

Essays on Innovation Strategies of Entrepreneurs and Startups

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ESSAYS ON INNOVATION STRATEGIES OF ENTREPRENEURS AND STARTUPS

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This dissertation is dedicated to the memory of my grandparents, all of which passed away during my Ph.D. study in America. Wish I accompanied their last moments.

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LIST OF SYMBOLS AND ABBREVIATIONS

BHD	Boston Heart Diagnostic
CP	Cardoas Pharma
CPC	Cooperative Patent Classification
GEE	Generalized Estimating Equations
ID	Identification
IPC	International Patent Classification
LBD	Learning-by-doing
PH	Proportional Hazard
USPC	U.S. Patent Office Classification

SUMMARY

This dissertation examines the mechanisms and factors that influence the choice and application of innovation strategies by high-tech entrepreneurs. As the competitive advantage of high-tech startups mainly originates from its knowledge-related resources, that is, its social capital, intellectual property, and human capital. This dissertation elaborates on these three knowledge-related resources. In the first paper, Dr. Rothaermel and I posit that the less visible, informal knowledge networks of individuals are a relevant source of information that drives the formation of future alliances between firms. By employing social network theories, we tested how certain structural characteristics of an informal knowledge network, such as the extent to which information is diversified and the information processing capabilities of key individuals, are positively correlated with the formation of future alliances. The second paper discusses the influence of intellectual property on a startup. In this chapter, I explored the impact of a novel innovation on the probability of a successful exit, the likelihood of forming strategic alliances and how such alliances influence the exit activity, and the mode of exit along with its financial returns. The third paper addresses the heterogeneity of the performance of serial entrepreneurs by exploring the moderators of the relationship between entrepreneurial experience and firm performance. The results indicate that education positively moderates the relationship between entrepreneurial experience and venture performance through both the learning-by-doing process and the self-selection process.

CHAPTER 1. INTRODUCTION

The focus of this research is technology and innovation strategies in the entrepreneurship context. This dissertation examines the mechanisms and factors that influence the choice and application of innovation strategies by high-tech entrepreneurs. The motivation for this inquiry is the desire to answer two broad questions: How do technology- and innovation-related resources create value and contribute to the competitive advantage of a firm? And how can firms appropriate value from specific technology- and innovation-related resources, particularly in terms of commercialization and cooperation strategies that complement the available resources of the firm? The competitive advantage of high-tech startups mainly originates from its knowledge-related resources, that is, its social capital, intellectual property, and human capital. This dissertation elaborates on these three knowledge-related resources in an attempt to answer the above two questions.

A tenet of the relational view of a firm is that strategic alliances are often required to gain and sustain a competitive advantage, particularly in knowledge-intensive industries. Not only do firms frequently rely on their prior alliances when they search for information and resources, but they also exploit these relationships to seek and establish new alliances. Although this strategy holds true for existing firms, new ventures face a conundrum: Since they generally do not possess prior alliances, how do they obtain information relevant for future alliance formation? In the first chapter, therefore, I explore this question jointly with Professor Frank Rothaermel. We posit that the less visible, informal knowledge networks

of individuals are a relevant source of information that drives the formation of future alliances between firms.

By employing social network theories, we hypothesize that certain structural characteristics of an informal knowledge network such as the extent to which information is diversified and the information processing capabilities of key individuals are positively correlated with the formation of future alliances. To empirically test these hypotheses, we selected 422 biotech startups founded between 2008 to 2014 from BioCentury. We use inventors' patent co-inventing data to construct an individual-level ego knowledge network for each startup. In this knowledge network, startups not only hold information about their own scientists but also receive information flow from the direct and indirect ties of their scientists. Therefore, the ego knowledge network for each startup consists of its own scientists, its coinventors, and the co-inventors of its co-inventors. We used the bi-component measurement in UCINET to count the number of knowledge blocks and the number of cutpoints for each ego network and tested how it was related to the probability of alliance formation. The results of the analysis show that the number of both the knowledge blocks and the cutpoints are positively associated with the probability of forming alliances.

The second chapter discusses the influence of intellectual property on a startup. While the characteristics of an innovation have persistent effects on the commercialization activities and performance of a startup, we know very little about how novelty, one of the most important characteristics of innovation, affects the likelihood of a successful exit or the mode of exit of a high-tech startup. To gain insights on how the novelty of an innovation

influences the selection and application of entrepreneurial strategy and potential performance, I have assembled comprehensive data on over 400 healthcare startups to study this question and report my findings in the second chapter. I draw the data from multiple sources such as CrunchBase, USPTO, Patentsview, Linked-in, Bloomberg, and Thomson SDC platinum. In addition, I use an improved measure of the novelty of innovation to objectively and quantitatively proxy the novelty of innovation for startups.

The second chapter also explores the impact of a novel innovation on the probability of a successful exit, the likelihood of forming strategic alliances and how such alliances influence the exit activity, and the mode of exit along with its financial returns. The main findings are as follows: (1) Startups with novel innovations are less likely to have a successful exit; (2) This negative effect of novelty is attributable in part to increased difficulty forming strategic alliances; and (3) for startups with novel innovations, the IPO is a more common exit mode than acquisition; and among startups that succeed in exiting by an IPO, those with novel innovations exit with higher valuation. The results of this chapter contribute to the entrepreneurship literature by providing evidence of how technology attributes may influence the application of commercialization strategies for high-tech startups and how the application of a particular commercialization strategy affects the performance of a firm.

High-tech industries are home to a large number of serial entrepreneurs. Although the performance of serial entrepreneurs is, on average, better than that of novice entrepreneurs, it varies widely. Chapter 3, therefore, addresses the heterogeneity of the performance of serial entrepreneurs by exploring the moderators of the relationship

between entrepreneurial experience and firm performance. Studies have investigated several factors that influence the expected performance of serial entrepreneurs. This study adds to the literature by examining the extent to which education, as an individual characteristic, is associated with the expected performance of serial entrepreneurs. Referring to experiential learning theory and Lazear's occupational choice model, this dissertation theoretically analyzes the effect of education on entrepreneurial learning-by-doing and self-selection processes, the two major determiners of the performance of serial entrepreneurs. The study includes a sample of individuals with various backgrounds from NLS97 and an empirical test of the joint effect of education on entrepreneurial learning-by-doing and self-selection. The results indicate that education positively moderates the relationship between entrepreneurial experience and venture performance through both the learning-by-doing process and the self-selection process. The results of this paper contribute to the literature on serial entrepreneurship and provides useful information for entrepreneurs when they are making reentry decisions.

Although the three chapters that make up this dissertation cover three areas—a social network analysis, innovation and technology management, and entrepreneurship—they are motivated by the same question: How can high-tech startups enhance their entrepreneurial performance? To address this question, I have drawn insights from diverse streams of research, including network theory, organizational theory, science economics, the technology market, entrepreneurship, learning-by-doing, and core strategy theories. The first chapter of this dissertation, employing a social network methodology, contributes to the literature on alliance formation; the second chapter, which establishes the relationship

between novelty and the exit mode of startups, contributes to the literature on the technology market; and the last chapter, which examines the moderating effect of education on both the learning-by-doing effect and the selection effect, contributes to the literature on serial entrepreneurship.

CHAPTER 2. THE NETWORK OF KNOWLEDGE NETWORKS: HOW INFORMAL TIES SHAPE THE FORMAL ALLIANCES OF STARTUPS

2.1 Introduction

The relational view of a firm (Dyer and Singh, 1998; Dyer, Singh, and Hesterly 2018) posits that the locus of competitive advantage is often not found within an individual firm but within its strategic partnerships. Critical knowledge, resources, and capabilities are frequently embedded in strategic alliances that span firm boundaries. In high-tech industries, strategic alliance networks often constitute the locus of innovation (Baum, Cowan, and Jonard, 2010; Ahuja, 2000; Powell, Koput, and Smith-Doerr, 1996). As critical complements create value from innovation as well as status endorsements, strategic alliances are particularly important to high-tech startups (Stuart, Hoang, and Hybels 1999; Baum, Calabrese, and Silverman 2000). For example, the early success of the electric car manufacturer, Tesla, as a new entry in the automotive industry, was aided by early strategic alliances with top-notch partners such as Daimler, Toyota, and Panasonic (Hoang and Rothaermel, 2016). Not only did these alliances provide fungible resources for the fledgling startup such as cash and a top-notch production facility, more importantly, each of these alliances allowed Tesla to access unique resources and capabilities: cutting-edge automotive engineering from Daimler; world-leading capabilities in lean manufacturing from Toyota; and expertise in and large-scale production of high capacity lithium-ion batteries from Panasonic.

Prior research has documented that firms tend to rely on their existing interfirm alliances to obtain information when searching for alliance partners (Gulati and Gargiulo, 1999). Alliance formation tends to be more prevalent in knowledge-intensive industries (Hagedoorn, 1993) because high-tech firms are increasingly in need of access to a diversified pool of knowledge and as thus depend more heavily on knowledge flows among their strategic alliances (Gomes-Casseres, Hagedoorn, and Jaffe, 2006). Although such received wisdom tends to hold for existing firms, new ventures face a conundrum: Since they generally do not possess prior alliances, how do they obtain information relevant for future alliance formation? As the market for alliances in knowledge-intensive industries is often crowded because of the flood of new entries ripe with information asymmetries, this question is particularly relevant for startups (Hoang and Rothaermel, 2010). To overcome information asymmetry and identify the best possible matches available, startups need to effectively exchange information to form alliances. The question of what factors influence flows of information and subsequent alliance formation by startups is strategically important, yet it demands more attention by researchers.

Evidence that can help answer this question is found in research showing that information flow between firms is facilitated by their existing networks of alliances. Both the current alliances and third-party alliance ties of a firm tend to be useful predictors of future alliance formation (Granovetter, 1985; Gulati, 1995; Gulati and Gargiulo, 1999). That is, an existing interfirm network is a strong predictor of future alliances because current interfirm alliances are an effective channel through which useful and reliable information for evaluating potential future alliances is transferred; imperfect information about a wide range of possible partners, however, increases search costs (Oxley, 1997; Gulati and Gargiulo, 1999).

Other evidence can be found in recent work that has drawn attention to the role of interpersonal knowledge networks in innovation, although prior work has mainly focused on large existing firms (Nerkar and Paruchuri, 2005; Carnabuci and Operti, 2013; Grigoriou and Rothaermel, 2014). They have found that the structure of the interpersonal collaboration networks deep within firms such as the range and cohesion, influence not only the innovation production and adoption of individual inventors (Nerkar and Paruchuri, 2005) but also the inter-organizational diffusion of knowledge and firm-level innovation (Reagans and McEvily, 2003; Singh, 2005; Grigoriou and Rothaermel, 2014). Not surprisingly, prior works have also found that the structure of the collaboration network influences organizational knowledge sourcing and knowledge generation (Liebeskind, Oliver, Zucker, and Brewer, 1996; Carnabuci and Operti, 2013).

Taken together, the prior literature indicates the following: First, alliance formation depends on the embeddedness of firms, and is even more critical in high-tech industries. Second, informal interpersonal knowledge networks embedded deep within firms influence knowledge diffusion and generation. Building on these findings, we advance the baseline hypothesis that the structure of a startup's informal interpersonal knowledge network affects the likelihood of its entrance into formal interfirm alliances. In this sense, the less visible informal interpersonal network is a predictor of the observable formal interfirm network. This notion is important for understanding potential sources of firm-level competitive advantage (Peteraf, 1991; and Dyer et al. 2018). In particular, interpersonal informal knowledge networks are not only firm-specific but also not readily observable by competitors, and thus are hard to imitate; all factors that can contribute to firm-level competitive advantage (Barney, 1991).

We empirically test how the structural characteristics of a startup's ego knowledge network at the individual level may influence the formation of interfirm alliances by

drawing a longitudinal sample of 422 biotech startups founded between 2008 to 2014 in the United States. To construct the interpersonal collaboration network, we use patent co-inventing data and, in particular, measure the number of knowledge blocks and cutpoints in each ego network. In line with our conjecture, we find that both the amount of diversified information and information processing limitations of key individuals deep within a firm are positively related to the probability of alliance formation by startups.

2.2 Theoretical Framework

2.2.1 Knowledge Networks and Information Flow

Social networks play a critical role in the information flow among firms (Gulati, 1998). This finding is especially true in knowledge-intensive industries, where information flows between startups and incumbent firms occur frequently (Baum et al. 2000; Rothaermel and Deeds, 2004). The biotech industry, for instance, is characterized by high rates of innovation and high levels of technological and competitive uncertainty (Reagans and McEvily, 2003; Liebeskind, Oliver, Zucker, and Brewer, 1996). As a result, startups and incumbents find it difficult to effectively communicate information and to form alliances. Moreover, the successful evaluation of external technology demands internal absorptive capacity, that is, the ability of a firm to assess and evaluate external knowledge as well as assimilate it (Cohen and Levinthal, 1990). Rapid technological change, however, frequently challenges the absorptive capacity of incumbents to assess the value of a new technology held by startups. Therefore, old-line incumbents are often less well positioned to assess and evaluate the new knowledge generated by startups, which in turn, frequently draws on the latest scientific discoveries (Liebeskind et al., 1996). Second, because of high technological and market uncertainty in the biotech industry, startups often struggle to predict the market potential of their technology and to identify incumbents that may possess

the appropriate complementary assets to commercialize the new technology (Pisano, 1997). In such a situation, an effective social network is an asset to the information collecting and screening activities of startups (Powell, 1990).

Incumbents frequently rely on the social networks of prior alliances to source information and select future alliance partners (Gulati and Garguilo, 1999). For biotech startups that frequently have no pre-existing formal *interfirm* alliances, we argue that the social network on which they rely in order to source information to form future alliances is the *intra-firm* network based on inter-personal connections between knowledge workers such as scientists. In high-tech industries, the competitive advantage of firms is often based on their knowledge-related resources (Eisenhardt and Martin, 2000; Grant, 1996), which nearly all corporate strategies for high-tech firms are either related to or under the influence of. Knowledge resides in a set of key people deep within the firm (Nerkar and Paruchuri, 2005) who, together with those with whom they interact and form social relationships, constitute the knowledge network of the focal firm (Phelps, Heidl, and Wadhwa, 2012). Because of the effectiveness of transferring tacit knowledge and reliable information, interpersonal networks play a critical role in the knowledge transfer process (Reagans and McEvily, 2003; Nerkar and Paruchuri, 2005). We posit that startups use information obtained from their informal interpersonal knowledge networks in their alliance formation decisions. Therefore, the interpersonal knowledge network is the social network through which startups collect information to evaluate potential partners that can help them commercialize their innovations.

Because patenting is the dominant method of tracking innovation in the biotech industry (Arora and Gambardella, 1987; Powell et al. 1996), we use patent co-inventing events to construct interpersonal knowledge networks. In reference to prior studies (Grigoriou and Rothaermel, 2014), each node in our network analysis represents an

inventor, and each tie represents a patent co-inventing event. The ties between co-inventors are social relationships, the primary channels through which new scientific knowledge is exchanged (Liebeskind et al. 1996; Oliver and Liebeskind, 1998). At the same time, these types of social relationships are also effective in the acquisition and transfer of information to the market (Uzzi, 1997). Because information passes through the social network, firms are informationally constrained by the patent co-inventing network in which they are embedded (Granovetter, 1985).

Similar to the firm-level network, the interpersonal knowledge network performs two functions in the information flow: information gathering and information processing (Paruchuri, 2010; Ahuja, 2000; Leonard-Barton, 1995). Since an individual's functions in gathering and processing information are influenced by his/her network position (Paruchuri, 2010), the information that passes through networks is influenced by the structural characteristics of the knowledge network. At an individual level, people acquire knowledge spillover from their direct and indirect ties, and from the knowledge spillover, actors receive information about not only the newest technology and innovations but also the potential market applications and commercialization conditions of the new technology. Since individuals are subject to cognitive limitations (Simon, 1956), the positions of the nodes in the network, or jointly, the structure of the ego knowledge network, impact the flow of information and influences what and how much information will be passed on and how the information will be received. Thus, the individual-level knowledge network among firms mirrors the neural network of the brain; therefore, it can be viewed as the "brain of the startup firm" (Gurney, 1997).

For the inventors in each startup, the amount of information that they are able to collect is constrained by the total amount of diversified information in their ego knowledge network. Inventors linked together by dense co-inventing ties belong to one knowledge

block. Because inventors in one knowledge block share not only a common knowledge base but also newly generated knowledge, they are internally coherent about their own information. Therefore, the total amount of diversified information in a knowledge network is determined by the number of knowledge blocks in the network. Information diffusion among diverse knowledge blocks depends on a few key players that bridge the blocks. In this paper, we explore two structural characteristics of networks that influence the formation of alliances via their effects on information flow among the knowledge networks: (1) the number of knowledge blocks and (2) the number of cutpoints.

2.2.2 Knowledge Blocks and Alliance Formation

The ego knowledge network of each focal firm consists of one or more knowledge blocks; and within each block, structural coherence is high, and among the blocks, it is low. Each knowledge block consists of a set of inventors who share a common knowledge base and work on solving a common set of problems (Paruchuri, 2010; Hansen, 1999). The inventors could be working on a series of research that follows one stream or different streams of one problem. They engage in extensive communication and cooperation, and any two of them are linked by multiple independent paths (Moody and White, 2003). For the coinventing knowledge network of the biotech industry investigated in this paper, each knowledge block represents a potential opportunity for alliance formation, for a knowledge block can hold the research pertaining to a new technology, a method of exploiting the innovation, or ways of commercializing/using it (Baum, Cowan, and Jonard, 2010).

We define a knowledge block as a group of inventors characterized by structural coherence. Different knowledge blocks are linked by a few cutpoints, the removal of which disconnects the information flow among the blocks (Borgatti, 2006). Although both knowledge blocks and cliques emphasize structural coherence within the blocks, the

knowledge blocks used in this paper differ from cliques in that everybody in a clique needs to be directly connected while individuals in knowledge blocks can be loosely linked to others as long as the connections take place along more than one path. The intuition behind this definition and measure is that scientists within a group, especially a large group, may work on a specific part of a joint project, but they may not have direct cooperation with all others in the same group.

Figure 1 marks the seven knowledge blocks of the firm Actinobac Biomed, Inc., which illustrates the difference between knowledge blocks and cliques. The large knowledge block in the top right of this figure, if measured by cliques, will be divided into two cliques from the middle, but the knowledge block measurement identifies them as one block. The inventors in this knowledge block, or two cliques, are researchers either from top Irish universities or scientists in several U.S. companies located in New Jersey. These inventors are linked through inventor number 6117632-1, Daniel Joseph O'Mahony, and inventor number 6703362-3, Imelda J. Lambkin. Both Drs. O'Mahony and Lambkin are Irish and started their careers in academia in America. Later on, both Drs. O'Mahony and Lambkin had successful careers at multiple U.S. biotech companies and served on the boards of several of them. Dr. Lambkin is currently a venture capitalist. Many patents generated by this knowledge block have an inventor team consisting of both Irish and American researchers. Even though not all of the inventors in this knowledge block have a direct connection with one another, it is predictable that they are knowledgeable about the work of others in this block.

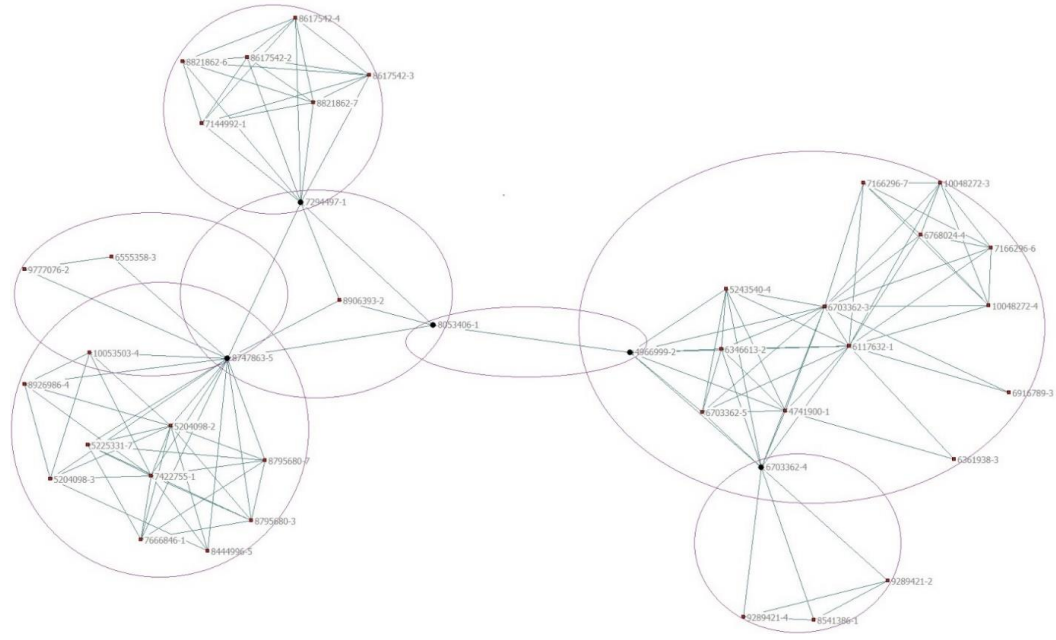


Figure 2.1- The knowledge network of Actinobac Biomed, Inc. with knowledge blocks marked.

