

**THE ROLE OF KEY RESOURCE PROVIDERS IN
NEW VENTURE RESOURCE ACQUISITION**

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ABSTRACT

This dissertation consists of three essays examining how new ventures acquire knowledge and how the acquisition of knowledge influences new venture outcomes. In Essay 1, I focus on how network connections affect entrepreneur's knowledge of the value of their idea and their decision to quit or persist. In Essay 2, I focus on knowledge diversity between the founding team and their peers, and how the interaction of knowledge affects quitting, acquisitions, and funding. In Essay 3, I focus on how a venture's need for external knowledge and experience change over time as the venture develops.

The first essay focuses on how entrepreneurs' networks may affect their assessment of their venture's potential and their decision to quit. I examine founder networks in entrepreneurial accelerator cohorts, and find that central ventures whose founding teams have greater access to information are more likely to quit. Consistent with my predictions, the results suggest that better access to information helps reduce uncertainties regarding the expected future returns of the venture. Similar to Lerner and Malmendier (2013), my findings suggest that with more information, founding teams revise expected future returns to a lower level than previously estimated, and this increases the likelihood that the venture will cease operations. I also find that the effect of network information on quitting is weakened by other internal and external sources of information. Specifically, the usefulness of information from networks and the likelihood of quitting diminishes when the entrepreneurs have prior founding experience and when the venture receives more external attention. Overall, this study sheds light on competing sources of information for new ventures and its implications for important firm outcomes.

The second essay investigates how access to specific types of knowledge affects both new venture learning and competition, which influences the outcome trajectory of the venture. I find that the relative similarity between the founding team's prior knowledge and the distribution of knowledge in the broader cohort influences venture outcomes. I find that startup teams with a high share of technical backgrounds in cohorts with a high share of founders with technical backgrounds are more likely to exit via quitting or acquisition, while technical teams in a cohort with a high share of entrepreneurial experience are also more likely to get VC funding. Similarly, startup teams with a high share of business backgrounds in a cohort with a high share of founders with business backgrounds are less likely to get VC funding, while the same team in a technical cohort is more likely to get VC funding. Overall, I highlight the significance of different types of knowledge – on the part of the founding teams and their peers—in shaping the ability of startups to navigate critical decisions regarding exit and financing.

The third essay explores the type of expertise and connections founders bring in through the appointment of early directors and how this evolves over time. I argue that as new ventures face pressures to rapidly learn and evolve, it must be the case that they seek out different types of expertise along the way. But we have no systematic evidence of who they seek out, when they seek them, and the mechanisms through which this occurs. Using data on the human and social capital of board members in 1,200 new ventures in the Computer Software industry, I develop several stylized findings. I find several systematic patterns in the experience and connections of directors appointed over time as ventures move through different stages of development.

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CHAPTER 1: WHAT AM I WORTH? CONNECTIONS TO PEERS, PIERCING ENTREPRENEURIAL OVERCONFIDENCE, AND VENTURE QUITTING

Introduction

The potential value of a new venture is inherently uncertain, and there is often little information upon which to base an estimation of its future profits (Landier & Thesmar, 2008). To reduce that uncertainty and develop more accurate estimations, entrepreneurs need a lot of information (Dimov, 2010; Golub & Jackson, 2010; Hallen & Pahnke, 2016; Jovanovic, 1982). Armed with more information, entrepreneurs can make better decisions regarding whether to quit or persist with their venture (Dimov, 2010; Jovanovic, 1982). But how do entrepreneurs get relevant information they can use to develop better predictions of their venture's future returns? In this research, we investigate the role of the founding team's network connections and the degree to which ventures with more robust networks have different performance outcomes.

A substantial body of research points to an entrepreneur's network as a key source of information and advice that aids in the entrepreneurial process (Hoang & Antoncic, 2003). Networks expose entrepreneurs to more information from which they can recognize more entrepreneurial opportunities (Ardichvili, Cardozo, & Ray, 2003; Birley, 1985; Smeltzer, Van Hook, & Hutt, 1991). Networks also send information to potential partners that can aid in the acquisition of resources (Hsu, 2007; Stuart, Hoang, & Hybels, 1999; Yli-Renko, Autio, & Sapienza, 2001). Much less is known about the role of networks in enabling more accurate estimates of a venture's expected returns and subsequently, the decision to quit or persist.

In this paper, we examine how network centrality affects venture quitting. We examine founder networks in entrepreneurial accelerator cohorts, and we argue that centrality exposes entrepreneurs to more information about the venture's quality. These informational benefits will reduce uncertainty about the venture's expected future returns, and affect whether entrepreneurs will quit or persist with the venture.

There are several ways in which information about venture quality may impact performance outcomes. However, there are several reasons to believe that information will have a negative effect on founders' expected value. First, entrepreneurs tend to be overestimate the value of their projects (Landier & Thesmar, 2008; Lowe & Ziedonis, 2006). Second, research suggests that more information enables more accurate assessments of value (Golub & Jackson, 2010; Hallen & Pahnke). Information from peers tends to reduce overconfident estimates (Arkes, Christensen, Lai, & Blumer, 1987; Camerer & Lovallo, 1999). For instance, Lerner and Malmendier (2013) examine the effects of information shared in MBA cohorts on both successful and unsuccessful entrepreneurship and only find evidence of a negative effect of information on entry.

We test our predictions using a novel dataset of the population of startups that have gone through cohorts in entrepreneurial accelerators. As we discuss in the next section, accelerators are a useful context for studying networks and new venture activity because founders are randomly sorted into cohorts. We find that ventures whose founding teams have greater access to information are more likely to quit. Consistent with our predictions, our results suggest that better access to information helps reduce uncertainties regarding the expected future returns of the venture. Similar to Lerner and Malmendier (2013), our findings suggest that with more information, founding teams

revise expected future returns to a lower level than previously estimated, and this increases the likelihood that the venture will cease operations.

We also examine boundary conditions of this relationship, especially how it may be strengthened or weakened by other internal and external sources of information. Specifically, we find that ventures whose founding teams have more prior entrepreneurial experience are less likely to quit. When the venture has an existing internal source of information that helps them predict expected returns, information gained through network centrality is less beneficial. We also find that ventures with greater external attention are less likely to quit. When the venture has an external source of information that helps reveal predicted future returns, information gained through network centrality is also less beneficial.

