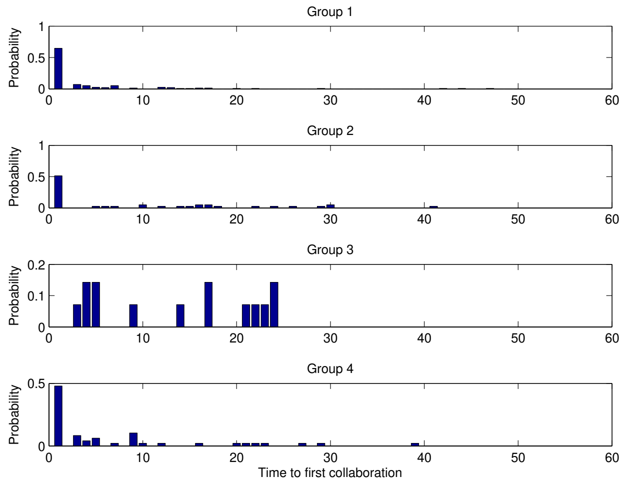


Figure 6: Time to first collaboration by groups

We also examined the influence of the initial wealth, network degree, and start-up time on the entrepreneurial process. Figure 7 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 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.

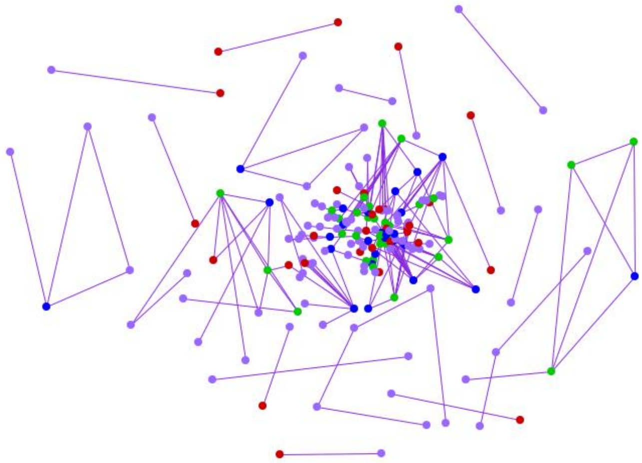
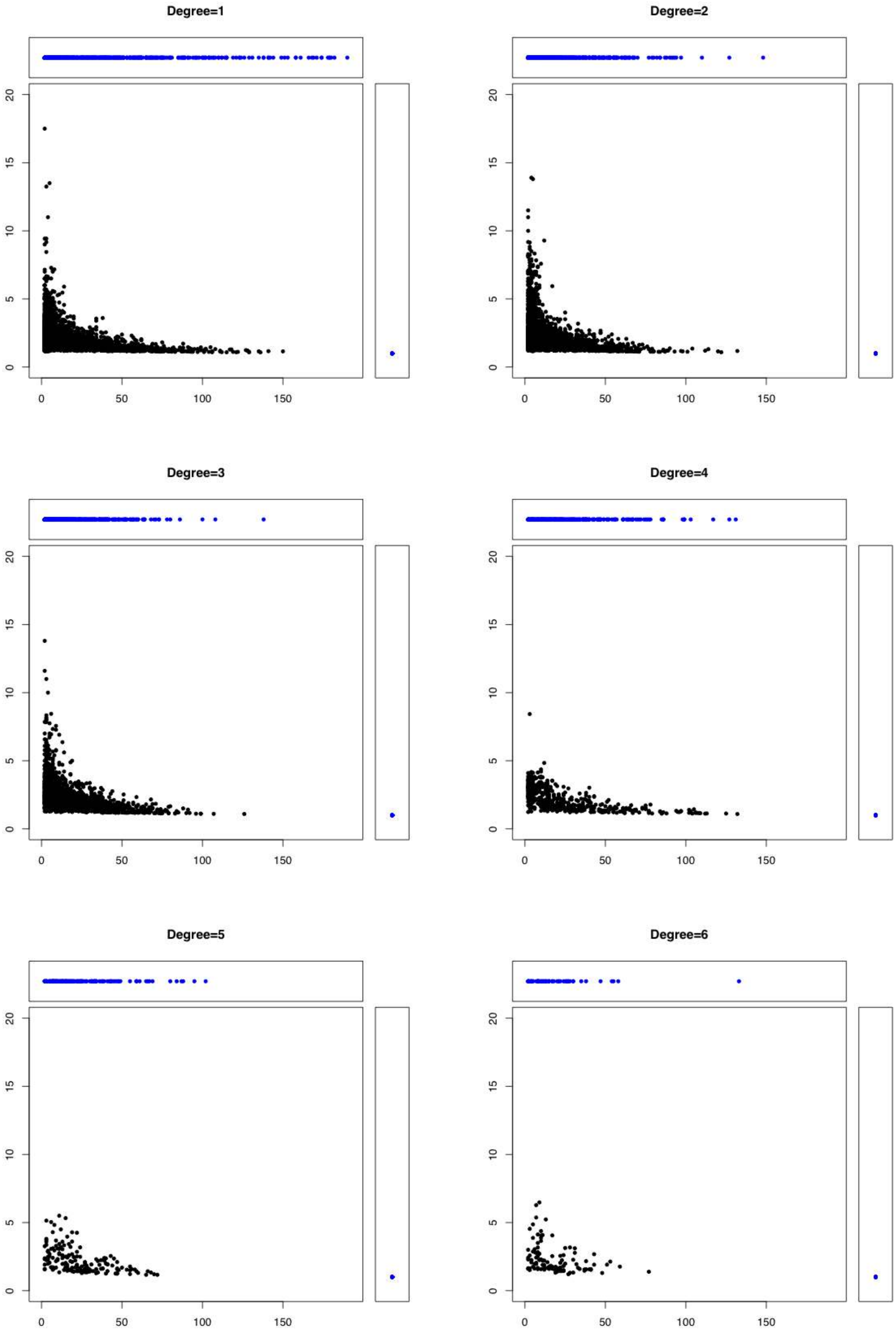