These knowledge blocks are linked by several cutpoints, through which information flows and blocks learn the existence of each other. Information about the various knowledge blocks that pass through the cutpoints is useful for reducing information asymmetry between startups and incumbents and facilitates the formation of alliances. In the process of alliance formation, the major challenge for startups is to identify potential alliance partners and learn the alliance environment in order to evaluate the value of the opportunities associated with the various partners (Baum et al., 2010). To mitigate risk and reduce searching costs, startups mainly rely on information in their current knowledge network (Gulati and Gargiulo, 1999). The number of knowledge blocks is positively associated with the number of potential partners for startups, and the divergent information flowing from these blocks leads to a more comprehensive understanding of the alliance environment, which increases the probability of an alliance formation (Wang and Rajagopalan, 2014). Therefore, the total number of blocks in a network is positively

associated with the potential opportunities for the alliance formation of a focal firm. Thus, this study hypothesizes the following:

Hypothesis 1: *The number of knowledge blocks in the interpersonal knowledge network of a startup is positively associated with the probability of alliance formation.*

2.2.3 Knowledge Cutpoints and Alliance Formation

The cutpoints in this paper represent only a few key players through whom information among the different knowledge blocks can pass. Cutpoints are similar to brokers (Burt, 1992), for both of them span structural holes. The difference between the two is that brokers emphasize the spanning effect of boundaries at an individual level (Burt, 1992) while cutpoints focus on the bridging effect of blocks within the entire network (Borgatti, 2006). An individual can be a broker through ties with people in multiple cliques. At the same time, two cliques, especially large ones, might have many brokers who act as channels of information flow between them. When two cliques are linked by multiple co-inventing ties, they share a proportion of a common knowledge base, and they are informationally coherent; therefore, we consider them to belong to one knowledge block. In this situation, no single broker has a significant influence on the information flow in the entire network as information flowing through other brokers will complement the needed information. Unlike brokers, cutpoints represent only a few individuals (at most, two in this project) who bridge the blocks. They are key individuals who influence the information flow of the entire network. In sum, all cutpoints might be brokers and only brokers who play a critical role in information flow to the entire network are cutpoints.

The most widely used measure of brokerage is Burt's (1992) network constraints (e.g., Ahujia, 2000; Nerkar & Paruchuri, 2005; Baum, Cowan, and Jonard, 2010; Paruchuri,

2010) and betweenness centrality (e.g., Baum, Cowan, and Jonard, 2010; Paruchuri, 2010). These measures, however, are at the node level and focus on the relationship between the ego node and its alternatives. In knowledge networks, several cliques may be bridged by multiple brokers. In this case, we would consider such cliques structurally coherent and representative of only one knowledge block because information may flow among cliques through several people with different perspectives and there is no information asymmetry. Also, the removal of any single broker, considered replaceable, would not hinder the information flow among the cliques. Cutpoints may be brokers, but not all brokers are cutpoints.

Take Actinobac Biomed, Inc. as an example to illustrate the difference between cutpoints and other brokerage measures. We used all three measures to calculate the brokerage of inventors in the knowledge network of Actinobac Biomed, the results of which are shown in Table 1. The network constraint measurement identified six brokers, the betweenness centrality measurement identified seven brokers, and the biComponent measurement identified five cutpoints. Among these inventors, only two, 8053406-1 and 4966999-2, were jointly identified as brokers by all three measures. Figure 2 depicts the knowledge network and the five cutpoints identified by the biComponent measurement. The deletion of the five cutpoints generates a network made up of isolated knowledge blocks, shown in Figure 3.

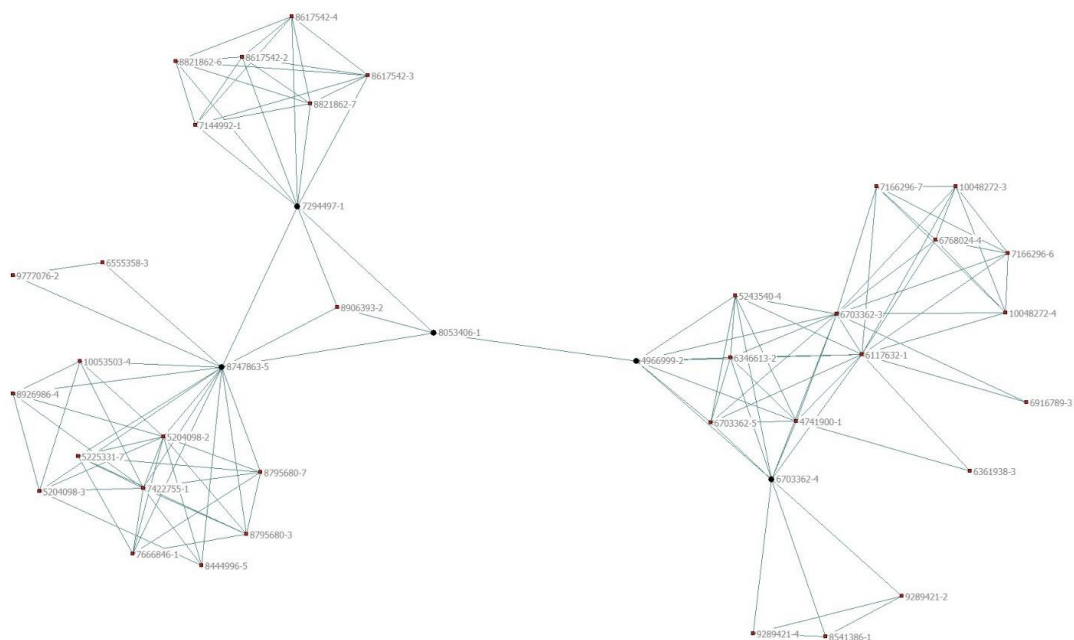


Figure 2.2 - The knowledge network of Actinobac Biomed, Inc. with cutpoints marked

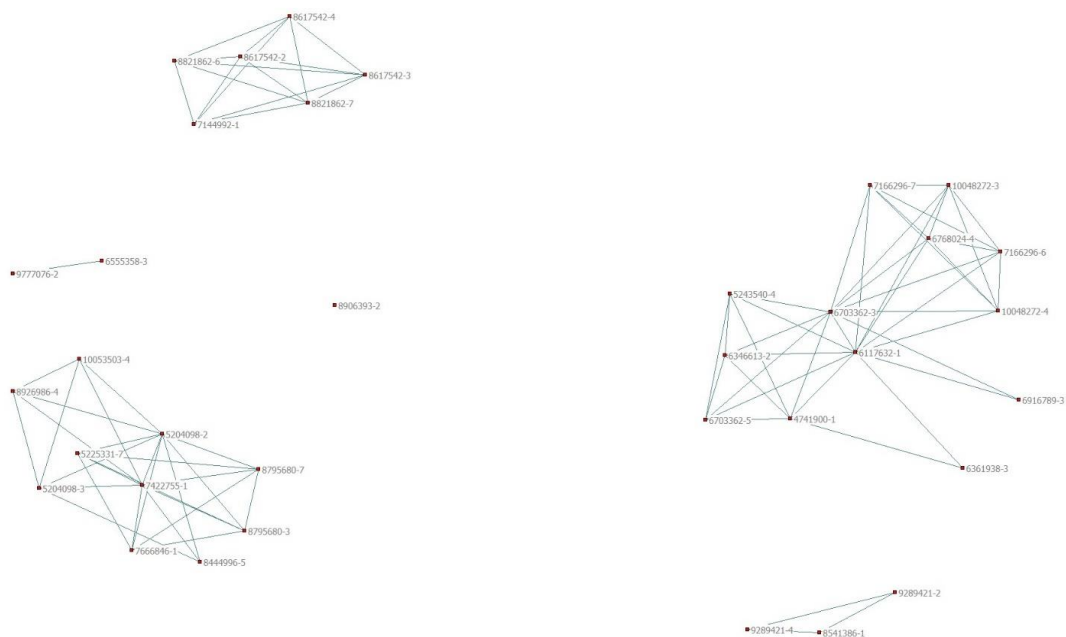


Figure 2.3 - The knowledge network of Actinobac Biomed, Inc. with cutpoints removed

Table 2.1 - Comparison of Brokerage Measurements

	Inventor_ID	Network Constraint	Betweenness Centrality	Cutpoints
1	6117632-1	0.25	117	0
2	6361938-3	1.13	0	0
3	6703362-4	0.33	108	1
4	6703362-5	0.49	0	0
5	6703362-3	0.27	96	0
6	6346613-2	0.49	0	0
7	4741900-1	0.42	16	0
8	5243540-4	0.49	0	0
9	4966999-2	0.39	374	1
10	6916789-3	1.13	0	0
11	7166296-7	0.56	0	0
12	7166296-6	0.56	0	0
13	10048272-4	0.56	0	0
14	10048272-3	0.56	0	0
15	6768024-4	0.56	0	0
16	7294497-1	0.35	198	1
17	8053406-1	0.58	378	1
18	8617542-3	0.56	0	0
19	7144992-1	0.56	0	0
20	8617542-4	0.56	0	0
21	8617542-2	0.56	0	0
22	5204098-2	0.35	6	0
23	5204098-3	0.55	1	0
24	7422755-1	0.35	6	0
25	8747863-5	0.21	350	1
26	8444996-5	0.77	0	0
27	7666846-1	0.56	0	0
28	8795680-3	0.56	0	0
29	8795680-7	0.56	0	0
30	5225331-7	0.56	0	0
31	8821862-7	0.56	0	0
32	8821862-6	0.56	0	0
33	8906393-2	0.93	0	0
34	8926986-4	0.65	0	0
35	10053503-4	0.65	0	0
36	9289421-4	0.93	0	0
37	8541386-1	0.93	0	0
38	9289421-2	0.93	0	0
39	6555358-3	1.13	0	0
40	9777076-2	1.13	0	0

Among all inventors, two of them, Dr. O'Mahony (6117632-1) and Dr. Lambkin (6703362-3), are identified as brokers by both network constraints and betweenness centrality, but not by our key player measure. There is no doubt that at the individual level, both have co-inventors from Ireland and New Jersey, and they themselves benefit from this diversified individual knowledge network. At the whole knowledge network level, however, the removal of any one of the two will not totally block the information flow within it, particularly as this knowledge block is made up of inventors with not only similar backgrounds but also likely ties that may not be shown in this patent co-inventing network. Such hidden ties, which will always accompany direct observable ties, increase the overall coherence of the network. Therefore, although the brokerage position of Dr. O'Mahony and Dr. Lambkin benefits them as inventors at the individual level, they are not the only key players strategically important to the information flow of the entire knowledge block.

The information received by the inventors in a focal firm is screened out and passed on by cutpoints in the ego knowledge network. The information-processing processes of cutpoints directly affect how much, what type, and which aspect of the information flow to the inventors of the focal firm. One factor that strongly influences the information processing of cutpoints is the number of knowledge blocks that a cutpoint bridges. When a cutpoint spans many knowledge blocks, its understanding of each knowledge block will be shallower than a specialist's in one area. In each knowledge area, some opportunities can be identified only by experts with a sufficient amount of specialized knowledge in that area, which cutpoints are less likely to have. One example is a cutpoint who is a productive star scientist. Such scientists, however, are very likely to be overwhelmed by diversified

information, which greatly reduces their ability to identify relevant information, leading to low-quality information flows (Paruchuri, 2010). Compared to communication with shallow gatekeepers and star scientists, a cutpoint who specializes in a certain area and bridges a few knowledge blocks is more productive. In a network, the information burden for each cutpoint declines as the number of cutpoints in that network declines. Therefore, we predict that the number of cutpoints in a network could increase the quality of information flow in that network and therefore increase the probability of alliance formation.

To illustrate the different information flow functions of cutpoints in networks with diverse structures, this study uses two sample knowledge networks: Boston Heart Diagnostic (BHD) (Figure 4) and Cardeas Pharma (CP) (Figure 5). BHD is composed of 43 inventors and 13 blocks and CP 53 inventors and 18 blocks. The sizes and the number of knowledge blocks in the networks are comparable, but BHD has six cutpoints while CP has only one. As shown in Figure 4, the inventor in the middle, the only cutpoint in the entire knowledge network, is responsible for all cross-block information communication. Compared to CP, BHD has six cutpoints more or less scattered around the network. As each cutpoint in this network bridges a few knowledge blocks, we expect the information flow in BHD to be more effective than that in CP. Thus, this study hypothesizes the following:

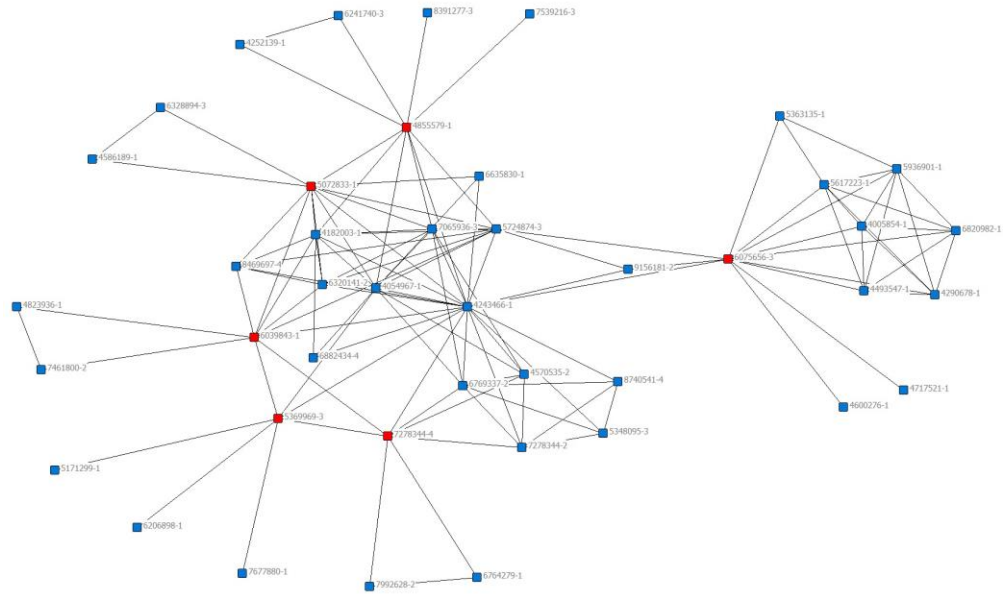


Figure 2.4 - The knowledge network of Boston Heart Diagnostics

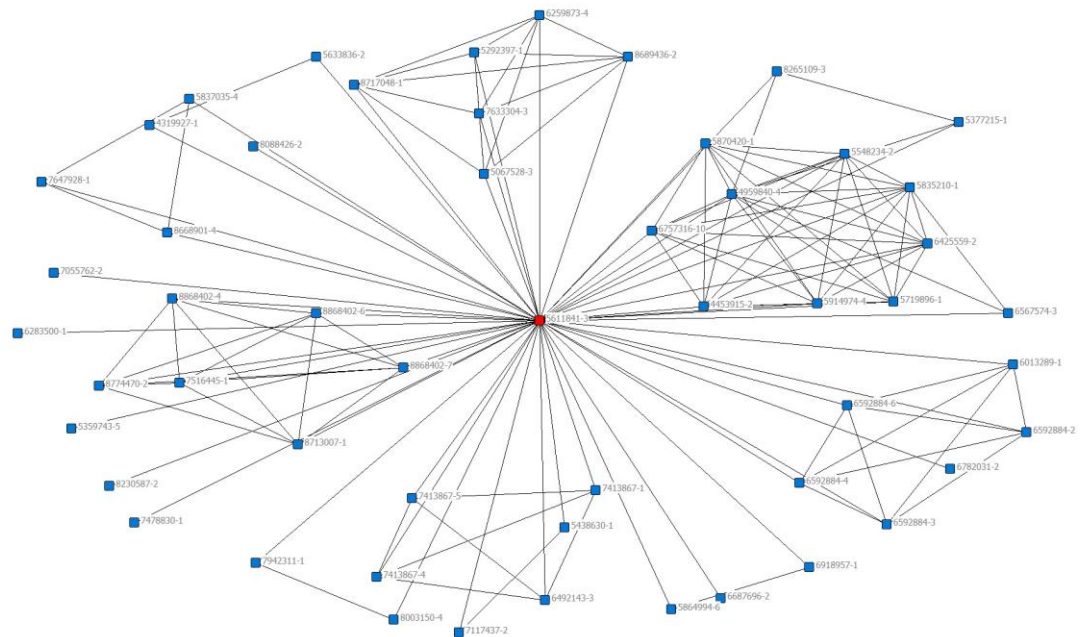


Figure 2.5 - The knowledge network of Cardeas Pharma

***Hypothesis 2:** The number of cutpoints in the interpersonal knowledge network of a startup is positively associated with the probability of alliance formation.*

2.3 Data and Empirical Strategy

2.3.1 Sample

This study draws a sample from the biotech industry for three reasons. For one, because the biotech industry is driven by innovation, the competitive advantage of most biotech companies originates in their basic R&D (Hoang and Rothaermel, 2010). Therefore, as R&D-related information constitutes a considerable weight in the information collecting processes of biotech firms, knowledge-related resources are a core consideration when they devise their corporate strategies. Therefore, the individual knowledge network of a startup channels a large amount of information in the alliance formation process, and the biotech industry is an appropriate context within which researchers explore how individual informal ties influence formal alliance formation. Another reason why the biotech industry aptly illustrates this relationship is that the motivation for forming alliances is strong in this industry, especially for startups seeking complementarity with large incumbents (Rothaermel and Deeds, 2004). Therefore, the number of alliances with the participation of startups is sufficient for the empirical study in this research. In addition, because of effective IP protection, biotech firms routinely patent their innovations. Because of the considerable amount of patenting, the patent co-inventing network effectively captures the interpersonal relationships of inventors.

The biotech startups in the sample used in this study come from BioCentury, a data source that provides information and analysis on the formation, development, and sustainability of life science ventures worldwide. BioCentury integrates news from multiple media sources and provides both basic firm information and up-to-date financial information and corporate activities from 2008. Because alliance formation is the

dependent variable and the full alliance data starts in 2008, our sample is limited to startups founded between 2008 and 2014. Our observation starts with the birth of a startup ends in mid-2018. Because the knowledge flow through ties that link two nodes geographically distant differs from that of ties that link two nearby nodes (Singh, 2005), limiting the analysis to a single country ensures that the knowledge flow through all co-inventing ties is comparable. As the United States is the major biotech market in the world, hosting around 70% of all biotech companies, we focus our analysis on U.S. biotech startups. After screening out several biotech startups that do not have patents, our sample had 422 biotech startups, covering at least 80% of the biotech startups in America.¹

We chose to use domestic patents issued by the U.S. Patent and Trademark Office, and all of the patent data used in this project, provided by Patentsview, were disambiguated. Patentsview generated the disambiguated assignee and inventor data by using a Bayesian supervised learning approach, the algorithms of which were jointly provided by the Fung Institute of Engineering Leadership and the Harvard Business School. In this dataset, each assignee and inventor was assigned a unique identification (ID) that could be used to track all patents related to that assignee and inventor. To assemble the patent data, we first acquired the unique assignee ID for each startup in our sample. We obtained around 60% of the assignee IDs by direct merging and the remaining 40% by manually checking keywords and double checking them by location. Using the unique assignee ID, we pooled all patents belonging to each startup and generated a host of unique inventor IDs for each startup, all of which was used in the construction of a knowledge network.

2.3.2 Construction of the Knowledge Network

¹ We checked the number of startups in some other leading pharmaceutical and biotech databases such as *Pharmaprojects* and compared the number of startups in their samples. We found that *Biocentury* provided the most comprehensive coverage of newly founded startups.

We used the patent and co-inventing data to construct an individual-level ego knowledge network for each startup. The scientists (patent inventors) of biotech firms are key individuals that hold the knowledge of the firms and exchange it with outside individuals. They not only effectively exchange information with other scientists with whom they are directly connected but also source and deliver information to and from scientists with whom they are indirectly connected through their direct connections (Gulati, 1999). In other words, the ego knowledge network for each firm consists of its own scientists, its co-inventors, and the co-inventors of its co-inventors. This individual-level ego knowledge network is the major channel through which startups source knowledge and information for alliances.

Although patent issuing is a one-time event, the ties among inventors may last. As a result, we had to make an assumption about the duration of co-inventing ties. Following the assumptions of former researchers (Grigoriou & Rothaermel, 2014), we assumed that co-inventing ties last for the five years following the patent issue date and then created ego knowledge networks based on five-year windows. For example, firms founded in 2010 have nine snapshots of network structures (i.e., 2005-2010, 2006-2011,...2013-2018).