Our paper makes several contributions to the literature. First, we extend the literature on networks in the entrepreneurial process to consider the role of networks in forming estimates of a venture's future value. Networks and access to information have been linked to identifying opportunities (Ardichvili, Cardozo, & Ray, 2003; Birley, 1985; Smeltzer, Van Hook, & Hutt, 1991, new venture performance (Yli-Renko, Autio, & Sapienza, 2001; Stuart, Hoang, & Hybels, 1999), and signaling venture quality to potential partners (Hochberg, Ljungqvist, & Lu, 2007; Hsu, 2007). In this paper, we show that networks play a role in reducing uncertainty for entrepreneurs regarding the quality of their venture. The ability of entrepreneurs to uncover their venture's quality, and make more informed decisions regarding whether they should persist or quit is essential to entrepreneurial success (Dimov, 2010; Eckhardt & Shane, 2003; Short, Ketchen Jr, Shook, & Ireland, 2010). We highlight the role of the founding team's network position,

prior entrepreneurial experience, and external attention as potential sources of information that enable better decisions.

Our findings also contribute to the literature on the social influence of peers. Prior research in this stream demonstrates how peers may affect entry into entrepreneurship (Kacperczyk, 2013; Lerner & Malmendier, 2013; Nanda & Sørensen, 2010). Much of this research tends to assume that all peers within a class or company are equally likely to be influenced by their social peers. For instance, research has demonstrated that the presence of more entrepreneurs in the same university affects cohort rates of entrepreneurship (Kacperczyk, 2013; Lerner & Malmendier, 2013). Our research adds a network component that demonstrates that not all entrepreneurs are equally affected by their peers. Connectedness within a cohort of peers matters to the flow of information and the extent to which an individual or founding team will be influenced.

In the next sections, we describe our empirical context of entrepreneurial accelerators and its usefulness for our study. We then review the relevant literature and develop our predictions regarding how founding team network centrality affects quitting. We describe how we collected our data and constructed networks of each accelerator cohort. We then empirically test our predictions. Finally, we discuss our findings and highlight implications and future research opportunities concerning founding team networks and venture quitting.

The Entrepreneurial Accelerator Setting

Our empirical setting is entrepreneurial accelerators. Entrepreneurial accelerators are fixed-term (usually three months), cohort-based, “boot-camps” for startups (Hochberg, 2016). During this time, startup founders receive intensive education and

mentoring, including seminars and networking opportunities with former entrepreneurs, venture capitalists, and other peer founders (Cohen, 2013). The program culminates in a “demo day” where all ventures pitch their ideas to a large audience of investors (Cohen, 2013). The programs’ limited duration, intensive mentoring and education in cohorts, competitive cyclical selection, and demo day pitch event distinguish accelerator programs from incubators or angel groups (Cohen, 2013; Winston Smith & Hannigan, 2015).

Prior research on accelerator programs shows that participating ventures reach important milestones, such as quitting, raising external capital, being acquired, and achieving customer traction, faster than non-participating startups (Hallen, Bingham, & Cohen, 2016; Winston Smith & Hannigan, 2015). Relative to startups funded by angel groups, startups in accelerators are more likely to receive the first round of follow-up funding sooner and are more likely to be acquired or fail (Winston Smith & Hannigan, 2015). The effect of accelerators on venture outcomes is largely attributed to networks and learning (Cohen, 2013; Hallen et al., 2016; Radojevich-Kelley & Hoffman, 2012). Cohen (2013) finds that many features of accelerator programs facilitate learning, such as mentoring and director experts. Surprisingly, Cohen (2013) also finds that ventures shared significant amounts of knowledge with each other through peer interaction, contrary to prior research findings that competing ventures should have limited knowledge flow (Messick & Mackie, 1989).

Accelerator cohorts provide a unique context to study how networks influence quitting decisions of entrepreneurs because founders are randomly sorted into cohorts. We construct networks that link founders by a shared affiliation with a prior work or school organization. A tie exists if two founders have worked at the same company or

attended the same school. Individuals who share the same prior affiliation also share the same language, routines, and understandings that facilitate communication (Beckman, 2006). Prior research argues that affiliation with the same organization or event is considered an indicator of an underlying social tie, or the opportunity for or precursor to tie formation (Borgatti & Halgin, 2011; Feld, 1981; Kadushin, 1966; Wasserman, 1994).

The affiliation networks that form in each cohort are then exogenous to the startup founders, which allows us to better isolate the effect of network position and access to information on quitting.

Theoretical Background and Hypotheses

Expected Future Returns and Entrepreneurial Opportunity Cost

The decision to persist or abandon a new venture depends on the match between the entrepreneur's opportunity cost and the expected returns of the venture (Arora & Nandkumar, 2011; Gimeno, Folta, Cooper, & Woo, 1997; Shane & Venkataraman, 2000). If the expected return is large enough to compensate for the opportunity cost, the entrepreneur will continue with the venture (Shane & Venkataraman, 2000). If the expected profit falls below the acceptable threshold, the entrepreneur will exit (Gimeno et al., 1997), as she can earn more in traditional employment or other opportunities.

Because of the novelty of entrepreneurial ventures, there is very little initial evidence on which to base an estimate of future returns (Landier & Thesmar, 2008). To make this estimate, entrepreneurs must be able to objectively assess their venture's quality (Dimov, 2010; Jovanovic, 1982). As founding teams receive new information, they update their estimates and their intention to quit or persist (Dimov, 2010). For instance, Jovanovic (1982) shows that, as ventures receive market information about their

efficiency over time, the ones that learn that their future profits have fallen below the value of staying in the industry will cease operations. Similarly, Dimov (2010) suggests that entrepreneurs that are privy to more sources of information, such as industry insiders, will make better decisions regarding whether to continue or abandon a particular venture.