Figure 7: Entrepreneurs' network by degree and wealth separation

We proposed 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.

Repeating the simulation process 100 times, this resulted in 27,300 nodes. 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 and exited the market in an initial stage. Figure 8 plots the remaining entrepreneurs' start-up times and survival times. The horizontal bar represents entrepreneurs who survived more than 200 simulation periods. The vertical bar represents entrepreneurs who did not collaborate during the entire simulation process and exited immediately. As shown in Figure 8, we plotted entrepreneurs' start-up time and growth by network degree after 200 simulation periods.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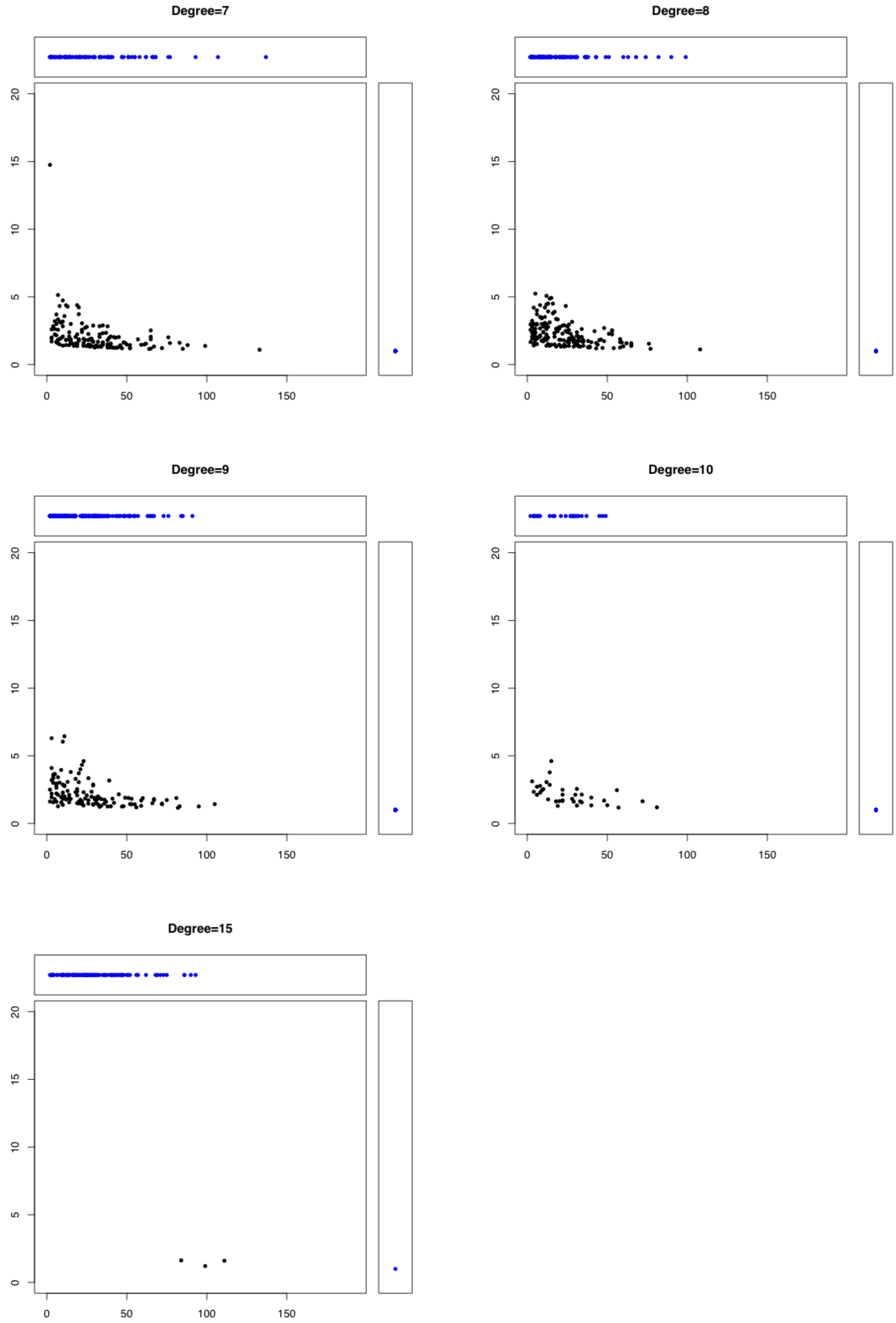
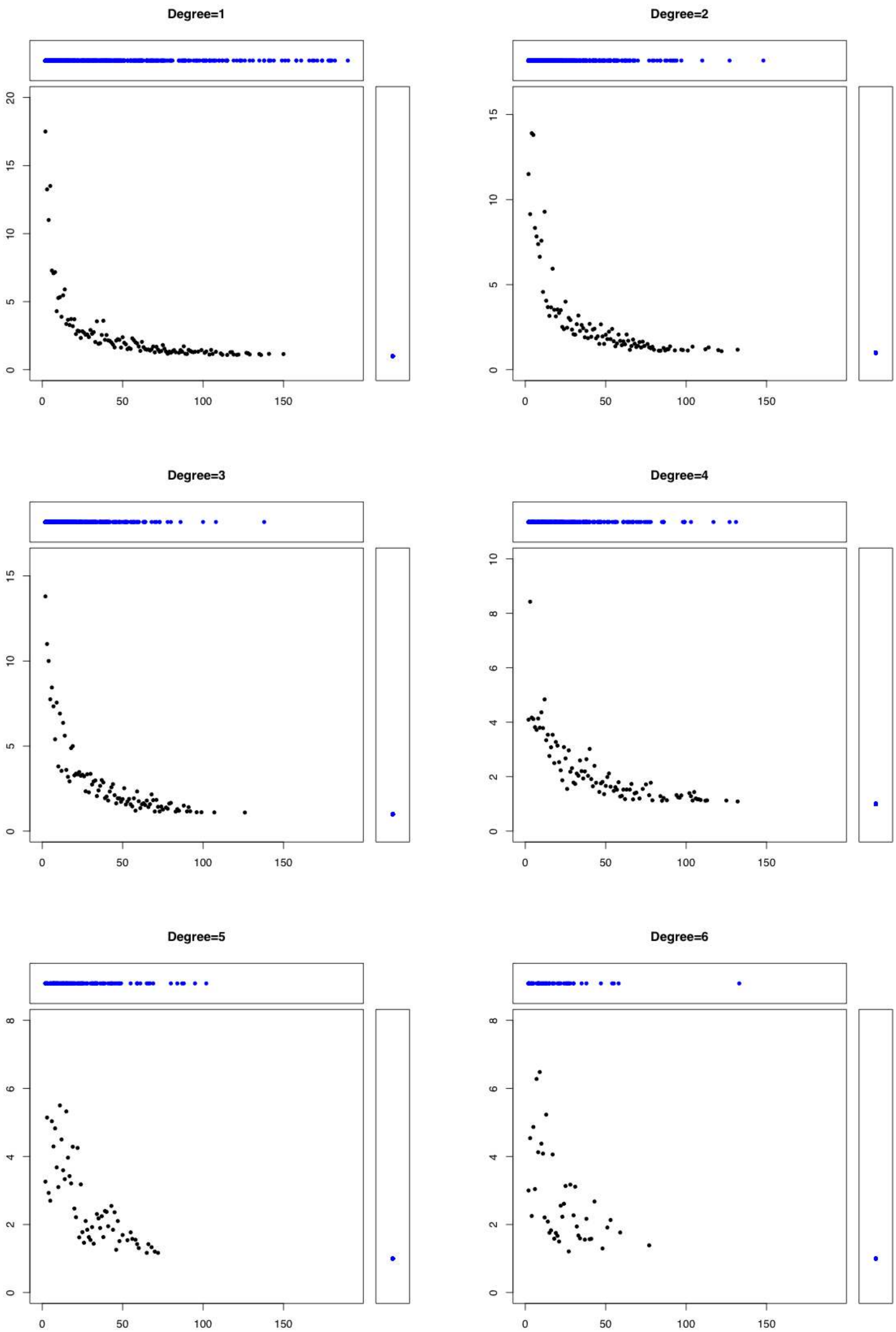