Despite the many snapshots, variation among the snapshots at different time windows was minor. One reason for this phenomenon was the small number of startup patents. The average startup in our sample had only 5.7 patents, most of which were invented by the same group of inventors. Therefore, the newly added patents in the later snapshots merely reinforced existing ties but did not expand the existing network. Secondly, even if some patents introduced some new inventors, these inventors were likely to be well-embedded in their current networks and already active in networks as co-inventors or the co-inventors of co-inventors. Thus, although the 422 firms in our sample generated 2,662 snapshots, only 981 knowledge structures exist. Among the 422 startups

in our sample, 207 of them remained the same knowledge structure from the beginning to the end of the observational period.

As we constructed our knowledge network based on issued patent data, we do not observe the collaborations that existed but instead were not portrayed by the patent data. Such latent ties may complement the knowledge network portrayed by patent co-inventing ties and channel information flows. Unfortunately, detecting hidden networks is difficult and this is a limitation of this project. Nevertheless, there is no evidence that observed hidden ties will lead to biased results or that their misidentification will increase the noise in the results. In addition, as the majority of these hidden ties existed within an organization or a region and were characterized by localization, we controlled the region with biotech clusters to reduce the noise caused by the hidden ties.

2.3.3 Variables

2.3.3.1 Independent Variables: Number of Knowledge Blocks and Cutpoints

To calculate the number of blocks and cutpoints, we used the UCINET 6 BiComponent.² As this method of identifying a cutpoint differs from that of most papers in this area, we provide a comparison of the major broker measures in the next paragraph. In this paper, the average ego network of a firm consisted of 458 individuals that belong to 84 blocks linked by 27 brokers (cutpoints). As shown in Figure 3, some knowledge blocks consist of only two or three individuals, including the cutpoints. These blocks resemble information fragments rather than clusters and are less useful in alliance formation. In order

²To see the detail of the algorithm, please check Moody and White (2003, pp. 123-124).

to reduce heterogeneity and retain the effectiveness of knowledge blocks, we considered blocks with three or more people as knowledge clusters.

2.3.3.2 Dependent Variables:

Among the 422 startups, 160 had formed alliances with incumbents by early 2018. The majority had only one alliance, and the highest number of alliances was 27. We tested our hypothesis with two dependent variables: (1) a dummy variable that equaled one for firms that had formed alliances; and (2) a count variable that equaled the number of alliances that a firm had.

2.3.3.3 Control Variables

Innovation Capability: The innovation capability of firms comes from the inventors of the firm and the technology they have. Firms with strong inventor capabilities are usually embedded in a large diversified individual-level knowledge network. At the same time, the high-quality technology they have will attract more potential alliance partners and facilitate alliance formation. Therefore, we controlled the effect of innovation capability by controlling the capability of inventors and the quality of innovation. We used citation-weighted patents to control for the quality of innovation and the patent number-weighted inventors to control for the capabilities of inventors.

Our observations of patent citations started in the year a patent was issued and ended in November 2018. The lack of observations after 2018 introduced a “truncation bias,” that is, the bias that stems from the longer period in which earlier patents can accumulate citations (Sampat, Mowery, and Ziedonis, 2003). To eliminate the truncation bias to ensure that patents issued in different years were comparable, we generated a denominator for

each year and used all 243,343 related patents to generate a patent pool. The denominators equaled the average number of citations for all patents issued during a specific year in the patent pool. The citation-weighted value for each patent represented the total number of citations of that patent divided by the corresponding denominator. The quality of innovations for each firm was the summation of all citation-weighted patents for that startup. The weighting factor for inventors was the number of patents they had. The capability of inventors for a startup was the summation of all weighted inventors for that firm.

Startup Size: The size of a startup was directly linked to the performance and the alliance formation of a startup. In this paper, we controlled for the size of startups by using the VC financing they had received. Because of the high cost of conducting biotechnology research and clinical tests, we assume that almost all biotech startups are supported by VC financing. The scale of the financing, however, varied, indicating the quality of the firm. To reduce the effect of a long tail in this paper, we took the log of the VC financing.

Geographic Location. Of the 422 startups, 72 were located in Massachusetts (mainly the Boston area) and 142 in California (mainly the San Francisco Bay area), and the rest were scattered throughout the United States. As analyzed above, inventors in regions geographically clustered with many biotech companies were more likely to have hidden ties that the co-patenting network did not capture but in which information was transferred effectively. Furthermore, geographically co-locating increases the likelihood of alliance formation; thus, to control for the effect of geographic clustering, we added location dummies for startups in Massachusetts and California.

Technology Area: Similar to geographic clustering, technological clustering increases the probability of the formation of alliances and knowledge networks. The largest two technology areas in our sampled biotechnology firms were cancer- and cardio-related diseases. Therefore, we also added technology area dummies for startups that developed cancer and cardio treatments.

To control for the influence from the external macro environment, we added dummies of the founding year of a firm. However, we were not able to control for the size of the network, which is highly correlated with the number of knowledge blocks and the number of cutpoints. Although we were not able to use nodes as a control variable, we reported the value of this variable in the data statistics. Since we controlled for the major endogenous factor in this process—the innovation capability of the startups, we assumed that the size of the network was exogenous from the alliance formation.

2.3.4 Models

The dependent variable in this study, alliance formation, was measured as either a dummy variable or a count variable and assumed only nonnegative integer values. The most widely used models in similar cases are logit models and negative binomial models with either fixed effects or random effects in which unobserved heterogeneity is controlled for. As mentioned in the network construction parts, around half of the sample had only one network, so the rest of the sample that could constitute a panel was too small and has selection bias in testing either the fixed effect or random effect models. Therefore, we only used logit and negative binomial models without fixed effects or random effects in the robustness testing.

As an alternative, we adopted Cox Proportional Hazard (PH) models. The estimation had the following specification:

$$\lambda[t|x(t)] = \lambda_0(t)\exp[z(t)'\beta]\exp(\omega'\delta),$$

where $\lambda_0(t)$ is a time-variant nonparametric baseline hazard function that portrays the average probability of alliance formation during the life cycle of a startup, which eliminates the age effect from the probability of the alliance formation of a startup. The scale factor $\exp[z(t)'\beta]$ contains time-variant variables and the scale factor $\exp(\omega'\delta)$ contains time-invariant variables. Another reason for using the Cox PH model is that our observations of alliance formation ended in early 2018, and Cox PH models eliminated the bias caused by right-hand truncation.

2.4 Results

2.4.1 Main Results

Table 2 provides descriptive statistics and correlations for all of the variables for the 422 observations in the sample. Although all firms in the sample were startups, they varied significantly on the majority of key variables, such as citation-weighted patents, patent-weighted inventors, network size, and the number of cutpoints and knowledge blocks. The two independent variables were highly correlated, and both were highly correlated with the size of the network, measured as the number of nodes in a network. Hence, to control for the effect of the size of the network, we did not directly add a number of nodes in our models. As described earlier, to control for the network size, we had the variables of human capital and the knowledge stock of startups. These two variables, together with citation-

weighted patents and patent weighted inventors, were significantly correlated with the number of nodes and expected to adequately control for the effect of network size.

Table 2.2 - Data Statistics

	Variable	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9
1	Alliances Dummy	0.37	0.48	0	1	1								
2	Number of Alliances	1.88	2.56	1	27	0.45	1							
3	Citation Weighted Patents	4.91	16.88	0	251.1	0.18	0.1	1						
4	Patent Weighted Inventors	106.8	152.3	1	1998	0.12	0.1	0.3	1					
5	Log(Financing+1)	4	1	1	992.9	0.11	0.1	0.1	0.0	1.0				
6	Nodes	17.64	2.55	0	5758	0.19	0.0	0.1	0.4	0.1	1			
7	CutPoints	6	1738	1	278	0.21	0.1	0.2	0.4	0.1	0.8	1		
8	BiComponent	28.51	38.76	0	1174	0.18	0.0	0.1	0.3	0.0	0.9	0.8	1	
9	Clusters	118.6	203.3	0	686	0.18	0.0	0.1	0.3	0.0	0.9	0.8	1.0	
1	Knowledge	2	1	0	2010.									1
0	Blocks	89.64	4	0	2014	0.18	7	6	8	8	6	4	0	
	Year Founded	3	1.84	#										
		CA		M										
1				A										
1	Region	137		72		213								
1		Cardiovascular		Cancer		Others								
2	Technology Area	83		4		235								

Because of the high correlation between independent variables, we tested the effect of independent variables in different models. Table 3 reports the Cox PH regression results for alliance formation. The independent variable in (1) to (4) was knowledge blocks and that in (5) to (8) was cutpoints. For each independent variable, the first models (1 and 5) included the independent variable only, the second models (2 and 6) added the

regional, category, and year dummies, the third models (3 and 9) added the log of VC investment to control for the external influence from VCs on both network expansion and alliance formation, and the fourth models (4 and 8) added citation-weighted patents and patent-weighted inventors to control for firm-level heterogeneity.

The results are statistically significant and support both hypotheses 1 and 2. For each unit change, however, the coefficient was small on an economic scale. Having one more knowledge block increased the hazard by 0.1% and having one more cutpoint increased the hazard of forming alliances by 0.8%. As the startups in this sample, however, had an average of 90 knowledge blocks and 29 cutpoints with a large variance, the overall economic effect contributed to our understanding of the influence of knowledge blocks and cutpoints. For example, startups in the 90% percentile with 222 knowledge blocks were approximately 22% more likely to form alliances than those in the 10% percentile with only one knowledge block. Correspondingly, startups in the 75% percentile with 37 cutpoints were 27% more likely to form alliances than those in the 25% percentile with only four cutpoints.

Table 2.3 - The Results of Cox PH Models on Alliances Formation

	Knowledge Blocks				Cutpoints			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Region Dummies		Yes	Yes	Yes		Yes	Yes	Yes
Category Dummies		Yes	Yes	Yes		Yes	Yes	Yes
Year Dummies		Yes	Yes	Yes		Yes	Yes	Yes
Log(VC Investment)			0.0837 +	0.0838 +			0.081+ -0.046	0.081+ -0.046
Citation Weighted Patents				0.007*				0.006*
Patent Weighted Inventors				-0.003				-0.003
Knowledge Network	0.002* *	0.001* *	0.001* *	0.001* *				-0.005 -0.006
CutPoints	0.000	0.000	0.000	0.000	0.007* *	0.007* *	0.008* *	0.008* *
					-0.001	-0.002	-0.002	-0.004
log_likelihood	- 871.25 4	- 776.33 1	- 774.28 4	- 682.27 5	- 885.07 8	- 786.68 7	- 769.68 2	- 792.04 3
N	422	422	422	422	422	422	422	422
Observations	2660	2660	2660	2660	2660	2660	2660	2660

Standard errors in parentheses + p<0.10 * p<0.05 ** p<0.01

The results related to the baseline hazard ratio of forming alliances also merit discussion. The cumulative baseline hazard, shown in Figure 6, appears to be increasing at a steady speed, and the overall scale of the baseline hazard is small, which indicates almost no generalizable effect of alliance formation, that is, one that could apply to all firms. It also indicates a lack of sensitivity of alliance formation to the life cycle stages of startups.

Alliance formation mainly depends on the endogenous heterogeneous resources of each firm. Unlike the baseline hazard, the year dummies show a trend. While the probability of firms forming alliances in 2008 is similar to that in 2012, the probability is higher in 2013 than in 2018. The peak of the average probability of alliance formation is 2016, which is twice as high as the probability of alliance formation in 2008.

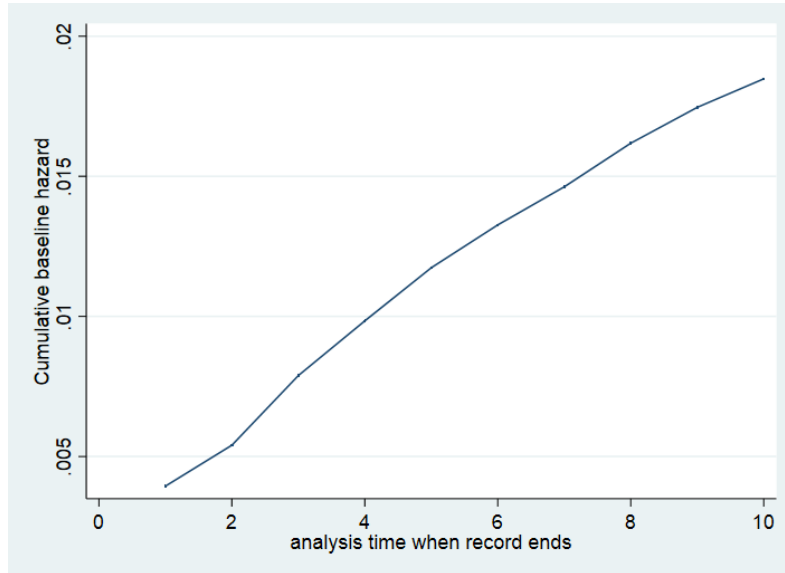


Figure 2.6 - The cumulative baseline hazard function

2.4.2 Robustness of Results

We used logit models and negative binomial models to test the stability of the results on two measures of the dependent variable: a dummy for having alliances and a count of the number of alliances. The results of the logit models are reported in Table 4, and the results of negative binomial models are reported in Table 5. The results of all models are consistent with those of the Cox PH models, and their coefficients are comparable in size. The only exception is that the coefficients of the cutpoints in some logit models, when tested by using Cox PH models, are slightly smaller than those in the corresponding

models. Thus, the results are qualitatively similar to the Cox PH model results and support both hypotheses 1 and 2.

Table 2.4 - The Results of Logit Models on Alliances Formation

	Knowledge Blocks				Cutpoints			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Region Dummies		Yes	Yes	Yes		Yes	Yes	Yes
Category Dummies		Yes	Yes	Yes		Yes	Yes	Yes
Year Dummies		Yes	Yes	Yes		Yes	Yes	Yes
Log(VC Investment)			0.049*	0.050*			0.051*	0.050*
Citation			-0.021	-0.021			-0.021	-0.021
Weighted Patents				0.041**				0.041**
Patent				-0.006				-0.006
Weighted Inventors				0.003				0.001
Knowledge Network				-0.004				0.004
CutPoints	0.002**	0.001**	0.001**	0.001**	0.007**	0.006**	0.004**	0.005**
	0.000	0.000	0.000	0.000	-0.001	-0.001	-0.001	-0.001
_cons	-	-	-	-	-	-	-	-
	0.515**	0.602**	0.599**	0.613**	1.254**	1.573**	2.742**	2.114**
	0.170	0.157	0.167	0.168	0.734	0.054	0.374	0.433
log_likelihood	-	-	-	-	-	-	-	-
	4748.0	4293.4	3598.4	3529.4	1679.6	1621.8	1519.1	1503.2
	90	21	91	13	28	49	49	24
N	422	422	422	422	422	422	422	422

Standard errors in parentheses + p<0.10 * p<0.05 ** p<0.01

Table 2.5 - The Results of Negative Binomial Models on Number of Alliances

	Knowledge Blocks				Cutpoints			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Region Dummies		Yes	Yes	Yes		Yes	Yes	Yes
Category Dummies		Yes	Yes	Yes		Yes	Yes	Yes
Year Dummies		Yes	Yes	Yes		Yes	Yes	Yes
Log(VC Investment)			0.047**	0.047**			0.0470*	0.047**
Citation Weighted Patents			-0.008	-0.008			-0.008	-0.008
Patent Weighted Inventors				0.003**				0.041**
Knowledge Network	0.156**	0.143**	0.134**	0.099**				0.001
CutPoints	0.026	0.028	0.028	0.031	0.003**	0.002**	0.001**	0.002**
_cons	0.154**	0.147**	-	-	-0.000	0.000	0.000	0.000
log_likelihood	0.027	0.279	0.515**	0.602**	0.189**	0.137**	-	-
	4839.16	4796.17	4298.32	4219.41	4856.57	4794.57	4397.15	4341.02
	0	5	4	2	8	5	3	4
N	422	422	422	422	422	422	422	422

Standard errors in parentheses + p<0.10 * p<0.05 ** p<0.01

The variable of knowledge network has been standardized in this model to increase the readability.

One concern regarding our results is whether the relationship between the independent and dependent variables are linear and whether their sizes remain the same among different groups. We added a variable that equals the square of the independent variable and re-tested all Cox PH models. The coefficient of the square of the knowledge

blocks was statistically significant, but the economic value was almost zero, and the coefficient of the square of the cutpoint was not significant. Therefore, the curvature was not a concern of this study. Another concern related to whether the results were driven by a few extreme values. To test this, we dropped the bottom and top 10% of the sample based on the value of the independent variable and tested the new sample using all models but found no significant differences from the main results, which excluded the possibility that the results were driven by extreme values.

2.5 Discussion

As firms are embedded in their existing interfirm alliance network, their current alliances and third-party alliance ties are useful predictors of future alliances. Although above theories could explain alliance formation for incumbents, it does not provide insights for startups that enter the market without existing formal alliances. This study hypothesizes that when formal alliances are lacking, it is individual-level informal ties that serve as channels for knowledge diffusion and information transformation. The study examines how the structural characteristics of the collaboration network of inventors influence the alliance formation of startups through their influence on information transformation. The theoretical analysis suggested that the number of knowledge networks, which expands the diversity of the knowledge stock in the network, and the number of cutpoints, which facilitate the efficiency of information transformation, are positively related to the alliance formation of startups. The empirical results support our hypothesis.

The results of this study suggest that the social capital of a firm may originate from its inventors and the fundamental unit of analysis of the social capital of organizations is the individuals in that organization. This paper contributes to the literature on alliance formation by being the first to introduce a cross-level analysis and adopt a micro-

foundation method. It also contributes by studying the effect of structural characteristics and the positions of individuals. Unlike former papers that focus on individual-level influences, this paper examines the individual effects on an organization. Our methodology and findings illustrate the possibility of a cross-level analysis in the social network area.

One limitation of this paper is that we assumed network ties were exogenous. Interpersonal ties, however, may be endogenously intentionally formed by inventors (Coleman, 1988). Although we have control variables on innovation quality, human capital, and firm size to reduce the potential effect of the capability of firms, the formation of individual ties may still be influenced by some unobservable firm-level decisions and activities that we were unable to capture. Therefore, the regression estimates could have overstated the true causal effect. Future work could mitigate such a problem by using an effective instrumental variable or conducting natural experiments.

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CHAPTER 3. THE NOVELTY OF INNOVATION AND EXIT ACTIVITIES OF HIGH-TECH STARTUPS

3.1 Introduction

In the Schumpeterian view of the entrepreneur, growth-oriented startups are typically tied to an innovation (Schumpeter, 1934), and the nature of this innovation has persistent effects on the long-term opportunities available to the firm (Nelson and Winter, 1985; Henderson and Clark, 1990; Tushman and Anderson, 1986) and its commercialization activities (Nerkar and Shane, 2007). Extant research on technology and startup activities has found that the attributes of the innovation influence the likelihood of commercialization (Nerkar and Shane, 2007), determine whether the commercialization is through new or incumbent firms (Shane, 2001), and affect the rate of growth of the new firm (Clarysse, Wright, and de Velde, 2011).

Among the many attributes of innovation, its novelty (or its pioneering nature), which offers startups a first-mover advantage both in terms of market positioning and movement down the learning curve (Levin, Klevoick, Nelson, and Winter, 1987; Ahuja and Lampert, 2001) and potentially undermines incumbent technologies (Tushman and Anderson, 1986), is one of the dimensions that characterize the technological opportunities and influences the commercialization strategy and performance of high-tech startups. Many startups with novel innovations have achieved great success, and these examples tend to be very familiar to us. For example, Netflix and other streaming content providers are rapidly replacing traditional cable and TV networks in the media industry, and have become household names. However, we tend to be less familiar with the frequent failures

of startups with novel innovations,³ thereby creating a false impression that novelty is necessarily good for performance. Indeed, we know little about the effect of novelty on the performance of startups in representative samples not subject to recall bias.

Although there is a growing literature examining the effect that novelty has on commercialization activities, these studies are almost all focused on the early stage of commercialization activities, such as the likelihood of entering production and access to venture capital funding (Nanda and Rhodes-Kropf, 2013; Samila and Sorenson, 2011; Nerkar and Shane, 2007; Shane, 2001).⁴ However, the effect of novelty on the longer term performance of startups and the financial return of novel innovation to external investors remains largely unexplored.

In this paper we consider new questions about the relationship between novelty and performance among startups. We first analyze the novelty-performance relationship by looking at the link between the novelty of innovation at the time of a firms' creation to the likelihood of it having a successful exit, whether in form of an IPO or being acquired. We think this is a good measure of performance in the sample we study (see, for example, Fuller and Rothaermel, 2012; Nanda and Rhodes-Kropf, 2013; Ewens and Rhodes-Kropf, 2015), especially as all firms in the sample have received external financing. To ensure a financial return to external investors, startups must establish an exit strategy, and firms are usually considered failures by VCs when they cannot successfully exit for many years.

³ The failure rate for innovative startups is close to 90 percent (Payne, 2014).