Networks as Sources of Venture Value Information

Individuals that can access the most information tend to be central players in their social networks (Golub & Jackson, 2010; Hallen & Pahnke, 2016; Uzzi, 1997). The trust, mutual understanding, and reciprocity embedded in one's social ties ease the transfer of information (Reagans & McEvily, 2003). Not only are one's social ties motivated to provide information but the information received from ties is more likely to be perceived as credible and trustworthy (Hallen & Pahnke, 2016; Reagans & McEvily, 2003).

Centrality in networks gives venture founders superior access to information (see review by Hoang & Antoncic, 2003). With more information, founders can gain insights from multiple evaluations of their venture which should enable them to form more accurate assessments of the venture's future value (Hallen & Pahnke, 2016; Lévesque & Schade, 2005; Yang, Narayanan, & Zahra, 2009). Golub and Jackson (2010) suggest that being networked to a large number of ties increases the amount of opinions received, and enables wiser, more accurate judgments of value. Lerner and Malmendier (2013) show that the close ties that form amongst MBA students in the same cohorts enable the assessment of entrepreneurial ideas. An individual's network ties are likely to provide opinions on the market potential of entrepreneurial ideas. Among founders in accelerator

cohorts, ties are likely to provide important information that can help founders better assess the venture’s expected value (Cohen, 2013).

Figure 1 summarizes the overall model and predictions laid out in the sections below. The solid line boxes are variables we can directly test, while the dotted line boxes are assumptions we cannot directly test. However, we do explore alternative ways to provide support for those assumptions in later sections.

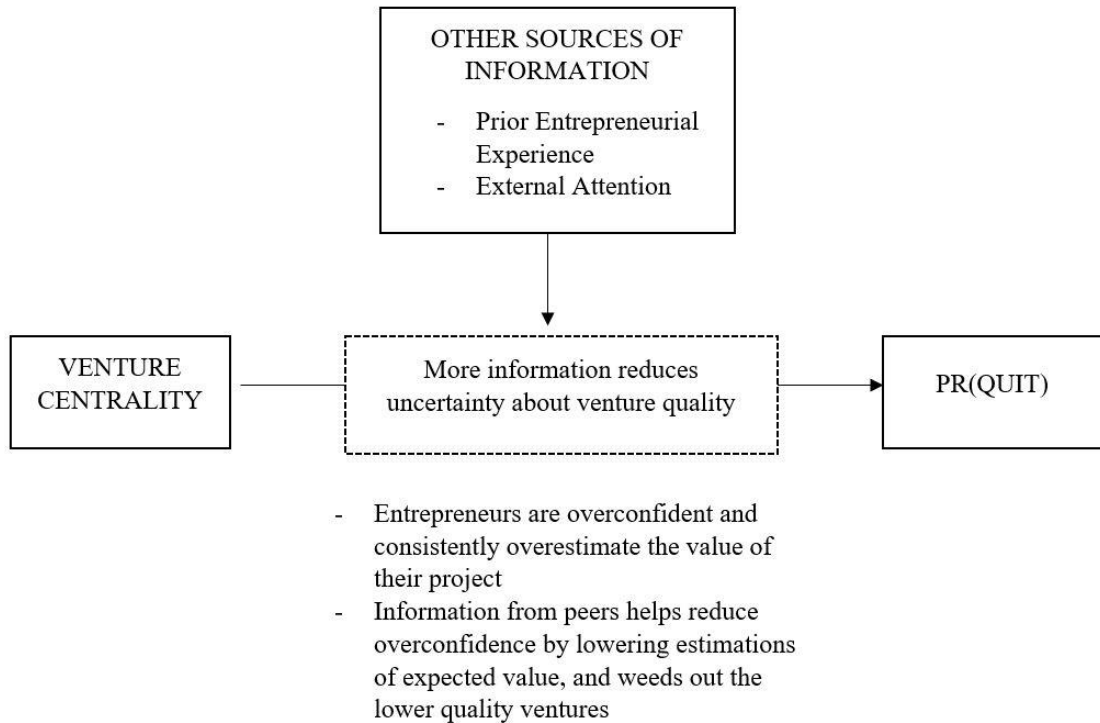


Figure 1. Summary of Hypotheses

More Information from Peers and Venture Quitting

We contend that central ventures will be more likely to quit because they receive more information that lowers their estimate of future profits. While information could reinforce or enhance the entrepreneur’s estimates or challenge and weaken the estimate

(McMullen & Shepherd, 2006), there are several reasons to believe that the effect of more information on the expected future returns will be negative.

First, research consistently finds that entrepreneurs are overconfident (Busenitz & Barney, 1994; Simon, Houghton, & Aquino, 2000). Overconfidence occurs when individuals fail to realize the limits of their knowledge (Bazerman & Moore, 2008; Zacharakis & Shepherd, 2001). Overconfident entrepreneurs tend to treat assumptions as fact and overestimate the probability of being right (De Carolis & Saporito, 2006; Simon et al., 2000). When entrepreneurs evaluate situations, they tend to focus on the strengths while downplaying the weaknesses (Palich & Bagby, 1995). Thus, entrepreneurs tend to overestimate the value of their idea, which can result in continued efforts on an unsuccessful idea (Lowe & Ziedonis, 2006).

Landier and Thesmar (2008) find that entrepreneurs display a consistent systematic upward expectation bias, in which they over-estimate the value of their entrepreneurial project. The authors argue that the most likely explanation is that overconfident individuals self-select into entrepreneurship. Individuals who leave traditional employment or the pursuit of other opportunities to become entrepreneurs tend to be those who overestimate the prospect of the project. In general, pessimists do not become entrepreneurs.

Prior research has shown that entrepreneurial overconfidence can significantly affect venture outcomes. The optimism of overconfident entrepreneurs negatively impacts both revenue and employment growth of the venture (Hmieleski & Baron, 2009), and can explain the high failure rates of new entrants (De Meza & Southey, 1996). These negative effects occur because overconfident entrepreneurs tend to commit fewer initial

resources to the new venture and deplete them too quickly (Hayward, Shepherd, & Griffin, 2006). Moreover, the authors suggest that, because entrepreneurs overestimate the value of the venture, they are less likely to reach a deal with investors for a liquidity event, making their venture at greater risk of defaulting on debt. Overall, this research suggests that entrepreneurial overconfidence has a negative effect on entrepreneurship.