Figure 8: Entrepreneurs' start-up time and growth by degree

(*x is start-up time, y stands for survival time*)

Figure 8 reveals no obvious relationship between start-up time and survival time. There are also no obvious differences between entrepreneurs based on the degree of their network. However, Figure 8, does imply that for a given start-up time, we can predict the optimal survival time. Therefore, for each simulation period, we plot entrepreneurs' start-up time and optimal survival time (as shown in Figure 9). Therefore, we reject H2.



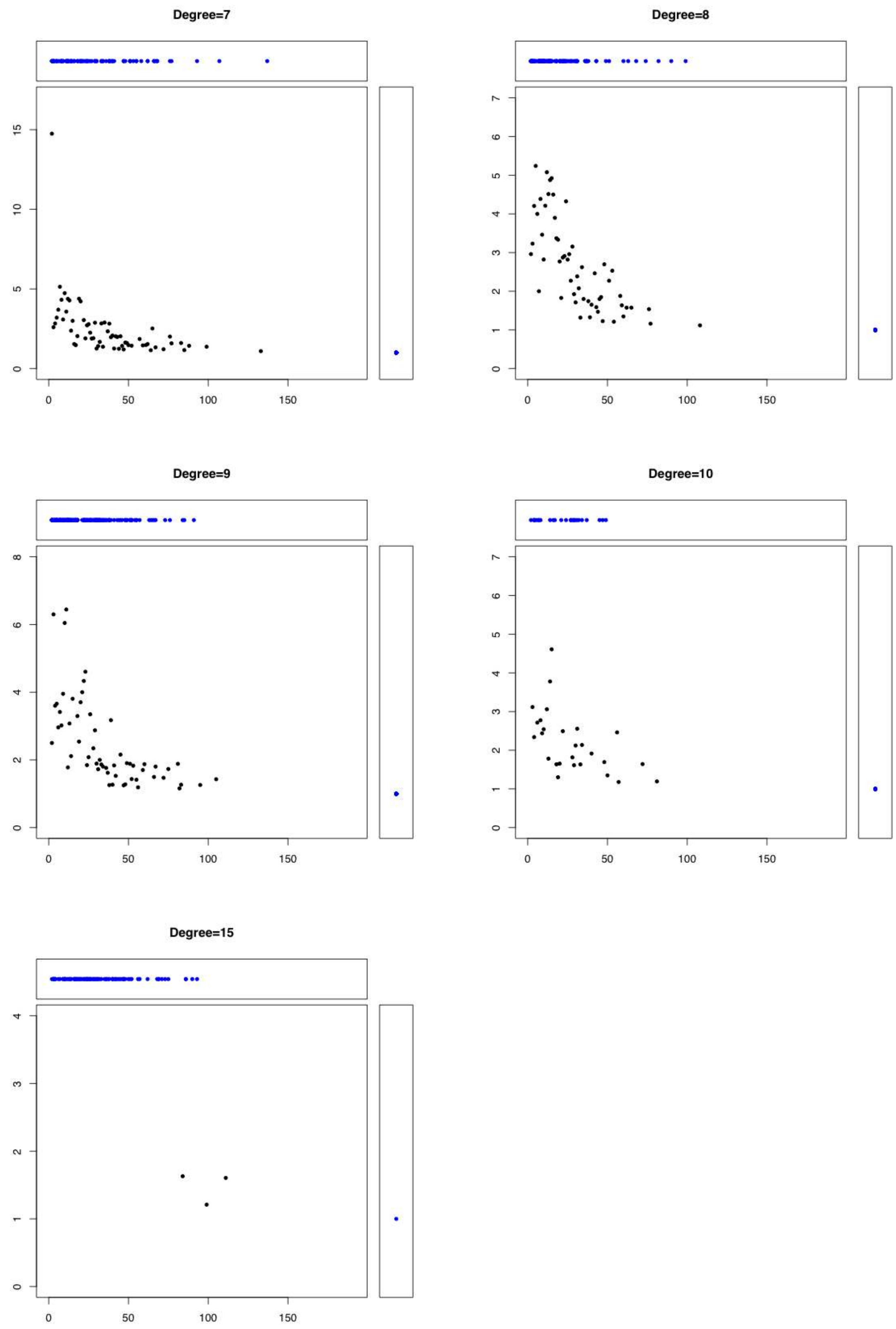
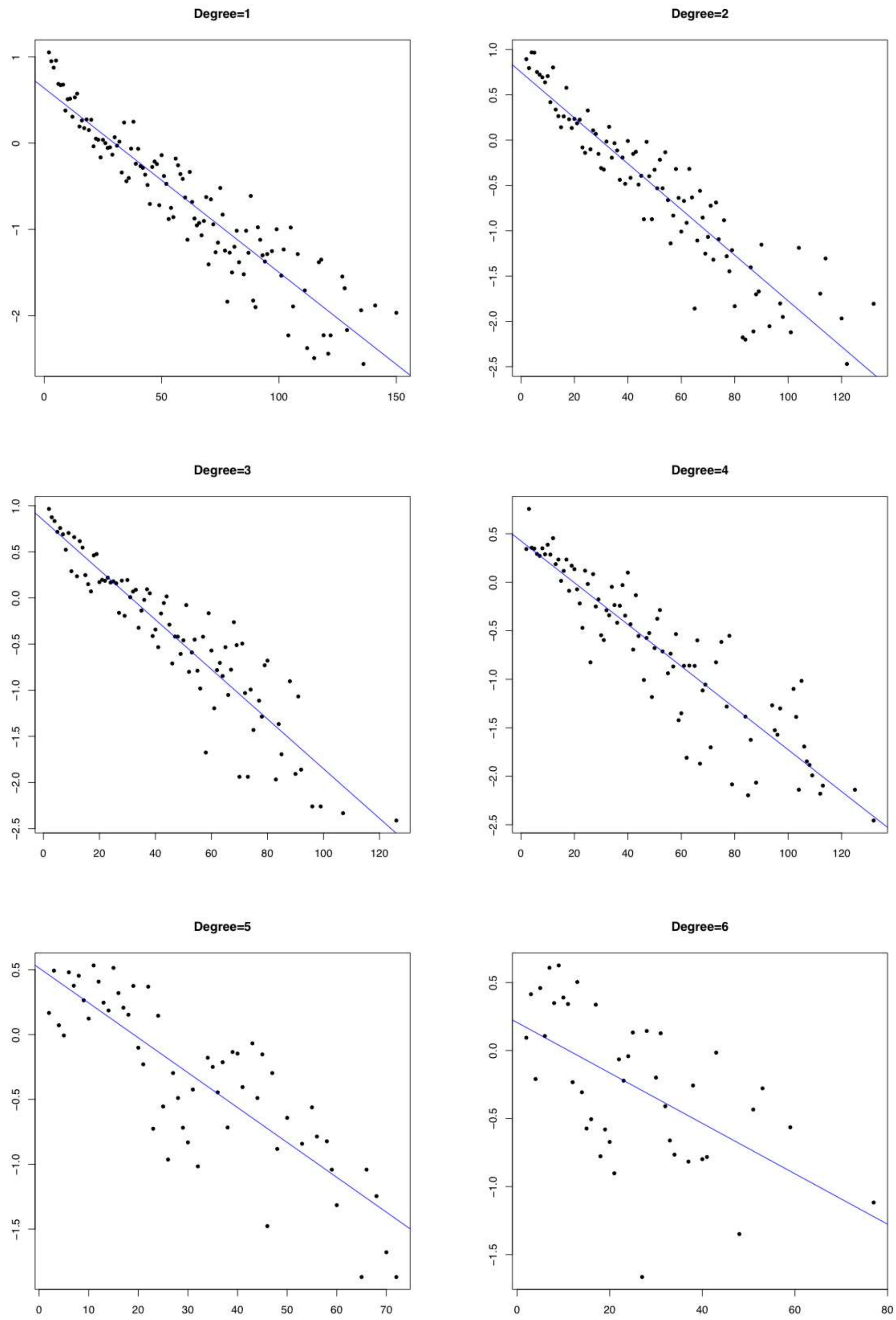