⁴ There is also a parallel literature studying novelty in incumbents. The research questions are mainly on: how the knowledge base influences the internal and external exploration activities of incumbents and the productivity of novel innovations (Hill and Rothaermel, 2003; Zhou and Wu, 2010; Zhou and Li, 2012); what strategies and resources are needed for incumbents to appropriate value from novel innovations (Chandy and Tellis, 1998; Sorescu, Chandy, and Prabhu, 2003); and what effect cooperative strategies have on the novel innovation (Prabhu, Chandy, and Ellis, 2005).

For startups hoping for a successful exit, the most important strategic task is to develop and commercialize their innovation, which requires the acquisition of complementary assets and capabilities. One of the most important methods for startups to acquire complementary resources and increase their early-stage performance is through forming strategic alliances with incumbents (Rothaermel and Boeker, 2007; Rothaermel and Deeds, 2004). In this paper, we therefore also analyze how the novelty of innovation influences the formation of strategic alliances, and how in turn alliance formation may influence the successful exit of startups.

A challenge in the study of novelty is to devise an objective scale with which to measure it. In the previous literature, two methods have been adopted. The first infers the novelty of innovations from surveys and retrospective coding, a method that is widely used by marketing scholars (Sorescu, Chandy, and Prabhu, 2003). One limitation of the survey approach is that it is difficult to avoid selection biases that lead to an overrepresentation of successful novel innovations because the ones that failed are not recalled by respondents (Sorescu, Chandy, and Prabhu, 2003). Another limitation of this type of measure is that they are more suitable for case studies or small sample analysis because of difficulty in collecting such data.

The second type of measure, which is capable of evaluating the novelty of innovations from a large unbiased sample, is patent-based, the most popular of which for some time was a backward citation-based measure that checks the number of technological subclasses a patent cites that outside its own classes (Ahuja and Lampert, 2001; Nerkar and Shane, 2007; Shane, 2001). Fleming (2001) proposed a variation of this measure, reflecting the notion that invention is a process of recombination of existing ideas that measures the frequency of new combinations of US Patent Office Classification (USPC) technology classes among all combinations in a patent. Recently, Uzzi, et al. (2013) and Verhoeven,

Bakker, and Veugelers (2016) made some improvements to Felming's measure and applied their measure to test the effect that novelty has on science and technology discoveries. Their work illustrates that using group-level International Patent Classification (IPC) codes is better than using subclasses from the USPC in researching questions related to the scientific impact of novel innovations (Verhoeven et al, 2016). However, the most suitable measure for questions about firm performance is under-explored.

This paper attempts improve upon these existing measures in several dimensions. First, the measure of novelty in this paper is based on the relatively new Cooperative Patent Classification (CPC) system, which was released in 2013. The CPC system is an extension of the IPC system and is now the main classification system in Europe, the United States, and many Asian countries. Similar to the IPC system, the CPC system has five hierarchy levels. The knowledge distance between classes at different hierarchy levels varies, which directly influence the probability of novelty and its extent. Pervious papers have used the subclass level (Fleming, 2001) and the main group level (Verhoeven et al, 2016), but it is unclear which knowledge distance is more suitable for management research. Therefore, this paper measures novelty at both subclass level and subgroup level. The results for the two levels of analysis are consistent, but the measure at subgroup level is more significant both economically and statistically.

In this paper, we use multiple data sources to construct a panel of 408 startups that received external financing in the healthcare industries, and we tracked the startups from their birth to their exit or the end of 2017. Our data sources enabled us to include a wide range of controls as we examine the relationship between novelty and performance. Our main findings are as follows: Novelty has a negative effect on likelihood that startups will have a successful exit, but very limited scale of this negative effect comes from the

difficulty to form alliances for startups with novel innovation. Furthermore, compared to acquisition, IPO is a higher probability exit method for startups with novel innovation.

The results of this paper provide useful information on how the novelty of innovation influences the commercialization strategy of startups and, therefore, influences firm performance. This paper contributes to the growing body of work analyzing how the novelty of innovation influences commercialization activities (Nanda and Rhodes-Kropf, 2013; Samila and Sorenson, 2011; Nerkar and Shane, 2007; Shane, 2001). Also, this paper complements the work examining the effect that novelty has on corporate strategies (Chandy and Tellis, 1998; Hill and Rothaermel, 2003; Prabhu, Chandy, and Ellis, 2005), although, in contrast to previous work that has the incumbent as the focus of analysis, this paper studies high-tech startups.

3.2 Theoretical Framework

It is widely accepted that the creation of innovation is a process of recombining existing knowledge and that innovation is either "a new relationship between previously combined components" or "a new combination of components" (Henderson and Clark, 1990; Fleming, 2001). In this paper, we define an innovation from new combinations of knowledge, which represents the degree to which an innovation differs from previous innovations in that field (Shane, 2001), as an innovation with the attribute of novelty.

It is true that the novelty of an innovation is the potential origin of the "first mover advantage" (Lieberman and Montgomery, 1988) and provides a learning curve advantage (Levin, Klevorick, Nelson, and Winter, 1987). Also, because of the substantial capital costs and technological support required to commercialize a novel innovation, firms with

more resources are in a better position to commercialize their novel innovations (Cohen and Klepper, 1996). However, high-tech startups, the majority of which are resource constrained, often lack the resources to manifest the advantages of their innovations while to bear the related risk and uncertainty.

The commercialization of novel innovations requires a long-term process of development that entails enormous technological risks. In the process of technological development, pure technological risks originate with an inventor's process of searching for unfamiliar components and combining new knowledge components (Fleming, 2001). As more and more inventors explore the use and the characteristics of a new technology, the risk will subside (Fleming, 2001; March, 1991). Through both formal and informal ties, the inventors in a specific area share their experience and knowledge at both organizational and individual levels (Ahuja, 2000; Stuart, 1998). In other words, the knowledge flow among inventors in one area facilitate the cumulative development of knowledge, so the risk that an innovation entails is alleviated. Thus, for conventional innovations, the technological risk involved in knowledge selection and recombination activities in the technology development process is limited. Unlike conventional innovations, novel innovations have been under-explored, so their technology development processes entail higher technological risk.

Because of the high market uncertainties involved in the market selection process, very few novel innovations have become popular radical innovations and achieve market success (Chandy and Tellis, 1998). Startups with a novel innovation enter a market (or submarket) at an early stage of an industry (Nelson and Winter, 1982), when little is known about how a new product will incorporate a novel technology and to what extent the novel innovation will fulfill the needs of key customers (Sorescu, Chandy, and Prabhu, 2003). Although all novel innovations enter the market with a hope of generating great economic

value, very few successfully pass through the market selection process (Nelson and Winter 1982; Sorescu et al., 2003). At the early stage of an industry, a great deal of uncertainty exists regarding the extent and time frame of the adoption of a product (Griffin, 1997). Also, the product from a novel innovation frequently enters the market with defects, which severely limits the realization of its value and increases the risks associated with the product (Suarez and Utterback, 1995). Furthermore, the application of a novel innovation must be legally sanctioned, generating even more market uncertainty. For example, although a variety of euthanasia drugs have been launched, only a few countries in the world have sanctioned their use but done so under limited conditions.

The reduction of the technology risk and market uncertainty associated with a novel innovation demands a strong commercialization capability to absorb, interpret, and commercialize critical information effectively (Lane and Lubatkin, 1998). Such a capability requires the synthesis of a variety of resources (Hill and Rothaermel, 2003; Sorescu, et al., 2003), which high-tech startups do not typically have. Therefore, because of the high technology risk and market uncertainty and the lack of resources, high-tech startups with a novel innovation have a lower probability of a successful exit. Thus, we posit the following hypothesis:

Hypothesis 1: *The novelty of an innovation of a high-tech startup is negatively associated with the probability of its successful exit.*

It is critical for startups, being both resource and capital constrained, to obtain resources and capabilities to reduce the risk and uncertainty involved in commercializing their novel innovation and increase the probability of a successful exit. An important method of acquiring resources and capabilities is the formation of alliances with incumbents. Rothaermel and Deeds (2004) found that biotechnology startups that

orchestrate an integrative alliance system that leverages the exploration and exploitation of alliances in a sequential fashion achieve superior product development performance. Forming alliances with incumbents enables startups to gain access to complementary assets (Arora and Gambardella, 1990), enhance their legitimacy (Baum and Oliver, 1991), and improve their early stage performance (Baum, Calabrese, and Silverman, 2000). Furthermore, strategic alliances can help startups resolve information asymmetry in the capital market, which directly increases the probability of an IPO (Ozmel, Robinson, and Stuart, 2012).

Even though the formation of alliances with incumbents is important to the successful commercialization of a firm's innovations, the novelty of an innovation actually hinders the formation of alliances, which partially contributes to the negative effect of novelty on the probability of a successful exit. Startups are more likely to enter strategic alliances to gain access to complementary assets when they are younger (Rothaermel and Boeker, 2007). However, when the startup is young, it is hard for others to incumbents to identify, evaluate, and write a contract in a novel innovation, whose market value and usage is unclear. Although the development processes resolve the information asymmetry and uncertainty related to a novel innovation, these processes also generate unique tacit knowledge that increases the difficulty and transaction cost for downstream alliances. Thus, the novelty of the innovation hinders the formation of all types of alliances between startups and incumbents.

The majority of novel innovations are early-stage technologies that originate from basic science discoveries, so they are far from the market stage (Jensen and Thursby, 2001). Because of their need for resources and experience in technological development, high-tech startups seek upstream alliances with incumbents. A novel innovation, which involves knowledge that is new to an entire industry and which lies beyond the boundary of the

knowledge base of incumbents, creates challenges to the absorptive capacity (Cohen and Levinthal, 1991) of incumbents to identify and correctly evaluate the potential value of the innovation. Because of the myopia of learning, incumbents are more likely to identify an innovation and its opportunities that closely relate to their current knowledge base (Levinthal and March, 1993). Thus, firms with novel innovations that are not a logical extension of existing knowledge find it more difficult to attract the attention of incumbents (Rosenbloom and Christiansen 1994). After all, even if an incumbent becomes aware of the existence of a novel innovation, the difficulty of understanding and evaluating its value (Rosenbloom and Christiansen 1994) may deter incumbents from forming alliances with a startup at an early stage.

In addition to the challenges to the absorptive capacity of incumbents, contracting an early stage novel innovation also poses challenges that hinder the formation of upstream alliances. For one, because of the information asymmetry, the perceived risk will be higher and the perceived value lower for incumbent than for startups, which decreases the likelihood of achieving an agreement on the value appropriation of the novel innovation (Somaya, Kim, and Vonortas, 2010). In addition, novel innovations entail more inherent uncertainty that includes both risks and potential opportunities, rendering the contract substantially incomplete (Aghion and Tirole, 1994). If an innovation eventually has broad application, an incomplete contract may result in an incomplete value appropriation by some parties. In some cases, value spillover may also lead to a conflict of interest in the product market. The difficulty of achieving an agreement regarding the value of an innovation and the substantial incompleteness of a contract hampers the formation of upstream alliances between startups with a novel innovation and incumbents.

After successfully developing their technologies, startups need to build specific downstream capabilities in order to commercialize their innovation (Somaya, Kim, and

Vonortas, 2010). The downstream capability need by startups are manufacturing, distribution, sales and marketing capabilities and human capital (Hoang and Rothaermel, 2010). Building downstream capability is both time consuming and challenging. For example, the value of a sales force in the medical device industry resides in the services it provides, which includes training doctors to use medical devices and solving medical disputes arising from the use of the devices. Thus, as the sales of medical devices rely on the trust and ties between sales forces and doctors, startups find it difficult to build such trust and ties within a short time. Incumbents, however, with their rich downstream capabilities, are natural strategic alliance partners for startups with well-developed technology (Rothaermel and Boeker, 2007). However, if startups with novel innovation are unable to form upstream alliances, then they will also find it difficult forming downstream alliances because incumbents lack the tacit knowledge generated in the technology development process.

Novel innovations pose extra challenges for downstream alliances because the cooperation between incumbents and startups demands the transaction of an enormous amount of tacit knowledge (Jensen and Thursby, 2001). A novel innovation, characterized by its newness and its close relationship to basic science, entails more tacit and complex knowledge (Jensen and Thursby, 2010). Because of its newness, however, novel innovations has been underexplored, so its development process requires more experiments that entail more time, a process that generates more tacit knowledge critical for the downstream commercialization process (Jensen and Thursby, 2001). Therefore, the successful formation of a downstream alliance that encompasses a novel innovation requires the successful transaction of tacit knowledge, which is a challenge to the absorptive capacity of many incumbents. Even if an incumbent is able to digest the tacit

knowledge, the knowledge transfer process will greatly increase the transaction costs of the alliance (Williamson, 1985).

Because the purpose of downstream alliances is to leverage existing complementarities between partners, incumbents usually enjoy a learning-by-doing effect by repeatedly forming downstream alliances with firms similar to them (Hoang and Rothaermel, 2010; Rothaermel and Boeker, 2007). The investment of the incumbents of downstream alliances, therefore, mainly focus on incremental improvements and refinements to existing routines (Hoang and Rothaermel, 2010). The downstream capabilities demanded by a novel innovation, however, are frequently unique (Somaya et al, 2010), requiring incumbents to make specific investments if they want to successfully commercialize the innovation. Not only does this entail extra cost, it represents a deviation from the core activities of the incumbent, which is what many incumbents reluctant to do.

We conclude that forming alliances is important for the successful exit of startups, especially those with novel innovations. The novelty of an innovation, nevertheless, hinders the formation of upstream alliances because incumbents find it difficult to recognize, evaluate, and contract a novel innovation at an early stage; and the novelty of an innovation hampers the formation of downstream alliances because it entails high transaction costs and investment in specific downstream capabilities. Following this logic, we expect to observe that the formation of alliances partially mediates the negative effect of novelty on a successful exit. Thus, we posit the following hypothesis:

Hypothesis 2: *The negative effect of the novelty of an innovation on a successful exit partially stems from the difficulty of forming alliances.*

Although not all novel innovations become valuable radical innovations that either create a new market or disrupt an existing market, all valuable radical innovations are characterized by novelty. When a novel innovation exhibits its market value, it is common for incumbents to acquire the new technology using external sourcing (Arora, Cohen, Walsh, 2016). Common external sourcing methods for incumbents are forming strategic alliances (Rothaermel, 2001), acquiring the firm (Higgins and Rodriguez, 2006), and hiring inventors (Bei, 2018). The previous discussion suggested that novelty hinders the formation of strategic alliances between startups and incumbents. Similarly, although acquisition is an important method for incumbents to gain access to an external innovation, they may cautiously use this approach to acquire a novel innovation cautiously because of the potential challenges of learning and integrating the diverse capabilities of the two firms (Lane and Lubakin, 1998).

Nonetheless, incumbents do sometimes acquire startups to enhance their novel innovations. On January 16, 2018, Celgene acquired Juno for \$9 billion to advance their research into a novel class of therapies known as CAR-T. Celgene and Juno, however, were not random strangers. Mark J. Alles, CEO of Celgene, stated that the purpose for the acquisition was the “shared vision to discover and develop transformative medicines for patients with incurable blood cancers.” As the knowledge base and the business strategy of the two firms were similar, Celgene and Juno began to form strategic alliances in 2015, and Celgene had already owned 9.7% of Juno’s shares before the acquisition. Therefore, not only did the acquisition of Celgene and Juno stem from similarities between the two, but it was also strengthened by former strategic alliances.

Startups with novel innovations often differ from incumbents with regard to their knowledge bases, business strategies, and organizational structures. The dissimilarity between startups and incumbents exacerbates knowledge transfer and the integration of

two firms (Higgins and Rodriguez, 2006). At the same time, as incumbents are likely to adhere to their current routines, a radical change in their routines will undermine the value of the assets they already have (Shane, 2001). In these situations, rather than acquisition, incumbents should prefer hire scientists and inventors who possess not only the required novel knowledge but also technological capabilities (Bei, 2018). Sourcing external innovation by hiring talent to join current R&D teams, incumbents can organically integrate and absorb novel knowledge that will more likely be consistent with their current business context and practice and thus increase the probability of success. Thus, startups with a novel innovation that choose to exit through acquisition have less likelihood of success.

To raise money, high-tech startups rely on strategic alliances, acquisition, and venture capital funding (Ozmel, Robinson, and Stuart, 2012). Although novelty has a negative effect on alliance formation and the probability of acquisition, it benefits startups by attracting VC funding (Shane, 2001; Samila and Sorenson, 2011; Cunningham, 2017), which raises the following question: If the novelty of an innovation is associated with high risk and a lower probability of a successful exit, why are VCs more inclined to finance novel innovations? One answer to this question is that VC investors, with mindsets of experimentation and a willingness to accept failure, embrace risk in their investments (Nanda and Rhodes-Kropf, 2013). The investment strategy for VCs is to bet on the small probability of a few extreme successes and bear the greater probability of a large number of failures. Nanda and Rhodes-Kropf (2013) quoted one VC investor as saying, “Our willingness to fail gives us the ability and opportunity to succeed where others may fear to tread.” Novel innovations, despite their higher failure rate, have the potential to become extremely successful by generating new industries or disrupting the current market (Shane, 2001), which is what VCs seek. In addition, VC funding also has a treatment effect on the

performance of a startup. Apart from providing financial capital, VCs, especially experienced ones, also benefit startups by connecting them with potential partners and increasing the probability of their forming strategic alliances (Lindsey, 2008). Many paper found that VC investment increases the probability of a firm's exit through an IPO.

Nanda and Rhodes-Kropf (2013) found that when VCs invested in riskier and more innovative startups conditional on going public, the startups are valued higher on the day of their initial public offering. In this paper, we believe the “risk and more innovative” comes from the novelty of innovation. Therefore, we expect to see a positive relationship between novelty and the IPO market value of a startup. Although predicting overall whether the benefits of more funding invested in a novel innovation and the treatment effect of VC funding exceed the risks involved in commercialization processes, firms with a novel innovation that exit through an IPO have a higher probability of success than those that exit through acquisition. Thus, we posit the following hypothesis:

Hypothesis 3: Exiting through an IPO is higher probability event than exiting through acquisition for startups with novel innovation, and among the firms that exit through an IPO, those with novel innovations have higher market value.

3.3 Setting, Data, and Empirical Strategy

3.3.1 Data

The sample consists of 408 startups with external financing in the healthcare area, followed by the time of entry until their exit or 2017, whichever is earlier. These 408 startups were screened out from Crunchbase. We began by selecting healthcare startups with external financing that were founded between 1990 and 2010 in North America. Then we matched firm names with patent assignee to screen out startups with a patent issued

within three years of their establishment and manually checked founding team information for each startup. Then we deleted the spinouts of incumbents since they are equipped with resources that differ from those of non-spinouts. After deleting samples with missing values for critical variables, 408 startups with external funding in the healthcare area remained in the sample. They included the biotech, pharmaceutical, medical device, and all other healthcare service industries.

We collected basic firm information from Crunchbase, acquired patent-related data from USPTO and other resources, and hand-collected founding team information. The variables acquired from Crunchbase included external financing, firm industry, geographic location, founding time, exit time, and exit mode. For the matching process, we used the Harvard Patent Disambiguated Assignee Dataset and obtained patent claim data from the USPTO Patent Claims Research Dataset, constructed by Marco, Sarnoff, and deGrazia (2016), and patent classification data from USPTO PatentViews. The hand-collected founding team information included the involvement of the inventor, the size of the founding team, and the entrepreneurial and industry experience and academic degrees of the founders. We combine the alliances data from Thomson Reuters SDC Platinum and BioCentury and merged the alliances data with our sample based on firm names. The market value for startups that exited through an IPO are collected from Yahoo Finance.

All startups in our sample received one or more rounds of funding from VC investors and/or other forms of investment. Because the potential of startups must be sufficient to attract at least one round of venture funding, the startups in my sample are more inclined to be on the right-hand side of the value distribution and have a high exit success rate compared to a random sample. However, because our paper focuses on testing the effect of a novelty on the performance of startups after they receive VC funding, this biased sample would not cause a problem for empirical testing.

3.3.2 *Variables*

3.3.2.1 Combinational Novelty of a Patent

This paper uses the pairwise combination of the CPC (cooperative patent classification) system as a proxy for the novelty of patents. This measure is based on the patent novelty measure conceived by Fleming (2001), Verhoeven, Bakker, and Veugelers (2016), and Uzzi et al. (2013). The classification assignment of the CPC system is based on the subject of the knowledge that the patent contains. Therefore, the knowledge elements used by a patent are represented by the technological classifications assigned to the patent by patent examiners, and the collection of the pairwise combinations of the technological classification are proxies for the knowledge recombination behind that patent. The patent is considered novel when it introduces a new knowledge element into the area, expressed as the appearance of a new pairwise combination of a CPC classification.