Receiving information about their venture's expected value from peer founders will diminish that overestimation (Lerner & Malmendier, 2013). Information gained from peers plays a crucial role in reducing overconfident estimates (Arkes, Christensen, Lai & Blumer, 1987). For instance, Lerner and Malmendier (2013) examine the effects of feedback about potential ventures on both successful and unsuccessful entrepreneurship and only find evidence of a negative effect of information. That is, they show that all of the reduction in entrepreneurship rates in MBA cohorts with more experienced entrepreneurs is due to the weeding out of bad ideas. Although fewer students in these cohorts go on to become entrepreneurs after graduating, the ones that do are more likely to be successful¹. By interacting with peers, individuals are forced to think through their decisions more thoroughly and review the source of knowledge on which they base their estimates. This tends to reduce overconfidence (Arkes, Christensen, Lai & Blumer, 1987).

¹ In Lerner and Malmendier (2013), although the fraction of successful entrepreneurs in cohorts with higher rates of pre-entrepreneurship is much higher than the fraction of successful entrepreneurs in low-entrepreneurship cohorts, the result is only marginally significant due to small numbers.

Thus, ventures that receive more information from their peers will be more likely to lower their overconfident estimates of the venture's expected returns below their reservation price and quit rather than continue to run the venture.

Hypothesis 1: The greater the founding team's network centrality in the cohort, the higher the likelihood of quitting.

Internal Sources of Information as a Substitute for Centrality

The human capital of the entrepreneur may provide an internal source of information that shapes the need for or use of information from peers. Research suggests that prior entrepreneurial experience gives founders more information to carry over into future ventures that increases their chances of survival (Delmar & Shane, 2006; Klepper, 2001; Taylor, 1999). Experienced entrepreneurs already possess information about opportunities, resources, and routines that puts their subsequent ventures ahead on the learning curve (Delmar and Shane, 2006).

Prior entrepreneurial experience also links entrepreneurs to existing networks of customers, suppliers, and resource providers (Delmar & Shane, 2006; Westhead, Ucbasaran, Wright, & Binks, 2005b). These networks provide key sources of information that can prevent failure from liabilities of newness (Arrow, 1974; Brüderl & Preisendörfer, 1998; Stinchcombe, 1965).

Prior entrepreneurial experience provides an alternative, internal source of information that may substitute for information gained from the venture's cohort network position. Research on information sources suggests that prior experience and network connections are two sources of information that new ventures can substitute for one

another (Bruneel, Yli-Renko, & Clarysse, 2010; Haunschild & Beckman, 1998; Uzzi & Lancaster, 2003). Bruneel et al. (2010) argue that entrepreneurs have limited information about operating in foreign markets, but can use information gained through exchange partners or through founder's prior experience to compensate. Haunschild and Beckman (1998) examine the effect of multiple information sources on the impact of interlock connections. They argue that the more information sources available to firms, the less impactful interlock connections will be for providing information. Further, research suggests that a new venture's internal information, such as the skills and capabilities of the founding team, may have a stronger effect on venture survival and performance than external networks (Littunen, 2000).

Hypothesis 2: The positive effect of centrality on quitting will diminish with the venture's prior startup experience.

External Sources of Information as a Substitute for Centrality

Ventures can also gain information on their future expected returns from external sources (Da, Engelberg, & Gao, 2011; Luo & Zhang, 2013; Viotto da Cruz, 2018), which shape the usefulness of centrality as a source of information (Haunschild & Beckman, 1998). Bruneel et al. (2010) suggest that external information can substitute for direct operating experience or founders' prior experience. Similarly, Viotto da Cruz (2018) analyzes new ventures on crowdfunding websites and finds that external information from crowdfunding participants reduces entrepreneurs' uncertainty regarding the potential market value of their new product. Her results suggest that external information

from crowdfunding websites can be a valuable source of information when entrepreneurs lack other sources of information about the market value of their product.

We argue that the receipt of attention from the public can serve as a highly credible external information source that dampens the usefulness of centrality. External attention can indicate that there is market potential or interest in the venture (Viotto da Cruz, 2018; Da, Engelberg, & Gao, 2013; Luo & Zhang, 2013). Prior research in finance shows that attention is a predictor of buying behavior and returns (Barber & Odean, 2007; Choi & Varian, 2009, 2012; Da et al., 2011). External attention is positively associated with home sales, unemployment trends, stock prices, and stock purchases (Choi & Varian 2009, 2012; Barber & Odean, 2007; Da et al., 2013).

Prior research has used Google search volume to quantify external attention for firms (Bank, Larch, & Peter, 2011; Da et al., 2011; Joseph, Wintoki, & Zhang, 2011). Da et al. (2013) argue that this is a direct, revealed measure of attention. If you're googling a firm, you are paying attention to it. Similar measures have been used in entrepreneurship research to examine new venture traction or potential. For instance, the number of Facebook "likes" and the number of page views have been used to assess market potential and project popularity (Gonzalez-Uribe & Leatherbee, 2017; Grewal, Lilien, & Mallapragada, 2006).

Attention is positively linked to firm value and outcomes. Petkova, Rindova, and Gupta (2013) show that the amount of attention a new venture receives affects how others value that venture, and the number of investments made by venture capitalists. Firms that receive persistent attention have increased perceived value and reputation in the public eye (Rindova, Petkova, & Kotha, 2007). Hallen (2008) examines the formation of a

venture's early investment ties and suggests that a venture's accomplishments can increase the amount of attention the venture receives. Attention then transmits information about the venture's quality that can increase the likelihood of investment (Hallen, 2008). Moreover, external attention can be a more credible source of information about the venture's quality because, unlike founder ties and human capital, attention captures revealed market interest (Hallen, 2008; Haunschild & Beckman, 1998).

Thus, the more attention a venture receives, the more external information available about the venture's quality, and less the entrepreneur will need to rely on information from their networks.

Hypothesis 3: The positive effect of centrality on quitting will strengthen with the venture's external attention.

Methods

Sample and Data

We collect data on startups that went through two of the top-ranked accelerator programs in the U.S., Y Combinator and TechStars. Both are among the first accelerator programs established and both maintain similar and consistent routines for cohort-based, fixed term programs, startup selection and mentoring. We first identify the population of startups that passed through each program between 2005 and 2011. Using the programs' websites and technology websites like Crunchbase, we were able to identify 394 startups and 933 founders that went through Y Combinator and TechStars.