Figure 2: Plot of entrepreneurs' start-up time and optimal survival time

(x is start-up time, y stands for survival time)

For a given start-up time we selected those entrepreneurs who had the longest survival time, which we plotted in Figure 9. We ran a regression analysis for entrepreneurs' start-up time and maximum survival time $\ln(\ln(t_{ms})) = \beta_0 + \beta_1 * t_s$. The relationship between maximum survival time and start-up time is presented in Figure 10.



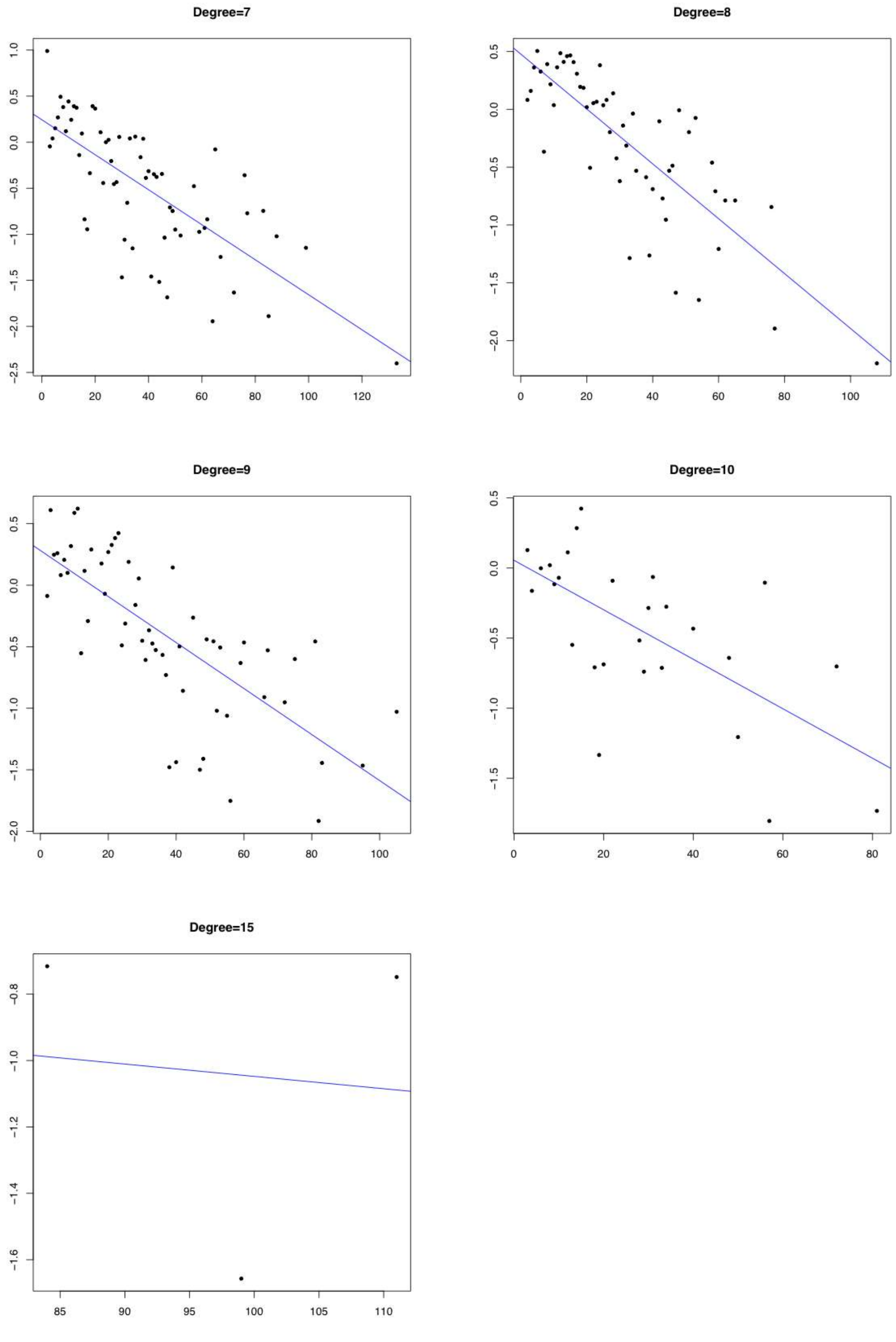


Figure 10: Regression analysis of start-up time and optimal survival time

Table A3 (see Appendix) illustrates the overall entrepreneurs' start-up time significantly predicted maximum survival time, b = -0.022, t = -37.85, p < 0.001 (shown in the last row). To further understand the results, we grouped entrepreneurs by their network degrees from degree 1 to degree 15 in Table A3. The start-up time explained a significant proportion of variance in the longest survival time, Adj- = 0.87, F (1,127) = 1432, p < 0.001. We found that entrepreneurs with a network degree from 1 to 10 significantly predicted the optimal survival time; however, the Adj- 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 model, we can predict entrepreneurs' optimal survival time on the basis of a given start-up time. Our regression analysis also showed that entrepreneurs with a lower network degree are better predictors than entrepreneurs with a higher network degree. As the maximum survival time is longer than regular survival time of entrepreneurs, therefore, we found that entrepreneurs' maximum survival time is significantly related to entrepreneurs' start-up time. Hence, we accept our hypothesis 2.