The CPC classification code is categorized into subdivisions that represent the knowledge element. A subdivision is based on a five-level hierarchy system that divides knowledge into nine sections and then into classes, subclasses, main groups, and subgroups.⁵ The technology distance is smaller for knowledge elements that differ more at the subgroup level than at other higher levels. Therefore, the risk and the value of introducing a knowledge element that is novel at several hierarchy levels are expected to

⁵For example, patent number 7700302 is in CPC class “A61K 39/39541.” “A” is the section number, and all patents classified into section A are human necessities. “A61,” a classification at the class level, represents medical or veterinary science. The classification at the subclass level for this patent is “A61K,” which represents knowledge about or preparation for medical, dental, or toiletry purposes. Under subclass “A61K,” this patent belongs to group “39,” the category of medicinal preparations containing antigens or antibodies, represented by the full classification at subgroup level “A61K 39/39541.” Based on the classification from section to subgroup, the knowledge used in the patent becomes more and more subdivided.

differ. To test the effect of the novelty of knowledge at various technological distance levels, we measure the novelty of a patent at the middle hierarchy, subclass, and subgroup (the lowest) levels. The CPC system contains approximately 650 different subclasses and more than 260,000 subgroups.

At the subclass level, the most widely used proxy of novelty is a dummy variable that equals one for patents that contain at least one pair of new classification combinations. To capture the novelty of a patent at the subclass level, this paper uses the smallest frequency of a patent's pairwise combinations, a measure generated by Uzzi et al. (2013). Instead of using a dummy to represent the appearance of a new knowledge element, using the frequency of pairwise combinations is more informative because it portrays the life cycle of a technology behind the knowledge used in the patent. Because innovation is both an input and an output to the technology area, the new knowledge combination will be selected and reused by other inventors, that is, a process of the evolution of that technology. The older a technology is and the more widely it is used, the higher the frequency of the pairwise combination. Hence, the frequency represents the evolution of the technology, a process in which uncertainty and value change.

My sample statistics show that when measured at the subgroup level, the majority of patents have at least one new pairwise combination, so the proxy of novelty used in this paper at the subgroup level is the proportion of novel combinations. As mentioned in the previous paragraph, the CPC system divides knowledge into 650 subclasses and 260,000 subgroups, generating 210,915 and 33,799,870,000 possible (but not necessarily existing in current patents) pairwise combinations at the subclass and subgroup levels, respectively. Because of the prevalence of new subgroup combinations in my sample, new subgroup combinations are more common than new subclass combinations. The difference in

knowledge at the various subclass levels is larger than that at the various subgroup levels.⁶ My proxy of novelty at the subclass level represents the newest knowledge combination of knowledge elements with some knowledge distance, and my proxy of the novelty at the subgroup level represents the overall newness of a knowledge measure in the smallest knowledge division.

In this sample, the mean frequency of a combination at the subclass level is 28,811 and the max value equals 526,394. The distribution of the frequency is highly skewed on the right-hand side. The frequency is calculated as the cumulative number of all patents issued after 1976. Therefore, the pairwise combinations of patents issued in later years will have a higher average frequency. To eliminate the effect caused by different years of issue, we standardize the combination frequency for patents issued in one year and find that after the yearly standardization, the distribution of combination frequency is still highly skewed on the right-hand side. To minimize the effects of outliers and facilitate regression, we take the natural log of the standardized value and find that the final distribution of the combination frequency at the subclass level is similar to a normal distribution with a mean of 0.89 and a max of 1.62. The distribution of the proportion of novelty at the subgroup level is also similar to the normal distribution with a mean of 0.45 and a max of 1. Figures 1 and 2 illustrate the distribution of novelty measured at the subclass and subgroup levels.

⁶Also take patent number 7700302 as an example. Besides its classification as “A61K 39/39541,” it can be classified as “C07K 2317/21” or “C07K 2317/76.” At the subclass level, “A61K” represents the knowledge or preparation for medical, dental, or toilet purposes, and “C07K” represents peptides. As it shows, “A61K” and “C07K” represent two different knowledge groups, and the knowledge distance is large. At the group level, “C07K 2317” represents immunoglobulins, and subgroup “21” characterizes immunoglobulins by their taxonomic origin from primates while subgroup “76” characterizes immunoglobulins by their effects. Therefore, any difference at the subgroup level in this case merely characterizes one material from another, and the knowledge distance is small. It is also common for one material to have a new combination at the subgroup level.

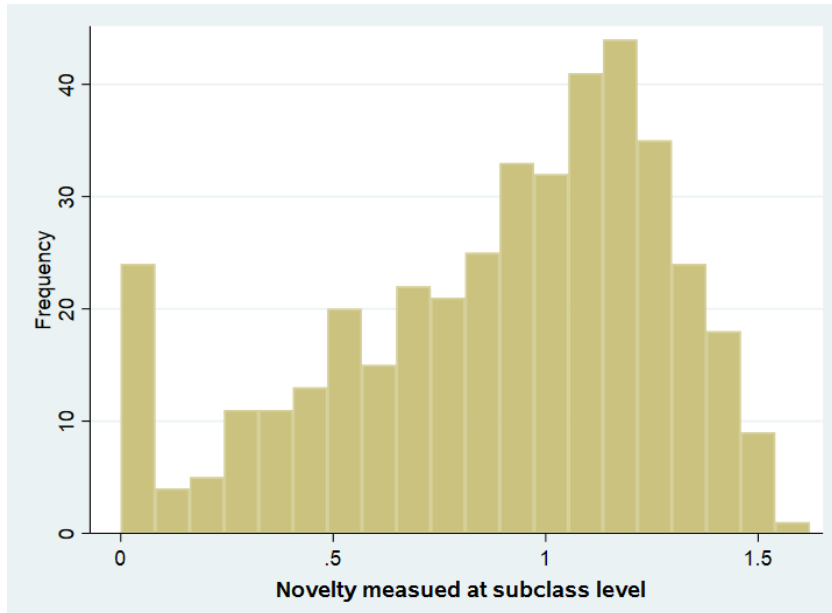


Figure 3.1 - Frequency distribution of novelty measured at the subclass level

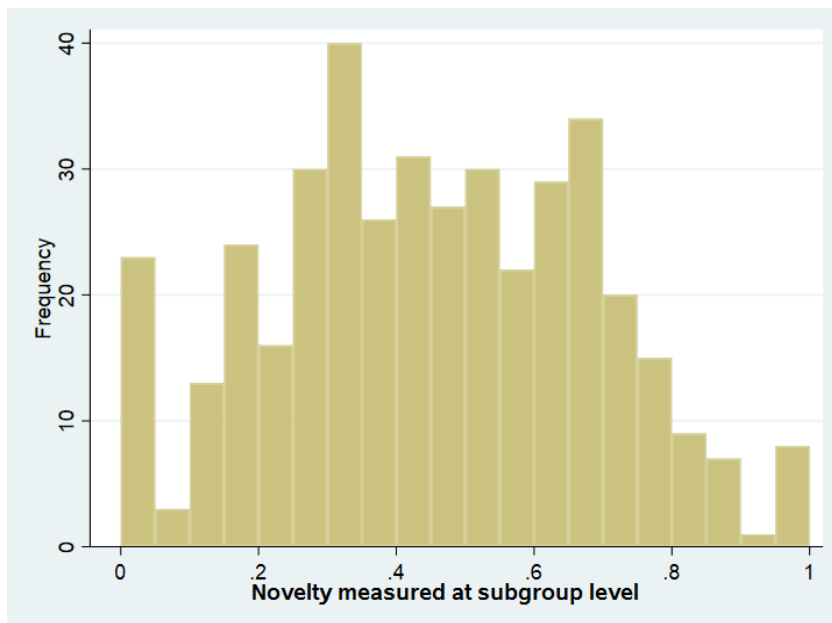


Figure 3.2 - Frequency distribution of novelty measured at the subgroup level

3.3.2.2 Alliances

To acquire more comprehensive data on alliances, this paper combines the alliance data from Thomson Reuters SDC Platinum with the data from BioCentury and finds that 95 out of the 408 startups formed alliances before their exit, and the average number of alliances was 0.7. To coordinate the different models, we include both the number of alliances and a dummy variable that represents the existence of at least one alliance in this paper.

3.3.2.3 Control Variables

Many papers have found that the performance of startups is influenced by their resources, human capital, funding, and the external environment, which includes the geographic location, the industry, and macroeconomic conditions. The most valuable resources for non-spinout startups in high-tech industries at the founding stage are their intellectual property, portrayed by the independent variables. To control for the human capital of a top management team at the founding stage, this paper selected five hand-collected variables and controlled for the external environment by both categorical variables and the empirical model, which will be introduced in a later section.

The Human Capital of a Top Management Team. All five variables of founders were hand-collected. The information source included LinkedIn, Bloomberg, CrunchBase, and company and university websites. To reduce the effect of missing values on some founders, we use team-level variables as controls. About 90% of the values are accurate and the remaining 10% randomly assigned.

Team size. As entrepreneurship demands a variety of skills, numerous studies on entrepreneurial team size have suggested that firms founded by larger entrepreneurial

teams usually show stronger performance than firms founded by a small team, and firms founded by entrepreneurial teams, on average, exhibit stronger performance than firms founded by individual entrepreneurs. To control for the influence of team size, this paper uses categorical variables that equal 0 if a firm was founded by an individual entrepreneur, 1 if a firm was founded by a small entrepreneurial team (i.e., teams with two to four members), 2 if the firm was founded by a large entrepreneurial team (i.e., teams with five or more people).

Entrepreneurial and industry experience. Both entrepreneurial and industry experience are important to the learning process of entrepreneurs when they acquire managerial and entrepreneurial knowledge. Many scholars that have analyzed the effects of entrepreneurial and/or industry experience on firm performance have found that they are positively related. This study adopts two dummy variables as proxies for the industry and entrepreneurial experience of a startup team. The dummy variable equals 1 when at least one of the founders in the team had industry/entrepreneurial experience. The absolute majority of entrepreneurial teams, except for a few academic teams, had at least one individual with industry experience.

Ph.D. or M.D. degree. Industries in the healthcare area are high-tech industries in which the successful commercialization of an invention depends on the founding team's expert knowledge in that area. A founding team that includes professionals with Ph.D. or M.D. degrees will influence the quality of an innovation and the success of commercialization. Therefore, we add a dummy variable equaling 1 if the founding teams had at least one professional with a Ph.D. or M.D. degree.

Founder inventor. This variable distinguishes between two types of technology commercialization models: The first is one in which an inventor commercializes the

technology he/she has invented, and the other is one in which entrepreneurs commercialize the technology they have licensed from the inventor. Since a great deal of knowledge is tacit and transferable only by the inventor, the technology commercialized by the inventor is advantageous to further R&D processes. Fuller and Rothaermel (2012) provided evidence that inventors choose to commercialize a higher quality technology, which is associated with greater commercialization success. Thus, we generate a dummy variable that represents the involvement of an inventor by manually checking the LinkedIn profiles of patent inventors to determine whether they were members of the founding team of the firm.

Geographic location. High-tech firms in close proximity may experience knowledge flow among them. Such a flow of knowledge influences the innovation quality of all firms in that cluster. Firms located in regions with a high density of VCs are more likely, on average to attract VC financing than firms located in regions with a low density of VCs. Thus, geographic clustering may influence innovation quality and commercialization performance at the same time. To control for the potential endogeneity of geographic clustering, we add dummy variables for states with a high density of high-tech startups and/or VCs, such as California, Massachusetts, Texas, Pennsylvania, and Florida.

Industry Dummies. Studies of markets for ideas and technology have found that the external commercialization environment may influence the commercialization strategies and final exit modes of startups. Those in our sample belong to biotech, pharma, medical devices, and other healthcare service industries, so we add dummies to control for the inter-industry effect.

External Funding. External funding sources for the sample firms are mainly venture capitalists (VC), debts, and government grants. VC funding accounts for the majority of overall external funding. Around 78% of the data are accurate and the remaining 22% missing this value are filled with the average value of the sample. The statistics of major variables are listed in Table 1 below.

Table 3.1 - Data Summary of Major Variables

	Mean	Std. Dev.	Min	Max
Count of Scope	5.65	7.44	1	84
Count of Scope^2	87.10	410.37	1	7056
Novelty (subclass)	0.89	0.39	0	1.62
Novelty (subgroup)	0.45	0.23	1	1
External Funding	58700000	69100000	187291	686000000
Log (eternal funding)	17.19	1.47	12.14	20.35
Alliance	0.61	1.97	0	23
Alliance Dummy	0.23	0.42	0	1
Founding Year	2001.34	4.75	1990	2010
Exit	Privet	Acquisition	IPO	
	202	123	83	
Industry	Medical Devices	Biotech & Pharma	Others	
	215	159	34	
Founding Team Size	Single Founder	Small Team	Large Team	
	137	252	19	
Founding Inventor Entrepreneur Experience	No	Yes		
	141	267		
Industry Experience				
	248	160		
Industry Experience				
	24	384		

3.3.3 Models

The most widely used model in this paper is the Cox Proportional Hazard model, a semiparametric model that examines the influence of technology attributes on the probability of a successful exit. The observation starts with the year a firm was founded and ends either at the firm's exit from the market or at the end of 2017 as right censored. The model specification, given below, is $\lambda[t|x(t)]$, the hazard function, which depends on $\lambda_0(t)$, a time-variant nonparametric baseline hazard function, $\exp[z(t)'\beta]$, a scale factor that contains time-variant variables, and $\exp(\omega'\delta)$, a scale factor that contains time-invariant variables:

$$\lambda[t|x(t)] = \lambda_0(t)\exp[z(t)'\beta]\exp(\omega'\delta) .$$

All independent and control variables that describe the founding condition are time-invariant. Therefore, to estimate them, we employ the time-invariant scale factor. Two types of time-varying variables may influence an exit decision: the age and the external conditions of a firm. The external conditions include financial market conditions, such as the three-month T-bill rate, industry conditions, such as the industry average debt factor and the industry concentration, and macroeconomic conditions, such as the volume of the IPO relative to mergers (Brau et al., 2013; Chemmanur et al., 2010). Since all external conditions are related to a specific fiscal year and used only as control variables, we add year dummies as the time-variant scale factor of the function. We also use the nonparametric baseline hazard function to adjust the hazard rate influenced by the firm age.

Apart from the Cox PH models, logit models are used not only in cases in which the time that the focal-event occurred is unclear but also as robustness tests. Furthermore, in testing hypothesis 3, which is the influence of a novelty on either an IPO or an acquisition, we use the competing risk models to reduce the problem of observation censoring caused

by an exit through a non-focal method. In this paper, startups successfully exit through one of two methods, an IPO and an acquisition. When testing the effect of novelty on one of the exit methods, the other exit method hinders the observation and/or the occurrence of the exit method of interest. In Cox PH models, startups exiting through the non-focal method are treated as a right-hand censor caused by a missing observation. If an acquisition and an IPO are uncorrelated events, then the independent censoring assumption will be fulfilled, and the Cox PH models will generate unbiased estimates. Startups that exit through an acquisition (IPO), however, would have also been more likely to exit through an IPO (acquisition) had the acquisition (IPO) not been possible. Also, the first exit method might have a treatment effect on the probability of exit through another method. For example, startups that successfully exit through an IPO have a higher probability of exit through acquisition (Fuller and Rothaermel, 2012).

To solve the problem of a censored observation resulting from a correlated exit method, this paper adopts the competing risk model that uses a sub-distribution hazard to adjust the estimations. In this method, the sub-distribution hazard model directly provides an estimated probability of exit through the focal method for startups that exit through the non-focal method. In other words, startups that experience a competing exit method remain in the observation set and risk exiting with an adjusted hazard function; however, they are no longer at a risk of exiting through the method of interest.

3.4 Results and Analysis

Table 2 presents estimates of the hazard of a successful exit as a function of the characteristics of a startup. The general results from the table show that the novelty of an innovation has a negative effect on the probability of a successful exit of a high-tech

startup. The negative effect of a novelty is consistent at both the subclass and subgroup levels. Furthermore, the influence at the subgroup level is more stable and larger in scale.

Table 3.2 - Effect of Novelty on a Successful Exit: Cox Models

	Novel at Subclass Level			Novel at Subgroup Level			All Novel	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	exit	exit	exit	exit	exit	exit	exit	exit
Novel (subclass)	0.287 -	0.356+	0.315+	0.217	0.112	0.0657		
Novel (subgroup)	0.184	-0.182	-0.185	-0.188	-0.2	-0.214		
				1.019*	1.143*	1.089*	1.153**	1.121*
				-0.33	-0.355	-0.366	-0.32	-0.352
Funding		2.67e-09***	2.43e-09**		1.93e-09*	1.71e-09+	2.19e-09*	1.72e-09+
		0E+00	-8E-10		-9E-10	-1E-09	-9E-10	-1E-09
Founding Year Dummies			Yes			Yes		Yes
Founder Inventor			-0.217			-0.194		-0.196
			-0.178			-0.178		-0.178
Team Size Dummies			Yes			Yes		Yes
Entrepreneurial Experience			0.21			0.218		0.221
			-0.164			-0.164		-0.164
Industry Experience			0.0417			0.0275		0.015
			-0.324			-0.32		-0.323
Ph.D. Degree			0.213			0.222		0.217
			-0.211			-0.213		-0.214
Location Dummies			Yes			Yes		Yes
Industry Dummies			Yes			Yes		Yes
Years Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	408	408	408	408	408	408	408	408
chi2	21.64	31.64	158.53	20.83	30.77	137.19	32.07	152.39
+P<0.10 *P<0.05 **P<0.01 ***P<0.001								

For both proxies at the subclass and subgroup levels, the smaller the value, the more novel the innovation is. As the results reported in Table 2 show relative risk ratios, a positive coefficient of a novelty represents a negative effect on a successful exit. In columns 1 and 4, which include only year dummies as controls for the macro environment each year, novelty at the subclass level is negative but not significant while novelty at the subgroup level is negative and significant ($p < 0.01$). When we add the amount of external funding received by the startups as a control, the results of which are shown in columns 2 and 5, the negative effect increased in scale and became significant at the subclass level. This phenomenon sheds light on the potential role of external financing, especially that from VCs, in the success of the exit of startups that might come from both a selection effect (only high-quality novel innovations are financed) and a treatment effect (improves the prospects for funded innovates).

The coefficients remain comparatively stable when we add other control variables. Columns 1 to 3 show the results of novelty at the subclass level. Because all novel innovations at the subgroup level are novel at the subclass level, in the models in columns 4 to 6, we add in novelty at the subclass level as a control so the coefficient at the subgroup level is the pure effect of novelty at the subgroup level. Columns 7 and 8, in which we did not add in the novelty at the subclass level, show that the coefficient at the subgroup level represents the overall effect of novelty at both the subclass and subgroup levels. Based on the results, the probability of a successful exit of a startup with an absolute novel innovation at the subclass level is 40% lower than that of a startup with a non-novel innovation. At the subgroup level, a one standard- deviation increase in novelty reduces the probability of a successful exit by around 65%. When we account for all types of novelty, the disadvantage of being novel leads to a 68% lower probability of a successful exit. We use logit models to conduct a robustness tests, the results of which are shown in columns 1 to

4 in Table 4. The coefficients of the logit models are consistent with the results of the survival analysis but relatively larger in scale.

We draw cumulative survivor functions from estimates of the Cox model. In Figure 3, the blue line represents the baseline survivor function. We use the coefficient of full novelty to calculate the scale factor to obtain the survivor function for startups with pure conventional innovations and novel innovations. The figure shows that novelty has a persistent negative effect on a successful exit and the effect increases with time. To show the effect of novelty on a successful exit more clearly, we draw hazard functions, shown in Figure 4, we mark startups with a novel innovation above the average sample value as the treatment group and the remaining startups as the control group. We run the full Cox model but replace the proxy of novelty by a treatment dummy and estimate the hazard functions for the firms in the treatment and control groups, the results of which are shown in Figure 4. The results show a lasting and increasing negative effect of novelty.

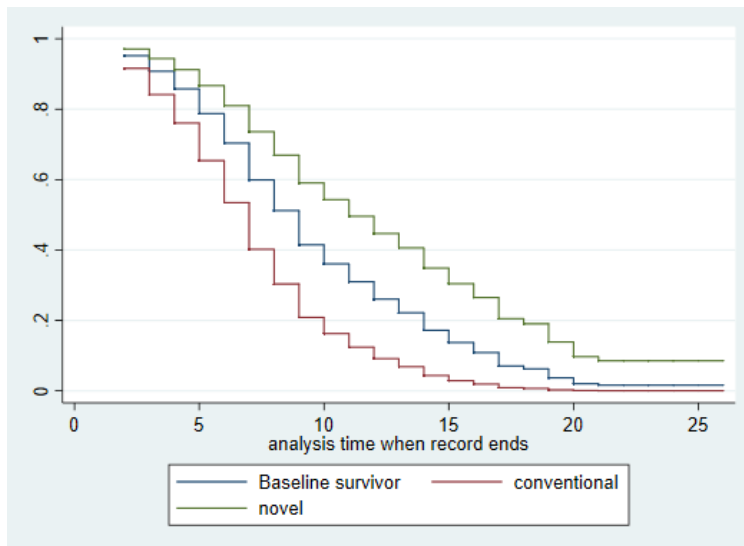


Figure 3.3 - The survival function of baseline startups, startups with conventional innovations, and startups with novel innovations.