We then track exit and funding outcomes for all startups through 2015. VentureXpert was the core source of data for investment and acquisition outcomes. We supplement the data on startup outcomes with information from Crunchbase on

investment and acquisition events, current status, and investor profiles. Finally, we searched SEC filings, databases of Forbes and BusinessWeek, and websites of startups and investors for missing or incomplete information. The online database Crunchbase is an open and public source of startup information, and includes key event details on many entrepreneurial outcomes, but is not always a complete source of data. We corroborated startup characteristics and event details by searching through startups' websites, SEC filings, and the popular business press. The extent to which our data collection process relied on corroborating sources depended in some part on the nature of the firm, founder, and entrepreneurial outcome. For example, firms that are acquired generally announce the deal in the media and online. Crunchbase lists firms that are shut down but to carefully corroborate this data we developed a careful process of tracking firms' activities and matching them to founder backgrounds. Firms that updated websites regularly and continued to post to existing social media network profiles were determined to be alive. However, a lapsed internet presence, coupled with a lack of popular press coverage and a change in career histories for the founders on LinkedIn or Crunchbase indicated that the firm had been shut down. We were able to confirm outcomes for 394 startups.

We then collect data at the founder level. We start by identifying each member of every founding team in our sample by searching LinkedIn, Crunchbase, technology blogs, and the startups' websites. Data from these sources began to build career biographies of each founder. To complete this data collection process however, we supplement the founder histories with extensive data from LinkedIn.com. For each founder, we collect data on each job held over the course of their careers, including dates, job titles and descriptions, and employer characteristics. This data was corroborated using

technology blogs, the popular business press, and founder profiles on other social media network platforms, such as Twitter and Github.

Constructing Networks

We construct a network for each distinct cohort using founders' career histories compiled from LinkedIn, Crunchbase, and popular press. We define a tie as an overlap in a prior work or school organization between two founders. Affiliation with the same organization or event is considered an indicator of an underlying social tie, or the opportunity for or precursor to tie formation (Borgatti & Halgin, 2011; Feld, 1981; Kadushin, 1966; Wasserman, 1994).

First, we construct a two-mode matrix, where rows indicate all startups in a cohort and columns indicate all prior organizations (employment or education prior to entering the accelerator) of all founders in the cohort. We entered a value of 1 for each cell that has at least one founder-organization match. For instance, one founder from the startup SwipeGood and one founder from the startup TalkBin had prior employment experience at eBay. Therefore, under the eBay column of this cohort's matrix, the row for SwipeGood took a value of 1 and the row for TalkBin also took a value of 1.

Using UCINET VI, we then converted the two-mode matrices to one-mode matrices, where both rows and columns are all startups in a cohort and a value of 1 indicates that two startups are connected by affiliation with the same organization. For instance, the row for SwipeGood had a value of 1 in the column of TalkBin because both startups had at least one founder that worked for eBay. Likewise, the TalkBin row of the

matrix had a value of 1 in the column of SwipeGood. We then used the one-mode matrices to analyze the network structure and positions of startups in each cohort.

The startups and cohorts varied in degrees of connectedness. Figure 2 depicts a cohort that displays several characteristics found in the networks in our sample. This network has multiple groupings of connections. Some startups are in the denser, more connected structure on the bottom left, while others have a few, de-centralized connections or no connections at all.

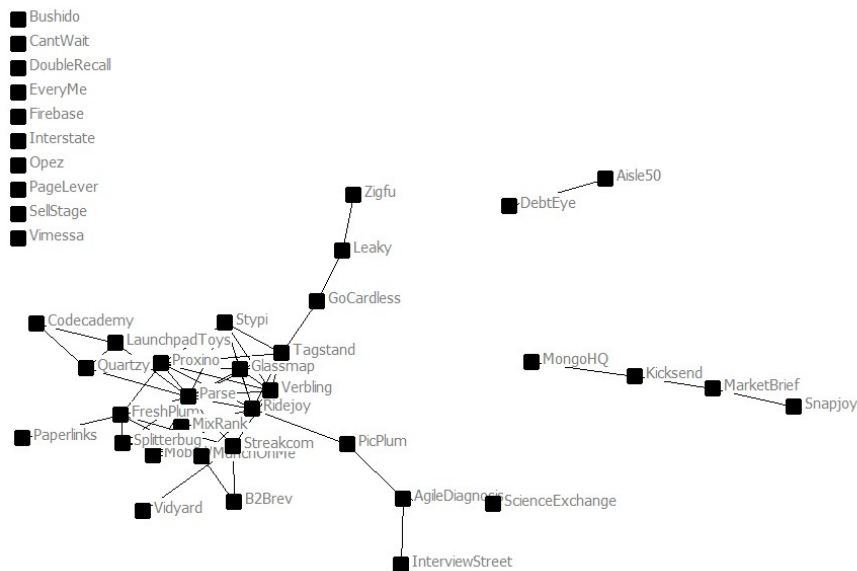


Figure 2. Sample Cohort Network

Measures

Independent Variables

Our main independent variable captures startup centrality in the affiliation network of each cohort. Closeness centrality captures the degree to which a startup is near other startups in the network (Freeman et al., 1979). The raw closeness score

indicates that a node, or a startup, is likely to receive information flows sooner (Borgatti, 2005). Because the number of potential partners and ties varies with each cohort, we also normalize the measure to be able to compare scores across cohorts (Wasserman & Faust, 1994; Soh, 2003). We calculate closeness centrality and all other network measures using UCINET VI (Borgatti, Everett, & Freeman, 2002).

Dependent Variables

We measure Quit as a binary variable, indicating whether a startup has ceased efforts on the current venture within one year of completion of the accelerator program.

Control Variables

We control for a number of factors that may affect startup outcomes. At the startup level, we control for the number of founders on the founding team (*NumFounders*) and the age of the startup at the start of the accelerator program (*Venture Age*).