We found that some never have a chance to collaborate with others and can still survive on their initial wealth. The start-up wealth allows entrepreneurs to survive even when they do not have a collaborator. This finding further confirms H1c and H1d. Thus, there is always a minimum survival time for an entrepreneur, which is calculated by the initial wealth divided by search costs (i.e., burn rate). We conclude that 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. As shown in Table A4 (see appendix), the survival probability increasingly grows as start-up time increases. Therefore, we accept H3.

Additionally, we examined entrepreneurs whose network degree was 1 and the number of collaborations during their entrepreneurial process was longer than one. We found that the maximum number of collaborations is 6. We further looked at entrepreneurs' network degree and collaboration with a histogram by network degree. We found that entrepreneurs with a lower network 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.

Conclusion

In line with Smith, Smith & Shaw's (2017) call to incorporate the online context into entrepreneurship social capital research, we focused on online networks and demonstrated the importance of entrepreneur's social capital and the extent to which these resources combine and interrelate in the new venture creation process. Given this research promise, this study analyzes digitally mediated interactions using LinkedIn data collected about entrepreneurs engaged in entrepreneurial networks in Amsterdam. Findings indicate that we can predict the entrepreneurial optimal survival time based on initial wealth and social network density.

We presented a network simulation model to describe the entrepreneurial process depending on the position of an entrepreneur in a given network. This simulation model predicted entrepreneurs' optimal survival time based on a given start-up time, wealth, and breadth of its social network. In our model, we found that entrepreneurial survival 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.

In our simulation model we assigned an initial wealth value to every entrepreneur. This value was a function of their online network connections, which included their connections with both entrepreneurs and non-entrepreneurs. In other words, the wealth we mentioned in our model is entrepreneurs' LinkedIn connections. Therefore, we argue that entrepreneurs with more LinkedIn network connections have more wealth for their collaboration. It only means that they have more information and resources to consume when they are searching for a collaborator. Or we can say they have more money to waste in the market. It does contribute to longer survival time in the market; however, we need further work to test if it is connected to entrepreneurs' performance.

We expected that entrepreneurs with a higher network degree would collaborate more with other actors. Here we refer entrepreneurs' network degree as the connections they have in their simulation network (the entrepreneurs' network among each other). Our simulation model only allowed entrepreneurs to collaborate with one entrepreneur at a time. Even though the entrepreneurs have more choices to collaborate, 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. This is because entrepreneurs' with fewer connections have fewer choices to collaborate with others. In the actual entrepreneurs' collaboration networks, entrepreneurs will consider collaborating with more than one node. Thus, we would consider simulating more entrepreneurs behaviors in future study.

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. Due to the limitations of our simulation model, it seems that entrepreneurs with a higher network degree had lower collaboration rates. Also, 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 survival rate. 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 survival rate 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. The contribution of the literature regarding the entrepreneurial start-up process helps us to understand how new firms come into existence and why particular entrepreneurial efforts succeed, while other attempts fail.

During the entrepreneurial process, the network can be used to search for information. By using simulation approach, we can predict entrepreneurial survival via our model. The methodology provides us more opportunities to test network collaboration theories and can be applied to actual entrepreneurs' activities. 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 during the whole entrepreneurial process. The real social network is more sophisticated than our model. As we have no data on geographical origin of the entrepreneurs, we have entered this interesting inference to our future research. In this paper, the main nodes in our network are entrepreneurs. In the future research, we need to include more roles such as investors and retailors for simulation in order to get closer to the reality. In addition, we need to test our model with entrepreneurs' actual network.

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