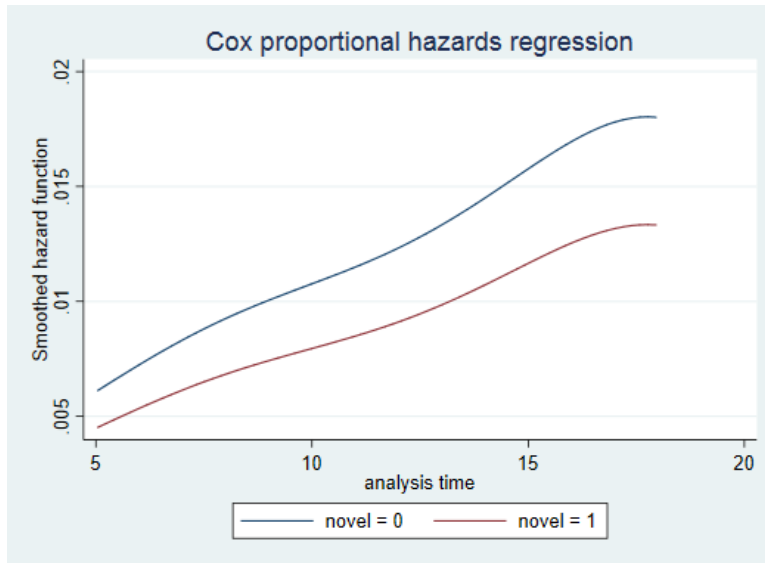


Figure 3.4 - The hazard function (exit probability) for startups with novel innovations and conventional innovations.

Table 3 shows estimates of the probability of forming alliances. Because firms may have more than one alliance, we use logit models when the dependent variable is an alliance dummy and negative binomial models when the dependent variable is the number of alliances. Columns 1 to 4 in Table 3 reports the results of the logit models and Columns 5 to 8 report the results of the negative binomial models.

The decreased novelty of an innovation increases the probability of forming alliances. Columns 1 to 8 show that this finding remains consistent. Having novel innovations not only decreases the probability of forming alliances (Columns 1 to 4) but also reduces the number of alliances (Columns 5 to 8). These results also have high economic significance: Compared to startups with the most novel innovations, startups with the most conventional innovations have a higher likelihood of forming alliances of 250%. The mean value of the number of alliances for startups is 2.6, and having conventional innovations increases the probability of having an additional alliance by

230%. The results in Table 3 also show that having VC funding increases the likelihood of forming initial alliances and further alliances, results consistent with those in Ozmel et al. (2012).

Table 3.3 - Effect of Novelty on Alliances: Logit and Negative Binomial Models

	Logit Models				Negative Binomial Models			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Number	Number	Number	Number	Dummy	Dummy	Dummy	Dummy
Novelty	0.698	1.703**	1.742**	1.512*	0.319	1.637**	1.553**	1.454**
(subgroup)	-0.508	-0.605	-0.617	-0.629	-0.556	-0.555	-0.564	-0.535
Funding		3.8e-09*	3.85e-09*	3.84e-09*		6.35e-09**	5.33e-09*	4.07e-09*
		1e-09*	1e-09*	1e-09*		1e-09*	1e-09*	1e-09*
Founding Year Dummies			Yes	Yes			Yes	Yes
Founder Inventor			0.307	0.644			-0.1	0.149
			-0.319	-0.341			-0.311	-0.294
Team Size Dummies			Yes	Yes			Yes	Yes
Entrepreneurial Experience			-0.034	0.092			0.269	0.286
			-0.281	-0.296			-0.271	-0.255
Industry Experience			0.356	0.597			0.301	0.43
			-0.573	-0.606			-0.558	-0.519
Ph.D. Degree			0.446	0.0679			0.383	0.204
			-0.394	-0.421			-0.379	-0.371
Location Dummies				Yes				Yes
Industry Dummies				Yes				Yes
N	408	408	408	408	408	408	408	408
chi2	1.9	56.87	66.85	89.98	0.33	70.05	76.72	112.19
*P<0.05 **P<0.01 ***P<0.001								

Table 4 shows how novelty and the formation of alliance influence the probability of a successful exit. Columns 1 to 4 list the results without alliances and columns 5 to 8 the

results of corresponding models with alliances. They show that having alliances increases the probability of a successful exit. Once we control for the founding team information, the positive effect of alliances dramatically decreased, which indicates that the formation of alliances is under the influence of the founding team. It may be that startups with stronger founding teams are more adept at forming alliances. It is also possible that a strong founding team partially substitutes for the positive effect resulting from the formation of forming alliances.

The coefficients of novelty listed in columns 5 to 8 are systematically smaller in scale than the coefficients of novelty listed in columns 1 to 4, indicating that the negative effect of novelty, in part, is the result of the difficulty of forming alliances. The difference in the coefficients is robust to the alternative measure of using an alliance dummy to replace the number of alliances. Although the negative effect of novelty is smaller in models that controlled the number of alliances, the scale differences are not very large, indicating that novelty exacerbates the formation of alliances, and the lack of alliances reduces the likelihood of a successful exit; the formation of alliances, however, accounts for very little of the effect of novelty on a successful exit. One explanation for this finding is that many startups with novel innovations that were unable to get complementary resources through alliances gain access to complementary resources through alternative sources. In general, the results shown in Tables 3 and 4 support hypothesis 2—that alliance formation partially mediates the negative association between novelty and a successful exit.

Table 3.4 - Effect of Novelty and Alliances on a Successful Exit: Logit Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Exit	Exit	Exit	Exit	Exit	Exit	Exit	Exit
Novelty	1.076*	1.038*	1.633**	1.787***	1.001*	0.933*	1.496**	1.677**
(subgroup)	-0.434	-0.453	-0.505	-0.518	-0.444	-0.462	-0.512	-0.524
Alliances					1.011***	0.979***	0.622*	0.642*
					-0.252	-0.255	-0.286	-0.298
log(Funding)		5.80e-09**	6.21e-09**	6.37e-09**		5.25e-09**	5.62e-09**	5.82e-09**
		-2.00E-09	-2.00E-09	-2.00E-09		-2.00E-09	-2.00E-09	-2.00E-09
Founding Year Dummies			Yes	Yes			Yes	Yes
Founder Inventor			-	-0.705*			-	-
			0.790**	-0.272			0.814**	0.750**
			-0.272	-0.278			-0.273	-0.28
Team Size Dummies			Yes	Yes			Yes	Yes
Entrepreneurial Experience			0.423	0.401			0.444	0.411
			-0.238	-0.242			-0.24	-0.244
Industry Experience			-0.589	-0.55			-0.626	-0.604
			-0.499	-0.507			-0.501	-0.509
Ph.D. Degree			0.496	0.359			0.448	0.34
			-0.317	-0.332			-0.318	-0.333
Location Dummies				Yes				Yes
Industry Dummies				Yes				Yes
N	408	408	408	408	408	408	408	408
chi2	6.26	19.2	76.49	84.71	23.4	34.75	81.32	89.42

*P<0.05 **P<0.01 ***P<0.001

In our sample, because we only count either IPO or acquisition, they are competing exit modes. Indeed, startups that existed by an IPO were acquired later than those that exited by acquisition, and startups that were acquired might have been able to go public if they had not been acquired. Because of the non-exclusiveness of an IPO and an acquisition,

we use competing risk models to coordinate the right censor problem caused by the non-focal exit mode.

In Table 5, we report the results of the competing risk model that examines the effect of novelty on acquisition. The coefficient of the full model in column 6 indicates that the probability of a successful exit for startups with conventional innovations is about 170% higher ($p < 0.05$) than that of startups with novel innovations, which indicates that novelty has a negative effect on an exit through acquisition. The coefficient of novelty is consistently negative but not significant in models with a control of location and/or in the industry of the startups, showing that the effect of novelty on acquisition might vary within an industry or region. Therefore, the external commercialization environment might influence the relationship between novelty and acquisition. After we control for all internal and external factors, the effect of novelty on acquisition is negative.

Table 3.5 - Effect of Novelty on Acquisition: Competing Risk Models

	(1)	(2)	(3)	(4)	(5)	(6)
	ACQ	ACQ	ACQ	ACQ	ACQ	ACQ
Novelty	0.657 -0.376	0.68 -0.379	0.677 -0.378	0.667 -0.382	0.797* -0.391	1.002* -0.414
Log (Funding)		0.386** -0.13	0.466** -0.158	0.429** -0.151	0.467** -0.157	0.499*** -0.15
Founding Year Dummies			Yes	Yes	Yes	Yes
Founder Inventor				-0.0457 -0.196	-0.0044 -0.197	-0.075 -0.208
Team Size Dummies				Yes	Yes	Yes
Entrepreneurial Experience				0.236 -0.19	0.286 -0.19	0.192 -0.191
Industry Experience				-0.397 -0.367	-0.431 -0.376	-0.473 -0.389
Ph.D. Degree				0.199 -0.25	0.185 -0.246	0.256 -0.25
Location Dummies					Yes	Yes
Industry Dummies						Yes
N	408	408	408	408	408	408
chi2	5	9.42	13.95	18.56	37.83	123.47
*P<0.05 **P<0.01						
***P<0.001						

Table 6 presents estimates of the hazard of exit through an IPO as a function of novelty and other control variables. In general, the effect of novelty on the probability of an IPO exit is unclear. The coefficients are negative and large on an economic scale but not statistically significant because of the large variance. This phenomenon indicates that the performance of startups with novel innovations varies greatly. Although the average

effect might be negative, some cases could be extremely successful, which explains why VCs have a strong incentive to invest in startups with novel innovations.

Table 3.6 - Effect of Novelty on an IPO: Competing Risk Models

Table 6: Effect of Novelty on an IPO: Competing Risk Models						
	(1)	(2)	(3)	(4)	(5)	(6)
	IPO	IPO	IPO	IPO	IPO	IPO
Novelty	1.007	0.942	1.089	1.106	1.102	0.717
	-0.539	-0.531	-0.587	-0.57	-0.565	-0.532
Log (Funding)		0.384**	0.460**	0.423**	0.460**	0.487**
		-0.138	-0.161	-0.153	-0.158	-0.151
Founding Year Dummies			Yes	Yes	Yes	Yes
Founder Inventor				-0.857**	-	-0.741**
				-0.262	0.961***	-0.265
Team Size Dummies				Yes	Yes	Yes
Entrepreneurial Experience				0.0737	0.141	0.184
				-0.258	-0.266	-0.266
Industry Experience				-0.0299	-0.0135	0.00831
				-0.383	-0.389	-0.4
Ph.D. Degree				0.289	0.277	-0.248
				-0.359	-0.371	-0.402
Location Dummies					Yes	Yes
Industry Dummies						Yes
N	408	408	408	408	408	408
chi2	4.92	10.17	18.82	60.55	121.45	138.85
*P<0.05 **P<0.01 ***P<0.001						

To test the large variance in the performance of startups with novel innovations, we collected the IPO market values of startups that exited through an IPO from Yahoo Finance. We divided the sample, consisting of 83 startups that exited through an IPO, into a high novelty group and a low novelty group based on the proportion of novel combinations in the subgroup. The average IPO market value for firms with high novel innovation was \$73.6 million and the corresponding value for the low novelty group was 54.4 million, a statistically significant difference. These value differences mainly stem from a few extreme value observations in the high novel group. Figure 5 shows the value distribution of the two groups and Figure 6 the estimated Kernel density distribution of the IPO values. The figures show that the value distribution of the high novel group has a long tail and the average value for startups with a novel innovation is slightly higher. This sample illustrates that when successful, a novel innovation will generate extreme value.

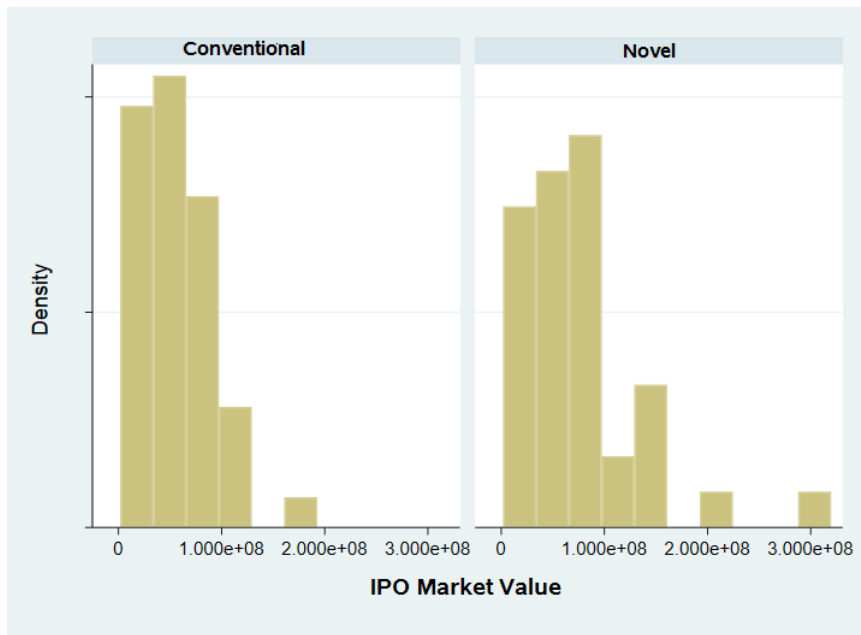


Figure 3.5 - IPO market value distribution

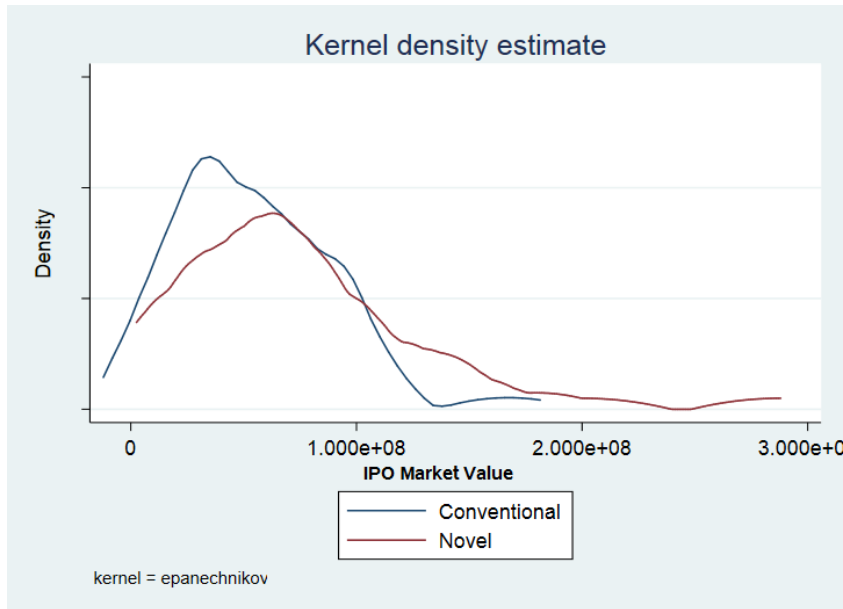


Figure 3.6 - Estimated Kernel density

This study explored the robustness of the principal results by using the Cox PH models and multinomial logit models to test the effect novelty has on exit modes. The results are available upon request. Although the coefficients of the multinomial logit models are large in scale than those of the Cox and competing risk models, the coefficients of the Cox and multi-logit models are consistent with those found by the competing risk models. One explanation for this difference is that multinomial logit models, which are cross sectional, are unable to control the effect of time-varying external factors. The scale differences are generated by the influences of external factors. Another explanation is that all of these models generate maximum likelihood estimates and are sample-specific results. When the sample size is large, the differences among the models will converge, which is not the case in this paper. Overall, however, the robustness tests support that finding that an IPO will lead to greater success for startups with novel innovations.

3.5 DISCUSSION

This article examined how the novelty of an innovation influences the performance of a startup, which is expressed as a successful exit through either acquisition or an IPO, and how this influence, in limited scale, stems from the effect of novel innovation on the formation of alliances. To identify the effects, we assembled comprehensive data on over 400 healthcare startups that received external financing between 1990 and 2010, drawing on several data sources: CrunchBase, USPTO Patent Views, the USPTO Trademark Database, Linked-in, Bloomberg, Thomson SDC platinum, and Yahoo Finance. We hypothesized that because of the high risk and market uncertainty associated with the commercialization process of a novel technological innovation, startups with such an innovation have a lower probability of a successful exit. We found that this negative effect partially stems from the difficulty startups with novel innovations have forming alliances. We also found that an IPO is the more likely exit mode for startups with novel innovations. All three hypotheses are supported by empirical tests.

The results of this study have several implications for research on strategy and entrepreneurship of technology startups. For one, our paper is the first to test how the novelty of innovation influences the performance and financial returns of high-tech startups, which provides empirical evidence that the attributes of innovation have a persistent influence on the commercialization process. This work also contributes to the entrepreneurship literature by testing how technology attributes may influence the application of commercialization strategies for high-tech startups and how the application of a particular commercialization strategy affects the performance of a firm. In addition, our study has improved the measurement of novelty, which provides a useful methodological tool for future researchers interested in examining the effects of novelty.

Although we used several models to conduct robustness checks and obtained consistent results in all alternate specifications, the empirical section still has some

limitations that need to be acknowledged. One is the potential issue of endogeneity. It usually takes three to six years before a startup exits, during which time it is under the influence of both time-variant and -invariant variables. For the time-invariant variables, although this paper added founding team variables, industry dummies, and founding year dummies to control for the persistent imbalance of commercialization capabilities that may relate to technology attributes, other factors such as the social network of founders and inventors may simultaneously influence the novelty of innovation, the formation of alliances, and the performance of firms.

For the time-variant factors, this paper added year dummies in the form of a time-variant scale factor to control for external conditions such as the financial market and macroeconomic situations. Nevertheless, we have not controlled for the strategic choices of firms, which may be inspired by their innovations and influence their performance. Although the issue of omitted variables may have created noise in the results, we found no indication that it would lead to biased results. Perhaps future research could apply a more accurate test to a dataset with all the required variables.

Another potential limitation of this paper is the generalizability of its results to other industries. Numerous studies have analyzed how the environment of an industry and the existence of a market for technology may influence the commercialization strategy and performance of a startup. Our paper is specific to healthcare industries, all of which have a comparable technological environment characterized by high intellectual property protection, intense competition, and high risk. It is likely that novelty will have a similar effect on industries that share the characteristics of healthcare industries. In industries whose environments differ, however, researchers could find a fertile area in which to conduct future work.

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CHAPTER 4. THE MODERATING EFFECT OF EDUCATION ON SERIAL ENTREPRENEURSHIP PERFORMANCE

4.1 Introduction

Firms founded by serial entrepreneurs⁷ who enhance their capabilities and accumulated resources from their past entrepreneurial experience perform, on average, better than firms founded by novice entrepreneurs (Eesley and Roberts, 2012; Gompers, Kovner, Lerner, and Scharfsterin, 2010; Lafontaine and Shaw, 2016; Paik, 2014; Parker, 2013; Toft-Kehler, Wennberg, and Kim, 2014). The performance of serial entrepreneurs, however, varies dramatically. Chen (2013) graphically analyzed the earning distributions of serial entrepreneurs and one-time entrepreneurs and showed a similar variance between the distributions of the two groups. Nielsen and Sarasvathy (2016) pointed out that the market for serial entrepreneurs is a market for lemons because of the excessive entry of entrepreneurs with low expectations of their performance. As the performance of serial entrepreneurs varies significantly, the identification of individuals from a divergent pool of serial entrepreneurs who will perform more successfully in their follow-on startups raises a critical question for entrepreneurs, investors, and policymakers.

To address the heterogeneity of the performance of serial entrepreneurs, which is expressed as the variation in the relationship between entrepreneurial experience and firm performance among individuals, a stream of research has tested the moderating factors affect this relationship. Assuming that improved performance depends on the similarities

⁷In this paper, serial entrepreneurs are sequential entrepreneurs that have found a subsequent venture only after leaving their previous one. This definition is similar to the definitions found in Park (2014) and Eggers and Song (2015).

between current and former ventures, several papers have detected moderating factors from the content, context, and time domains and found that the results of former ventures (Eggers and Song, 2014), industry similarities (Lafontaine and Shaw, 2016; Toft-Kehler, Wennberg, and Kim, 2014), temporal similarities (Parker, 2013; Rocha, Carneiro, and Varum, 2015; Toft-Kehler, Wennberg, and Kim, 2014), and geographic similarities (Toft-Kehler, Wennberg, and Kim, 2014) are factors that are positively associated with the relationship between entrepreneurial experience and follow-on firm performance. These factors, which describe similarities among ventures from various domains, are external variables.

Although external factors influence the performance of serial entrepreneurs, it is the heterogeneity of individuals that plays a more critical role in determining the performance of serial entrepreneurs (Rocha, Carneiro, and Varum, 2015; Nielsen and Sarasvathy, 2016). Therefore, investigating individual characteristics that influence the performance of serial entrepreneurs is theoretically feasible and important. Numerous papers that relate to occupational choice have found that education (Lucas, 1978; Jovanovic, 1994), risk preferences (Barton, 2000), skill diversification (Lazear, 2002), and financial condition (Evans and Jovanovic, 1989) are characteristics influencing the entrance of individuals into entrepreneurship and their performance. The extent to which these characteristics influence serial entrepreneurship in a dynamic process has not been well studied.