We used the industry tag assigned by Crunchbase to create dummy variables for six distinct sub-industry clusters: Music, Gaming, and Media; Social Media, Location, and Mobile Apps; Payment and Commerce; Web Business; Underlying Technology, and Other Industry. We also include a dummy variable for startups located in Silicon Valley.

At the cohort level, we control for the number of founders in each cohort (*Cohort Size*), the year that the cohort program began (*Year Dummies*), and the overall density of the cohort network structure.

Table 1 provides a summary of all variables, including the measurement and their use in other studies.

Table 1. Summary of Variables

Variable	Measurement	Use in Prior Studies
Venture Quitting	Equals 1 if venture ceases operations, 0 otherwise	Dehlen, Zellweger, Kammerlander, and Halter (2014), Gimeno et al. (1997), Uzzi (1996)
Venture Closeness Centrality	The reciprocal of the sum of the degree distance to each other venture team	Powell, Koput, and Smith-Doerr (1996), Soh (2003)
Prior Entrepreneurial Experience	Equals 1 if one or more individuals on the founding team have previously founded a venture	Colombo and Grilli (2005), Folta, Delmar, and Wennberg (2010), Zhang (2011)
External Attention	Log of average search volume index on Google during the accelerator program	Da et al. (2011), Choi and Varian (2012)
Venture Age	Number of months from venture founding to the start of the accelerator program	Stam and Elfring (2008)
Num Founders	Count of number of individuals on the founding team	Colombo and Grilli (2005)
Cohort Size	Count of number of individuals in each accelerator cohort	Uzzi (1996)
Network Density	Ratio of existing ties in the network to the number of possible pair wise combinations of ventures	Schilling and Phelps (2007)

Estimation Methodology

Given the binary nature of the dependent variable, we use a probit model to estimate the probability that a venture will quit (Wooldridge, 2015). First, we enter all control variables to examine their influence on venture quitting (Column 1 of Table 4). Then, we entered the key independent variables, centrality (Column 2), the interaction term between centrality and prior entrepreneurial experience (Column 3), and the interaction term between centrality and external attention (Column 4).

Results

Table 2 provides descriptive statistics and Table 3 provides correlations of all variables. Consistent with our main argument, venture centrality is positively correlated with venture quitting, though the correlation is not significant. Consistent with prior research on entrepreneurial experience, having prior experience is negatively and significantly correlated with quitting. The age of the venture also is negatively and significantly correlated with quitting, supporting the idea that the mortality rate of the firm diminishes with the liability of newness. Attention is also negatively and significantly correlated with venture quitting. We further test these relationships using probit regressions. Table 4 shows regression results.

Column 1 of Table 4 shows the effect of controls on the likelihood of quitting. As predicted, firms with greater attention are less likely to quit, and firms with more entrepreneurial experience are less likely to quit. Older firms and firms in Silicon Valley are also less likely to quit. Column 2 of Table 4 shows the results when we add in centrality. The coefficient on centrality is positive and significant (0.732, $p < 0.05$), providing support for Hypothesis 1. The greater the venture's centrality in the network,

Table 2. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Quit	394	.22	.41	0	1
Centrality	393	.60	.44	0	1
Attention	319	10	9	0	66
Venture Age	394	1.69	2.59	0	15.6
Num Founders	394	2.23	.75	1	5
Density	383	.57	.22	.05	1
Firm Entr Exp	394	.53	.38	0	1
Silicon Valley	394	.60	.49	0	1
Cohort Size	394	40	26	8	82

Table 3. Correlations

	1	2	3	4	5	6	7	8	9
1 Quit	1.00								
2 Centrality	0.03	1.00							
3 Attention	-0.15*	-0.08	1.00						
4 Age	-0.07	0.06	0.08	1.00					
5 NumFounders	-0.03	-0.08	0.02	-0.13*	1.00				
6 Density	0.01	-0.38*	0.02	0.06	0.01	1.00			
7 Entr Exp	-0.20*	0.05	0.00	-0.00	0.24*	-0.16*	1.00		
8 Silicon Valley	-0.03	-0.08	0.03	-0.17*	0.12*	0.07	-0.05	1.00	
9 Cohort Size	-0.10*	-0.06	0.08	-0.17*	0.16*	-0.02	0.06	0.78*	0.01

*p<0.05

the greater the probability the venture will quit. We calculate the marginal effects of centrality at low (25th percentile) and high (75th percentile) levels. Holding all other variables constant at the mean, a low centrality firm has a 6% probability of quitting while a high centrality firm has a 17% probability of quitting. High centrality ventures are about three times more likely to quit than a less connected venture.

Column 3 of Table 4 shows the moderating effect of prior entrepreneurial experience. In hypothesis 2, we predicted that ventures with prior entrepreneurial experience may benefit less from centrality because they have an existing internal

Table 4. Probit Regression Results

VARIABLES	DV: Quit (binary)			
	(1)	(2)	(3)	(4)
Centrality (+)		0.732** (0.346)	0.925** (0.359)	1.902** (0.805)
Centrality*EntrExp (-)			-0.578** (0.269)	
Centrality*Attention (-)				-0.678** (0.328)
<i>Firm Controls</i>				
Attention	-0.329** (0.129)	-0.338*** (0.130)	-0.311*** (0.116)	0.175 (0.277)
Venture Age	-0.222** (0.0925)	-0.259*** (0.0925)	-0.312*** (0.0832)	-0.315*** (0.0991)
Num Founders	0.181 (0.370)	0.156 (0.359)	0.284 (0.370)	0.783** (0.345)
Entrepreneurial Exp	-0.893* (0.458)	-1.068** (0.501)	-1.086** (0.449)	-0.839** (0.382)
Silicon Valley	-0.807** (0.331)	-0.454* (0.274)	-0.846*** (0.172)	-0.297 (0.248)
<i>Cohort Controls</i>				
Cohort Size	0.372** (0.185)	0.272 (0.204)	0.297** (0.139)	0.236 (0.186)
Density	0.155*** (0.0430)	0.375*** (0.0821)	0.252*** (0.0418)	0.298*** (0.0712)
Constant	-0.0339 (0.841)	0.697 (1.093)	0.177 (0.813)	-0.119 (1.285)
Year Dummies	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes
Log likelihood	-65.71	-64.07	-63.16	-60.85
R ²	.2058	.2257	.2380	.2646
Observations	212	212	212	212

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

information source. Our results support this prediction. The interaction term between centrality and firm entrepreneurial experience is negative and significant (-0.578, $p < 0.05$). Figure 3 shows this interaction. Again, to put this finding in perspective, we calculate the marginal effects. When the venture is central in the cohort but have no prior entrepreneurial experience, the venture has a 22% likelihood of quitting. However, when the venture is central and has at least one founder with prior entrepreneurial experience, the venture has a 9% likelihood of quitting. These results suggest that having prior experience may give ventures another source of information about their value that diminishes the usefulness of network centrality, providing support for hypothesis 2.