Several studies have noted the strong influence of education on entrepreneurial performance. In addition to Lucas (1978), numerous papers have theoretically and empirically studied the relationship between formal education and entrepreneurial outcomes (Van Der Sluis, Praag, and Vijverberg, 2008). This stream of research has found that formal schooling is linked to stronger entrepreneurial capability, so it is positively related to the entrance into entrepreneurship and the subsequent entrepreneurial

performance (Van Der Sluis, Praag, and Vijverberg, 2008). Recent studies of serial entrepreneurship used education as a control variable to test entrepreneurial experience and performance and found a positive effect of education on firm performance across all ventures (Chen, 2013; Lafontaine and Shaw, 2016; Parker, 2013; Rocha, Carneiro, and Varum, 2015; Toft-Kehler, Wennberg, and Kim, 2014). The results of these papers, however, not only varied with regard to the extent of the effect of education but also differed significantly with regard to the main effect of entrepreneurial experience and entrepreneurial performance.⁸ These findings indicate that the relationship between education and serial entrepreneurship is much more complex, not a simple positive one found by existing literature.

This paper explores the influence of education on the performance of serial entrepreneurs from a dynamic perspective. The performance of serial entrepreneurs is mainly influenced by both the entrepreneurial learning-by-doing (LBD) process and the self-selection process (Chen, 2013; Rocha et al., 2015; Nielsen and Sarasvathy, 2016). Following this framework, we investigate the effect of education on serial entrepreneurship performance via its influence on the entrepreneurial LBD and self-selection processes.

Our analysis suggests that a stronger learning ability and a broader knowledge base, both associated with more education, allow individuals to learn more from their entrepreneurial experience. Such knowledge facilitates the follow-on entrepreneurial LBD process and expands the gap between individuals with more education and those with less education. Thus, education has a moderating effect on the entrepreneurial LBD process.

⁸For example, using a sample of MIT alumni, Eesley and Roberts (2012) found that one more entrepreneurial experience increased the financial performance by more than 50%. However, in another study using a sample of incorporated retail stores in Texas, Lafontaine and Shaw (2014) found a weaker positive relationship than that found by Eesley and Roberts (2012). In addition, testing in NLS79, in which sample entrepreneurship included self-employment, Chen (2013) found that the entrepreneurial learning-by-doing effect was almost zero and therefore not significant.

At the same time, because they have better outside employment opportunities, individuals with more education experience a stronger selection effect when they enter serial entrepreneurship than those with less education. We test our hypothesis using a sample of entrepreneurs selected from NLS97, a representative sample of the U.S. population. The results show that education positively moderates the relationship between entrepreneurial experience and venture performance and this moderation effect originates from both the entrepreneurial LBD and self-selection processes. Entrepreneurs with more education, indeed, learn more from the same amount of entrepreneurial experience and are more likely to exit entrepreneurship through an efficient self-selection process if they have a lower entrepreneurial capability.

Contributing to the literature on serial entrepreneurship, this study is part of the growing body of research identifying the factors that explain the individual heterogeneity of the relationship between entrepreneurial experience and venture performance (Eggers and Song, 2014; Lafontaine and Shaw, 2016; Rocha, Carneiro, and Varum, 2015; Toft-Kehler, Wennberg, and Kim, 2014; Parker, 2013). Complementing former studies that have examined external factors, this paper studies how education, as an individual characteristic, might moderate the focal relationship. The results of this paper provide insights into a new perspective that acknowledges the importance of individual characteristics and thus contribute to the ongoing discussion.

4.2 Theory Construction

The relationship between entrepreneurial experience and venture performance is the joint effect of both the entrepreneurial LBD and self-selection effects. The LBD that takes place within the context of entrepreneurship is a process in which entrepreneurs acquire generalizable knowledge from a past entrepreneurial experience and apply it to future

entrepreneurship activities, which enhances venture performance (Politis, 2005). Entrepreneurship and employment are substitutable career choices. For entrepreneurs, especially serial ones, the decision to set up a current business is a result of the self-selection process. Self-selection into a current venture by serial entrepreneurs is influenced by both intrinsic and extrinsic conditions related to venture performance. Since the performance of those that choose to exit an entrepreneurial venture are not observable, the final observed relationship between entrepreneurial experience and venture performance stems from a biased sample under the influence of self-selection. Thus, this project analyzes the effect of education on serial entrepreneurship performance from the influence of both LBD and self-selection.

4.2.1 Education and Entrepreneurial Learning-by-Doing

The positive relationship between an individual's aggregated entrepreneurial experience and new venture performance mainly originates from the entrepreneurial LBD effect (Politis, 2005). The entrepreneurial LBD process is experiential in nature (Politis, 2005). During this process, entrepreneurs create generalizable knowledge from their entrepreneurial experience and apply it to their follow-on ventures, which enjoy enhanced performance. When a task is complex, however, knowledge generation and transformation processes become more difficult (Kolb, 1984). As no two ventures are the same, entrepreneurs will encounter a unique set of challenges every time they start a new venture. The differences among ventures create challenges for effective knowledge generation and application, that is, entrepreneurial LBD (Kolb, 1984; Toft-Kehler et al., 2014). Therefore, only generalizable knowledge, which an entrepreneur can apply in a new entrepreneurial context to improve venture performance, is the valuable result of LBD, which effectively increases the entrepreneurial capabilities of individuals.

In light of such challenges, strong absorptive capacity, which depends on an individual's learning ability and knowledge base, could facilitate entrepreneurial LBD (Cohen and Levinthal, 1990). Because education is positively associated with learning ability and knowledge storage, those with more education, who are stronger at knowledge generation and transformation, are expected have a stronger entrepreneurial LBD effect and generate more entrepreneurial knowledge with the same amount of entrepreneurial experience. The generated entrepreneurial knowledge is both the output of past entrepreneurial experience and the input of the current learning process. More generated entrepreneurial knowledge will facilitate the entrepreneurial LBD of those who are well-educated and further expand the gap between them and less-educated individuals. Therefore, the average difference between the performance of firms run by well-educated and less-educated entrepreneurs increases as the amount of entrepreneurial experience increases, and this relationship is potentially positively moderated by education.

The above deduction is based on an assumption that the amount of knowledge worth learning is sufficient for all entrepreneurs. Some scholars have taken an interest in cases in which individuals with more education are already equipped with all or a majority of the knowledge they need to establish a firm while others are not. Thus, less educated individuals, who have more to learn, will exhibit a stronger LBD effect. The empirical results of prior studies, however, have shown that samples composed of a large proportion of entrepreneurs with strong educational backgrounds are more likely to exhibit a stronger LBD effect than samples with a considerable number of less educated individuals.⁹

⁹For example, Eesley and Roberts (2012), analyzing a sample of MIT alumni, found a positive learning effect of over 70% while Chen (2013) analyzed a dynamic sample of serial self-employed individuals and found no LBD effect.

Therefore, cases of interest are less likely to change the direction of the moderating effects stemming from education, which leads to our following hypothesis:

Hypothesis 1: *Individuals with more education experience a stronger learning-by-doing effect than those with less education, which contributes to the positive moderation effect that education has on the relationship between the entrepreneurial experience and stronger financial performance of an entrepreneurial venture.*

4.2.2 Education and Re-enter into Entrepreneurship

Apart from the stronger learning-by-doing effect, the moderation effect of education also originates from its influence on serial entrepreneurship. Numerous papers in the past have theoretically and empirically studied the factors that influence entrepreneurship. Although a number of studies have identified factors positively associated with an individual's probability of pursuing entrepreneurship—individual capability (Lucas, 1978; Astebro, Chen, and Thompson, 2008), innovativeness (Schumpeter, 1934; Holmes and Schmitz, 1990), risk-tolerance (Knight, 1921; Vereshchagina and Hopenhayn, 2009), the property of Jacks-of-all-trades (Lazear, 2002; Wagner, 2006), and wealth (Evans and Jovanovic, 1989), few have examined the factors influencing entrepreneurs' decisions to re-enter an entrepreneurial venture after an initial venture. In this paper, we analyze the role education plays in serial entrepreneurship and how it not only explains the formation of a market of “lemons” in serial entrepreneurship but also influences the relationship between entrepreneurship experience and firm performance.

One of the biggest differences between individuals' entrance into serial entrepreneurship is that the decision is made with more information about their entrepreneurial efficiency. During an entrepreneurial experience, individuals passively learn their entrepreneurial capability, the value of their entrepreneurial opportunities, and

information about the external entrepreneurship environment, all of which jointly contribute to a more accurate evaluation of their entrepreneurial efficiency (Jovanovic, 1982). Although many factors, such as the quality of the opportunity and managerial experience, are generally positively related to the entrepreneurial opportunity and could be used to assess its prospects, concise knowledge of one's entrepreneurial efficiency is unknown before that individual becomes an entrepreneur. This situation fosters the phenomenon of the excess entry of entrepreneurs, which leads to the high entry and high failure rates of startups in almost all industries (Hogarth and Karelaia, 2002). Once individuals understand their entrepreneurship efficiency, they will compare the tradeoff between self-employment and working for others and reenter an entrepreneurial venture only if the expected utility of self-employment is higher than the utility of being employed.

The effect of education on entrepreneurial efficiency and its value in the job market value show little correlation. Based on Lazear (2002), the job market value of individuals is associated with their best skills while entrepreneurial efficiency is limited by their weakest attributes. Just as the majority of high-school students do not have a major while college students do, the higher the education is, the more specialized the training is. Therefore, education may not only enhance one's overall capability but also augment some of the specialized skills of that individual at a faster rate, which indicates that education enhances their job market value much faster than it does their entrepreneurial efficiency. As entrepreneurs make re-entry decisions by comparing the utility of self-employment and that of being employed by others, education leads to greater external job-market opportunities and entrepreneurial efficiency for re-entry. As a result, well-educated entrepreneurs experience a stronger selection effect than less-educated entrepreneurs in the re-entry decision process.

Because individuals in the two tails of the ability distribution are more likely to experience job market friction and enter entrepreneurship, the ability distribution of first-time entrepreneurs has fatter tails (Astebro, Chen, and Thompson, 2011). After passively learning their entrepreneurial efficiency, well-educated entrepreneurs with a greater likelihood of re-entering entrepreneurship are more likely to select out of entrepreneurship. Therefore, the market of serial entrepreneurs contains a disproportionate number of low-ability individuals. This deduction is consistent with the empirical findings of Nielsen and Saravathy (2016), who found that the serial entrepreneurship market a market for lemons caused by a strong Type II error and a weak Type I error; in other words, too many low ability individuals with a small chance of success mistakenly re-enter serial entrepreneurship while those most likely to succeed do not. An explanation for this phenomenon is the divergent effect of education on the selection of serial entrepreneurship.

As the above analysis shows, the external job-market favors more educated people, which indicates greater entrepreneurial utility for self-selected re-entry, the result of which is a positive relationship between education and venture performance. However, the self-selection process, which takes place simultaneously with the passive learning process, is gradual and progresses as individuals participate in entrepreneurial activities. Since the passive learning process is more effective during an individual's first several ventures (Jovanovic, 1982; Kim, Aldrich, and Keister, 2006), the self-selection effect decreases as entrepreneurial experience accumulates. That is, the selection effect of education positively moderates the relationship between entrepreneurial experience and venture performance, but the moderating effect decreases with time. Thus, we posit the following:

Hypothesis 2: *More highly educated individuals make better decisions with regard to serial entrepreneurship, which contributes to the positive moderation effect education has on the relationship between entrepreneurial experience and stronger financial performance of an entrepreneurial venture.*

Because the moderation effect of education originates from its positive influence on the entrepreneurial LBD process and the self-selection process, we predict that the overall moderation effect of education on the relationship between entrepreneurial experience and firm performance will also be positive. Thus, we posit the following:

Hypothesis 3: *Education has a positive moderation effect on the relationship between entrepreneurial experience and the financial performance of an entrepreneurial venture.*

4.3 Empirical Setting

4.3.1 Sample

The sample of this paper consists of 9,704 observations from 2,928 entrepreneurs surveyed in the National Longitudinal Survey of Youth 1997 (NLS97). The NLS97 contains information about 8,984 individuals selected from 96,517 U.S. households, a process that ensures that the distribution of the 8,984 individuals represents the U.S. population with regard to major demographic characteristics. (The large variance of individuals facilitated our testing of the moderation effect of education on serial entrepreneurship.) NLS97 collected and recorded the employment information of individuals in 17 rounds of surveys that covered a period of 19 years beginning in 1997. The first survey sampled the individuals when they were 12 to 17 years old. The continuous tracking of work experiences in this longitudinal study recorded successive changes in the individuals' employment status that began when they entered the workforce, which not only provided a sufficient number of entrepreneurs but also allowed the tracking of serial entrepreneurship activities.

Entrepreneurship is broadly defined as people who work for themselves. Approximately a third of individuals in NLS97 had at least one entrepreneurship experience. As distinguishing the entrepreneurial income of multiple ventures established in the same survey year was virtually impossible, we deleted a handful of entrepreneurs who had established more than one venture in any survey year. After deleting several hundred entrepreneurs with missing data on core variables (e.g., highest degree, entrepreneurship income), the sample of this paper consisted of 2,928 entrepreneurs, 1,776 of whom had only one entrepreneurial experience, 686 two, 300 three, 112 four, and 54 five or more. These individuals were comparable on the highest degrees, but the number of total ventures was negatively associated with annual entrepreneurship income. The data statistics of key variables by each entrepreneurship group are presented in Table 1.

Table 4.1 - Entrepreneurship Summary

# of Ventures	# of Individuals	Years of Managerial Experience	log(Entrepreneurial income)	log(Salary)	Highest Degree
1	1776	0.3384009	9.44333	8.313338	1.28491
2	686	0.2463557	9.339978	8.124914	1.344023
3	300	0.1333333	9.142507	8.010294	1.383333
4	112	0.0625	9.078746	7.84201	1.419643
5	32	0.375	8.535593	7.855028	1.5625
6	14	0.3571429	9.188048	8.483428	1.285714
7	4	0	8.413118	8.431369	2
8	3	0	7.941757	4.996323	1.666667
12	1	0	10.30899	9.954133	1

4.3.2 Variables

The **dependent variable** used in this paper is the financial performance of the new ventures, that is, *entrepreneurial income*. According to Hamilton (2000), entrepreneurial

income is the sum of the draw, or the amount of money withdrawn in the form of a salary, and retained earnings, or the amount of reported profit of the business (Hamilton, 2000). NLS97 does not provide a measure of the amount of income reinvested by entrepreneurs to expand their businesses, so the entrepreneurial income in this paper is measured as the sum of salaries and profits. Because entrepreneurial income is severely skewed on the right-hand side, we took the natural log of entrepreneurial income, as many other researchers have done.

The **independent variable** in this paper is the measure of entrepreneurial experience and education. In this paper, entrepreneurial experience is measured as the *number of ventures* and the *years of entrepreneurial experience*, and education is measured as the *highest degree attained* by that entrepreneur. Because ventures vary in their survival time, we add in the “years of entrepreneurial experience” as a complementary independent variable to the widely used variable “number of ventures” and use it as a robustness test in the major models. The highest degree attained is a four-level categorical variable that equals 3 for individuals with a graduate degree, 2 for those with a college degree, 1 for those with a high-school diploma, and 0 for all others.

We target the **control variables** of this paper to eliminate potential endogeneity from factors that simultaneously influence the education of an entrepreneur, the selection to enter an entrepreneurial venture, and the performance of the venture. We controlled for demographic characteristics (i.e., race, birth year, and gender), family financial conditions (i.e., the family’s financial assets when an individual is 20 years old and non-financial assets when the individual is 20 years old), individual capabilities (i.e., years of managerial experience and annual salary as a worker), and whether the follow-on venture is in the same industry as the former venture. The data statistics and correlations are shown in Table

1. We acquired accurate values for race, birth year, and gender, but the values for other variables contain 10% to 30% missing values that are replaced by the sample mean.

Table 4.2 - Data Statistics

Variable	Mean	S.D.	n							
Year	2007.61	4.29	9704							
Years of Entrepreneurial Experience	2.13	2.39	9704							
# of Ventures	2.04	1.25	9704							
Years of Managerial Experience	0.55	1.40	9704	-	0.0651*	1				
Same Industry Dummy	0.46	0.50	9704	0.0226	0.0263	1				
Financial Assets	3197.19	17984	9704	0.0294	0.0249	0.016	1			
Non-Financial Assets	15692.8	38095	9704	0.027	0.0512*	0.0485*	0.1869*	1		
Log(Entrepreneurial Income)	9.59	1.14	9704	0.0617*	0.1695*	0.1142*	0.0727*	0.0418	1	
Log(Salary)	8.02	2.23	9704	-	0.2042*	0.1226*	-0.0057	0.0484*	0.0565*	1
Birth Year	1981.89	1.38	9704	-	0.1134*	0.1493*	0.1903*	0.0101	0.0673*	0.2807*
Gender	Male		1566	-	0.0607*	0.1493*	0.1903*	0.0101	0.0673*	0.2807*
	Female		1362							
Race	Black		693							
	Hispanic		588							
	Mixed Race		32							
	Non-Black/ Non-Hispanic		1615							

4.3.3 Empirical Strategy

Since entrepreneurship activities occur sequentially while all control variables are cross-sectional variables, one of the main empirical concerns is heterogeneity across time, which is under the influence of the former startup and impacts later performance. Such a problem can be solved by mixed-effect models and generalized estimating equations

(GEEs). While mixed-effect models fit subject-specific models, GEEs fit marginal models, so the fitting of GEE is easier and more efficient. Therefore, as the treatment effect, that is, the effect of entrepreneurial experience on firm performance, is of primary interest in this paper, we adopt GEEs (Wang, 2014) to test the main effect and use OLS with an adjusted standard error and random effect models for a robustness test. The models produce consistent results.

Among the 2,928 entrepreneurs in this sample, only about 40% (1,152) were serial entrepreneurs that established two or more startups, a finding that is consistent with the self-selection theory that entrepreneurs make their decisions to re-enter entrepreneurship only after their initial entrepreneurial experience and only those with comparatively higher entrepreneurial efficiency self-selected to be serial entrepreneurs. Therefore, the results of the GEE models represent a joint effect of LBD and self-selection. Although it is impossible to separate the effects of self-selection and LBD, the Heckman selection model could estimate the effect of self-selection and adjust its influence in the main models to report the effect of LBD. The differences between the coefficients of the GEE models and the Heckman selection models show the effect of self-selection.

For more robust identification, the selection equation in the Heckman selection model requires an exogenous variable excluded from the main equation as an exclusion restriction. As analyzed in the theoretical section of this paper, education is directly linked to the external opportunities of entrepreneurs, which influence the selection to enter serial entrepreneurship. One of the most important components of the utility of external opportunity is the pecuniary income. In this project, we use the average annual income¹⁰

¹⁰The average annual income data were collected from Occupational Employment Statistics that were relisted by the Bureau of Labor Statistics at <https://www.bls.gov/oes/tables.htm>. The merging of NLS97

of the job one had immediately before that individual entered entrepreneurship as a proxy of the utility external opportunity and use it as an instrument in the selection equation.

4.4 Results

Table 3 reports the results of the GEE estimation of the relationship between entrepreneurial experience and venture performance as well as the moderating effect of education on this relationship. The results of this paper, which illustrate the joint effect of entrepreneurial LBD and self-selection, are used to test hypothesis 3. Entrepreneurial experience is measured as the number of ventures in models 1 to 3 and as the years of entrepreneurial experience in models 4 to 6. Models 1 and 4 include the entrepreneurial experience only, models 2 and 5 use all control variables, and models 3 and 6 add in the interaction term of the independent variable and the degree.

data with Occupational Employment Statistics data is based on the information provided at <https://www.nlsinfo.org/sites/nlsinfo.org/files/attachments/12124/NLSY97%202002%20Census%20I%20and%20O%20Codes.pdf>.

Table 4.3 - The Results of Generalized Estimating Equations on Log (Entrepreneurial Income)

	(1)	(2)	(3)	(4)	(5)	(6)
# of Ventures	0.246*** (0.0135)	0.192*** (0.0135)	0.0523 (0.0275)			
Years of Entrepreneurial Experience				0.106*** (0.00479)	0.0863*** (0.00496)	0.0280** (0.00996)
Highest Degree		0.0930*** (0.0197)	-0.0694* (0.0308)		0.113*** (0.0209)	0.0508* (0.0230)
Gender		-0.339*** (0.0310)	-0.338*** (0.0312)		-0.328*** (0.0300)	-0.329*** (0.0302)
Birth Year		Yes	Yes		Yes	Yes
Race		Yes	Yes		Yes	Yes
Managerial Experience		0.139*** (0.00966)	0.137*** (0.00968)		0.116*** (0.00975)	0.111*** (0.00978)
Same Industry		Yes	Yes		Yes	Yes
Household Financial Controls		Yes	Yes		Yes	Yes
Year Dummies		Yes	Yes		Yes	Yes
log(Average Salary)		0.0578*** (0.00686)	0.0585*** (0.00693)		0.0660*** (0.00730)	0.0667*** (0.00737)
# of firms * Degree			0.113*** (0.0164)			
# of years * Degree						0.0452*** (0.00668)
_cons	9.194*** (0.0252)	9.428*** (0.0698)	9.624*** (0.0778)	9.382*** (0.0175)	9.533*** (0.0656)	9.617*** (0.0671)
Observations	9704	9704	9704	9704	9704	9704
Individuals	2928	2928	2928	2928	2928	2928

Notes: 1. Model 1 to 3 use the number of ventures as the independent variable and model 4 to 6 use years of entrepreneurial experience as the independent variable. Model 1 and 4 include the independent variables only, model 2 and 5 utilize the full control variables, and model 3 and 6 add in the interaction term of the independent variable and the degree. 2. Standard errors in parentheses, significance is marked as: * p<0.05 ** p<0.01 *** p<0.001.

The results presented in Table 3 show that having one more venture experience, on average, increases the financial performance of startups by 20% and that the effect of one

extra year of entrepreneurial experience is 8.6%. After adding the interaction factor, the coefficient of entrepreneurial experience decreases markedly and becomes non-significant when measured as the number of ventures. The coefficient of the interaction effect of education and entrepreneurial experience is significant both economically and statistically, which supports the first hypothesis: that education has a positive moderating effect on the relationship between the entrepreneurial experience and venture performance.

Based on the regression results of model 3, we calculated the average marginal effects of education and entrepreneurial experience, the results of which are shown in Figure 1. The figure shows that the differences between the effects of education widen as entrepreneurial experience increases. In a second venture, the firm performance of individuals with a graduate degree is 14% more successful than the sample average and that of individuals with high school diplomas is 6% less successful than the sample average; none of the coefficients, however, are statistically significant. In the fourth venture, the firm performance of individuals with a graduate degree is around 50% more successful than the sample average while that of high school dropouts is 60% less successful than the sample average.

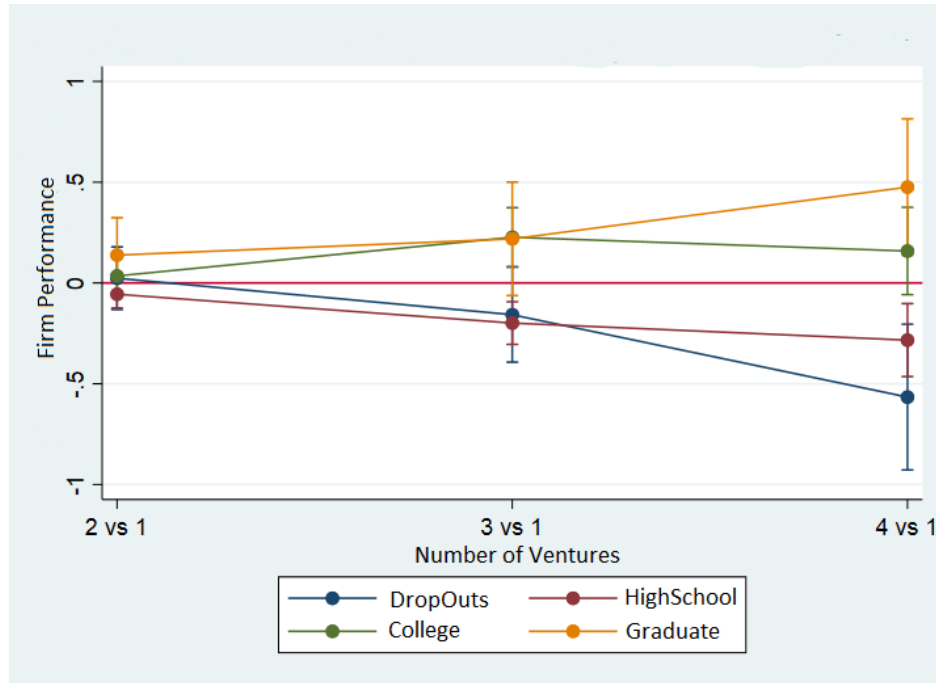


Figure 4.1 - The marginal effect of education and entrepreneurial experience.

The independent variable used in this paper, the highest degree attained, is a discrete categorical variable with four values. As the moderating effect of education of any two consecutive categories might differ, the moderating effect of education tested in this paper might be nonlinear. To test the potential nonlinearity effect, we divide the sample into four segments based on the highest degree attained by the individuals and separately test the relationship between entrepreneurial experience and venture performance for each segment, the results of which appear in Table 4. On average, having one more venture will enhance firm performance by 12%, 28%, and 37% when an entrepreneur holds a high school degree, a college degree, and a graduate degree, respectively. Entrepreneurs who dropped out of high school, the least educated in the sample, have an LBD effect of 17% from one venture experience. The coefficients of entrepreneurial experience of the four segments are shown in Figure 2 with a 95% confidence interval. In general, the scale of

the positive relationship between entrepreneurial experience and venture performance is positively related to the education of individuals, but the relationship is nonlinear with a disturbance by the segments consisting of high school dropouts. The empirical results above support hypothesis 3: that education moderates the relationship between entrepreneurial experience and venture performance.

Table 4.4 - The Results of Generalized Estimating Equations on log (Entrepreneurial Income) by Education Groups.

	(1)	(2)	(3)	(4)
	High-School Drop Outs	High-School Graduates	College Graduates	Graduate Degree Holders
# of Ventures	0.165*** (0.0418)	0.123*** (0.0181)	0.283*** (0.0251)	0.369*** (0.0536)
Gender	-0.403*** (0.0889)	-0.380*** (0.0384)	-0.247*** (0.0668)	-0.295* (0.133)
Birth Year	Yes	Yes	Yes	Yes
Race	Yes	Yes	Yes	Yes
Managerial Experience	0.0345 (0.0667)	0.109*** (0.0134)	0.149*** (0.0162)	0.205*** (0.0360)
Same Industry	Yes	Yes	Yes	Yes
Household Financial Controls	Yes	Yes	Yes	Yes
log(Average Salary)	0.0446** (0.0145)	0.0619*** (0.00911)	0.0394 (0.0204)	0.0817 (0.0492)
_cons	9.151*** (0.181)	9.561*** (0.0844)	9.560*** (0.169)	10.29*** (0.361)
N	935	5428	2652	689

Notes: 1. Model 1 includes high-school dropouts only, model 2 includes high-school graduates only, model 3 includes college graduates only, and model 4 includes people with graduate degrees only. 2. Standard errors in parentheses, significance is marked as: * p<0.05 ** p<0.01 *** p<0.001

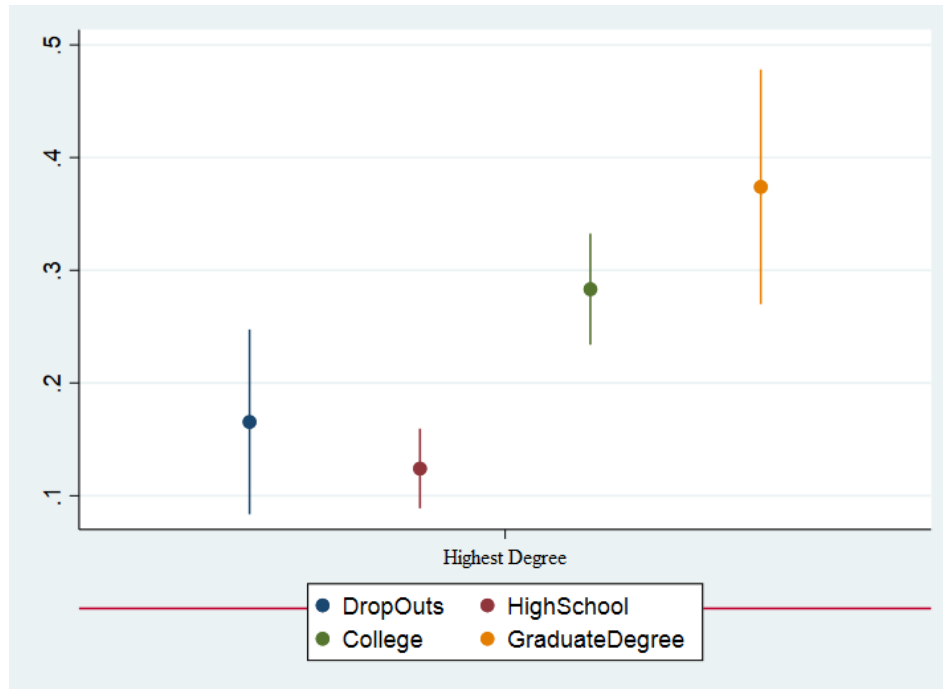


Figure 4.2 - The average effect of one entrepreneurial experience by the various education groups in the GEE model.

The results of the Heckman selection model are listed in Table 5. As this selection model is a two-step model, the results of the main effects are shown in the upper part of the table and those of the selection effects are shown in the lower parts. The entrepreneurial experience, represented by the number of ventures in models 1 to 5, is measured as years of entrepreneurial experience in models 6 to 8. Models 1 to 3 and 5 to 8 have the same variables in the selection model and the main model while models 4 and 5 have the log (i.e., external opportunity cost) as the exclusion restriction variable.

Table 4.5 - The Results of Heckman Selection Models on Log (Entrepreneurial Income)

	-1	-2	-3	-4	-5	-6
Main Effect						
# of ventures	0.0691**	-0.0695	-0.0368			
	-0.025	-0.0477	-0.0307			
Years or Entrepreneurial Experience				0.0452***	-0.0202	0.0161
				-0.0113	-0.0223	-0.013
Highest Degree	0.044	-0.0970*		0.0441	0.00378	
	-0.0238	-0.0481		-0.0237	-0.0266	
High-School Graduates			0.206***			0.203***
			-0.0568			-0.0566
College Graduates			0.190**			0.185**
			-0.0641			-0.0639
Graduate Degree Holders			0.203*			0.199*
			-0.0829			-0.0826
Gender	-0.286***	-0.289***	-0.291***	-0.284***	-0.287***	-0.286***
	-0.0338	-0.0339	-0.034	-0.0338	-0.0338	-0.0339
Birth Year	Yes	Yes	Yes	Yes	Yes	Yes
Race	Yes	Yes	Yes	Yes	Yes	Yes
Managerial Experience	0.173***	0.170***	0.180***	0.167***	0.166***	0.174***
	-0.0151	-0.0151	-0.0152	-0.0152	-0.0152	-0.0153
Same Industry	0.181***	0.184***	0.199***	0.175***	0.177***	0.188***
	-0.0377	-0.0377	-0.0379	-0.0377	-0.0377	-0.0378
Household Financial Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
log(Average Salary)	0.0483***	0.0484***	0.0420***	0.0503***	0.0504***	0.0451***
	-0.00817	-0.00817	-0.00825	-0.00818	-0.00818	-0.00824
# of firms * Degree		0.0945***				
		-0.028				
# of years * Degree					0.0459***	
					-0.0136	
_cons	8.960***	9.157***	8.970***	9.010***	9.060***	8.906***
	-0.0885	-0.106	-0.0984	-0.0814	-0.0827	-0.0893
Selection Model						
# of firms founded	-0.312***	-0.312***	-0.244***	-0.312***	-0.312***	-0.243***
	-0.00614	-0.00614	-0.00536	-0.00614	-0.00614	-0.00532
Highest Degree	-0.952***	-0.949***		-0.953***	-0.951***	
	-0.046	-0.046		-0.0459	-0.0459	
High-School Graduates			0.115			0.113
			-0.062			-0.062
College Graduates			0.153*			0.150*
			-0.0701			-0.0702
Graduate Degree Holders			0.149			0.145
			-0.0909			-0.091
Gender	-0.149***	-0.149***	-0.146***	-0.150***	-0.149***	-0.147***
	-0.0399	-0.0398	-0.0371	-0.0399	-0.0398	-0.0371
Birth Year	Yes	Yes	Yes	Yes	Yes	Yes
Race	Yes	Yes	Yes	Yes	Yes	Yes
Managerial Experience	0.00674	0.00671	0.0692***	0.00679	0.00675	0.0688***
	-0.016	-0.016	-0.0147	-0.016	-0.016	-0.0147
Industry Control	0.162***	0.162***	0.214***	0.162***	0.162***	0.214***
	-0.0437	-0.0436	-0.0407	-0.0437	-0.0437	-0.0408
Household Financial Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
log(Average Salary)	-0.0259**	-0.0259**	-0.0544***	-0.0259**	-0.0259**	-0.0542***
	-0.00958	-0.00958	-0.00906	-0.00958	-0.00958	-0.00906
# of firms * Degree	0.569***	0.569***		0.570***	0.570***	
	-0.0205	-0.0204		-0.0204	-0.0204	
_cons	2.783***	2.779***	2.344***	2.782***	2.779***	2.337***
	-0.109	-0.109	-0.108	-0.109	-0.109	-0.108
log-likelihood	-9893.246	-9410.062	-9891	-9414.292	-9408.621	-9890.93
N	7317	7317	7317	7317	7317	7317

Note: 1. The models in this table use entrepreneurial income as the dependent variable in the main equation (top) and the restart as the binary dependent variable in the selection equation (bottom).

2. Model 1 to 3 use number of ventures as the independent variable and model 4 to 6 use years of entrepreneurial experience as the independent variable. Model 1 and 4 utilize the full control variables, model 2 and 5 add in the interaction term of the independent variable and the degree, and model 3 and 6 treat degree as a category variable with the group of high-school dropouts as the reference group.

3. The superscript denotes the statistical significance of the coefficients at the following levels: *p<0.05 **p<0.01 ***p<0.0001.

The effect of education on individuals' selection to enter serial entrepreneurship is negative, and the coefficient is statistically significant and stable across all models. Models 3 and 8 treated education as a categorical variable, and the results show that the more education one has, the less likely that individual will enter serial entrepreneurship. Compared to high school dropouts, individuals with a high school degree, a college degree, and a graduate school degree are 60%, 130%, and 190% less likely to enter serial entrepreneurship. These results are consistent with our theory that more education is associated with a stronger self-selection effect.

In model 5, the coefficient of the exclusion restriction variable is negative, as expected, but not significant. This finding indicates that education is positively correlated to one's annual income, but education provides more external utility beyond a higher salary. In model 6, in which we drop the highest degree in the selection model, the coefficient of the exclusion restriction greatly increases in scale and becomes significant. These results indicate that the instrument we use is weak and that the selection stage in the Heckman selection model has limited power in controlling the effect of self-selection. Therefore, the results show the upper bound of the main effect of LBD.

The selection model produced several interesting findings. One was that the management experience, which is positively related to individuals' entrepreneurship performance, is also negatively related to the selection to enter serial entrepreneurship. This finding might explain the formation of the lemon market of serial entrepreneurship. It could also indicate that the managerial experience is another individual characteristic that moderates the relationship between entrepreneurial experience and firm performance. In addition, the results of this paper are consistent with the theory that the self-selection effect decreases with time and converges to zero. That is, the more firms one has launched, the

more likely that individual will set up another venture, especially if the next venture is in the same industry as the former one.

The coefficients of the “main effects” are adjusted by the selection effect. Table 3 shows that models 1 and 2 are comparable to models 2 and 3, and models 6 and 7 are comparable to models 5 and 6. These results suggest that the LBD effect of having one more entrepreneurial experience improves the financial performance of new ventures by 8% at most, which is much lower than the results of the GEE model found. Similarly, although significant, the scale of the coefficients of education estimated by the Heckman selection models is around 50% of the corresponding models estimated in the GEE model, and the moderation effect of education declined to around 30%. The results of the Heckman models support Hypothesis 1: that education has a moderation effect on the entrepreneurial LBD process. These results are consistent when the entrepreneurial experience is represented by years of entrepreneurial practice. The scale difference between the coefficients of the GEE and Heckman Selection models, which indicate that self-selection plays an important role in increasing the positive relationship between entrepreneurial experience and venture performance and the moderation effect of education, partially stems from its influence on the self-selection process, which supports Hypothesis 2.

To test the potential non-linear moderation effect of education on the entrepreneurial LBD process, we also used Heckman selection model in tests of the four separate samples that were segmented based on the highest degree of the entrepreneurs, the results of which appear in Figure 3. Compared with the scale of the coefficient in Figure 2, that in Figure 3 is smaller while the variance is much larger. Similar to the results that do not account for the selection effect, the scale of the positive relationship between entrepreneurial experience and venture performance is positively related to the education of individuals;

the relationship, however, is nonlinear. The large variance of the results of the Heckman selection model indicates that the positive effect of self-selection on the relationship between entrepreneurial experience and firm performance mainly stems from the fact that people with potentially low venture performance are selected to exit entrepreneurship. Thus, the results generally support hypothesis 2: that well-educated people experience a stronger effect of selection to enter serial entrepreneurship, which contributes to the moderation effect of education on the relationship between entrepreneurial experience and firm performance.

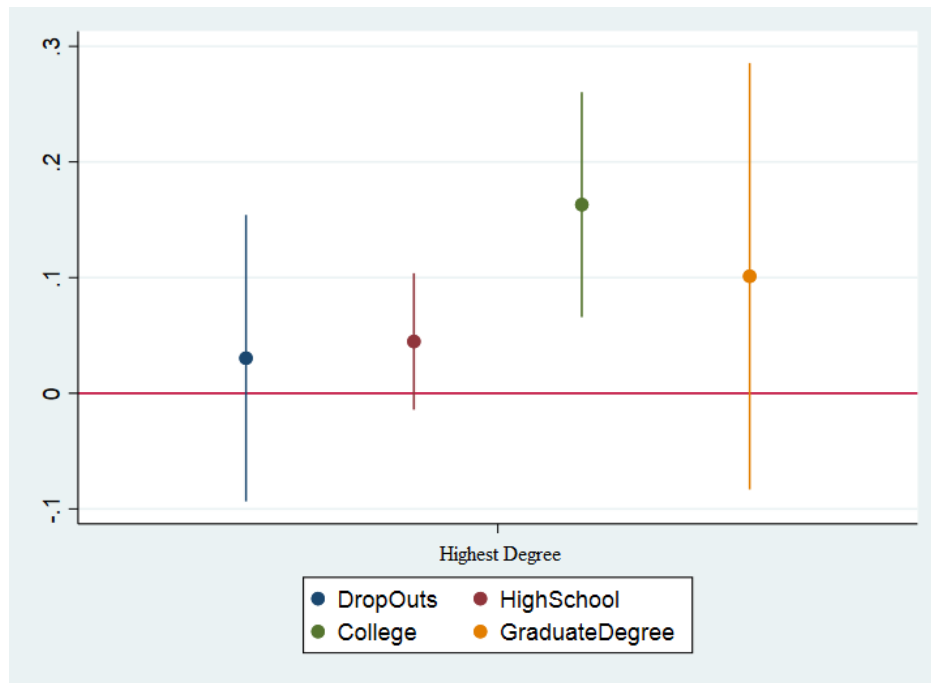


Figure 4.3 - The average effect of one entrepreneurial experience by the various education groups in the Heckman selection model.

4.5 Conclusion and Discussion

In this study, we explored how education is an individual characteristic that moderates the venture performance of serial entrepreneurs, expressed as a positive relationship between entrepreneurial experience and venture performance. As the venture performance of a serial entrepreneur is under the influence of both the entrepreneurial learning-by-doing (LBD) and self-selection effects, we analyzed the influence of education on the focal relationship by its influence on these two processes. Using experiential learning theory and Lazear's occupation choice model, we hypothesized that education positively moderates both the LBD and self-selection processes and found that the moderating effect of education on the LBD process increases with time while its effect on self-selection drops markedly, rapidly converging to zero. The empirical testing indicates that education positively moderates the relationship between entrepreneurial experience and venture performance. Education influences the self-selection process by effectively screening out individuals with low entrepreneurial efficiency.

The goal of this study was to explore the effect of education on the performance of serial entrepreneurs as an important yet understudied topic in the economics of entrepreneurship. Using a comprehensive longitudinal dataset, we empirically explored how education moderates the relationship between entrepreneurial experience and venture performance through its influence on the LBD and self-selection processes. Although this study was a macro-level project, the key findings of this paper indicate an interesting direction of micro-level research. The independent variable used in this paper, education, was a proxy of some micro-level individual factors that directly affect the relationship, such as the effect of education on the LBD process reflected by the strong correlation between education and learning ability. Therefore, by following this stream of micro-level research, one might be able to explain the mechanism from an individual psychological

perspective. The value of this paper is that it showed that education, different from learning ability, is a more accessible variable that can apply to many other situations.

One limitation of this paper is that the exclusion restriction variable, the annual income of the most recent job of the entrepreneur, is a weak instrument. Thus, the selection step of the Heckman model used in this paper had limited power of estimation. Therefore, the LBD effect (the main effect of the Heckman model) was an upper bound of the real LBD effect while the self-selection effect was a lower bound. Future research could use stronger instruments to improve the accuracy of estimation of the Heckman selection model.

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