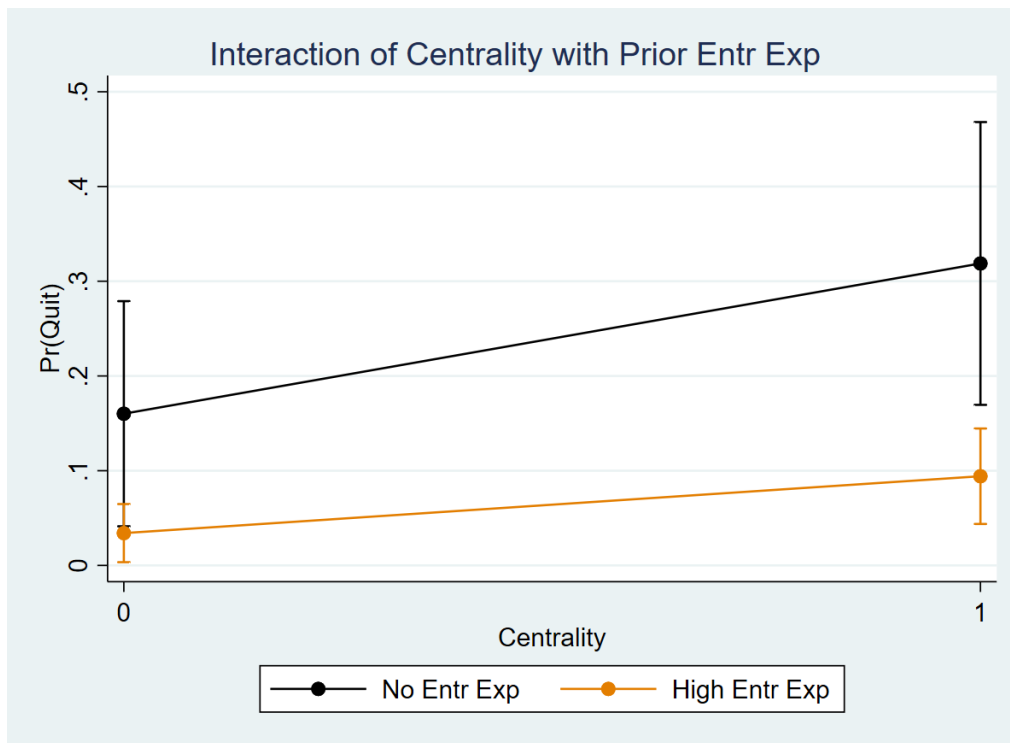


Figure 3. The Interaction of Centrality and Prior Entrepreneurial Experience

Finally, we test the hypothesis that attention also diminishes the usefulness of centrality on quitting (Column 4 of Table 4). The coefficient on the interaction between

centrality and attention is negative and significant (-0.678, $p < 0.05$), providing support for H3. Figure 4 shows this interaction. The more attention the venture receives from external sources, the weaker the relationship between centrality and quitting. The marginal effects show that a central venture that receives little external attention has a 26% likelihood of quitting while a central venture with a lot of attention has a 10% likelihood of quitting. These results provide support for our prediction that attention provides external information that founding teams can use to estimate expected value, which diminishes the effect of centrality as an information source.

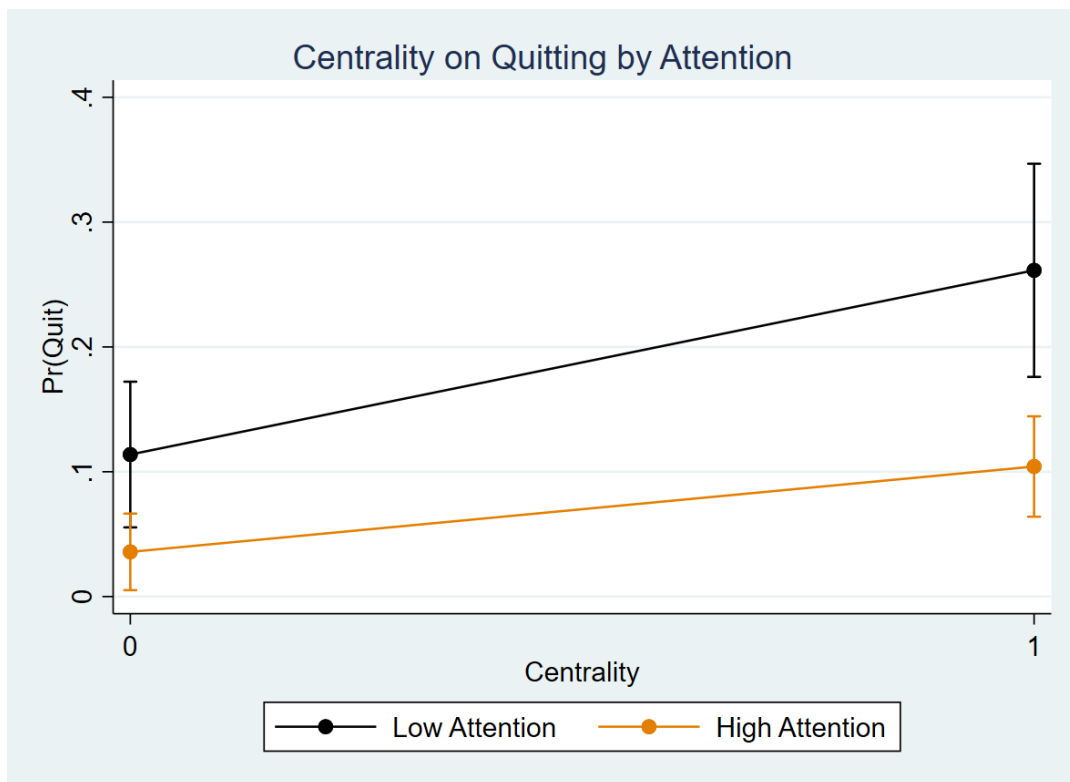


Figure 4. The Interaction of Centrality and Venture Attention

Supplemental Analysis: Deal Quality

We address the case for a weeding out effect. We predicted that the effect of centrality on quitting was due to a weeding out of bad ideas. If this is the case, the central ventures that do not quit should be of higher quality than the peripheral ventures. We examine whether the central surviving firms are worth more. We use data on the amount invested, or the round size, if the venture survives and gets funding. Higher funding amounts represent higher resource commitments and are strong indicators that VCs anticipate higher expected returns from the ventures receiving higher amounts (Wong, Bhatia, & Freeman, 2009).

Table 5 shows the differences in average expected funding amount between low and high centrality ventures. Overall, ventures with greater centrality receive higher funding amounts. Between ventures with no connections and highly central ventures, the difference in funding is about \$160,000. Central ventures that are very different from their cohort receive about \$277,000 more than ventures very similar to their cohort. Similarly, central ventures with at least one founder with prior founding experience receive \$426,000 more than central ventures with no prior experience. These results suggest that, among the ventures that survive, the ventures more central in the network have higher expected values than their less connected counterparts. The group that receives the highest expected funding amounts are the central ventures with prior entrepreneurial experience. But even among the ventures with high prior experience, being connected results in higher round amounts.

Table 5. Average Funding Amounts by Venture Centrality

VARIABLE	Low Centrality	High Centrality
Overall	\$181,679	\$341,123
Novice Entrepreneurs	\$81,785	\$122,700
Experienced Entrepreneurs	\$372,812	\$559,316

Discussion and Conclusion

In this research, we draw on network and entrepreneurship literatures to theorize that founding teams with more robust networks will have access to more information about their venture's quality. We argue that more information will reduce uncertainty about the venture's expected returns. As a result, founding teams will revise expected future returns to a lower level than previously estimated, and this increases the likelihood that the team will quit rather than persist with the venture. We argue that more information from cohort networks will have a negative effect on estimates due to an overconfident overestimation of venture value.

Overall, we predicted that the greater the startup's network centrality, the higher the likelihood of quitting. We find support for this prediction. In addition, we also find that startups with alternative information sources benefit less from central network positions. Because experienced entrepreneurs have more information from past experience, they are less likely to quit and less likely to need information from peers. Startups that receive substantial external attention also have more information about their expected future value. This external information reduces their likelihood of quitting and reduces the impact of information gained from the cohort network.

Our results provide several interesting findings that contribute to the literatures on networks in entrepreneurship and the social influence of peers. First, the literature on networks in entrepreneurship has found an abundance of benefits to having more robust networks (Hoang & Antoncic, 2003). We demonstrate that networks play an important role in another venture outcome - quitting. While scholars have documented the effect of networks on venture survival, we believe that the composition of the network is significant for quitting when composed of peer founders.

Our findings also contribute to the literature on the social influence of peers. While existing research tends to assume that all cohort peers are equally likely to be influenced by their social peers (Lerner & Malmendier, 2013; Kacperczyk, 2013), we show that connectedness matters to the flow of information and the extent to which an individual will be influenced. Moreover, we shed light on why peers may have a negative effect on entrepreneurship. Our results suggest that information from peers lowers estimates because entrepreneurs tend to overestimate the value of their ideas.

Limitations and Future Research

Our study has a number of limitations that provide areas for future research. First, we intentionally studied two of the top accelerators because their programs have had the longest record of reproducible routines that allowed for comparison. However, this may limit the generalizability of our findings. Although we believe that peers are sources of information about venture quality in and outside of accelerators, future research could examine our results in settings that are less regimented, in accelerators that are younger, or with firms that aren't as early stage as the ones in our sample. Prior research has

suggested that the importance of some network ties and configurations change with the life cycle of the venture (Hite & Hesterly, 2001). It would be of theoretical importance to examine whether ties to peers change in importance as the venture matures and more sources of information become available.

Second, the accelerator setting introduces randomization bias. In the real world, people choose to be connected to others. It is highly unlikely that, other than in accelerators and MBA cohorts, founders will be artificially and randomly thrown together. However, we believe that this context does add value in that it allows us to examine and isolate the effect of network position.

Finally, although we predict a negative effect of information on entrepreneur's estimates of value due to overconfidence, we recognize that information may have other effects on venture development. Peers may also transmit information that raises entrepreneurs estimates or is used to further develop their ventures. A natural question arises: what happens to the central ventures that don't quit? If the negative effect is a weeding out effect, where bad ideas are discouraged, then it must be that the better ideas are encouraged. We explored what happens to the central ventures that don't quit given that we had data on other outcomes. However, we found insufficient theory to inform what the performance outcome would be for these ventures. It was unclear whether, contingent on survival, a central venture would be more likely to receive follow-on funding or be acquired. Future research would benefit from the development of theory that would enhance our understanding of the outcome trajectories for these ventures.

In summary, this study explores how a founding team's network position affects venture quitting based on information access and the adjustment of estimates of the

venture's future returns. Relative to less connected ventures with little information access, central ventures with more information are more likely to lower their estimates and cease operations. However, the usefulness of information from networks and the likelihood of quitting diminishes when the entrepreneurs are experienced and when the venture receives more external attention. Thus, our study sheds light on competing sources of information for new ventures and its implications for important firm outcomes.

CHAPTER 2: PEERING INSIDE: PEER COMPOSITION, FOUNDING TEAMS, AND STARTUP OUTCOMES

Introduction

Startups balance simultaneous pressures to rapidly learn and evolve while also differentiating themselves from similar firms in competition for resources. A growing literature on “peer effects” points to the particular salience of learning from the combined experience of similar individuals for nascent entrepreneurs, such as deciding to enter into entrepreneurship (Kacperczyk, 2013; Nanda & Sørensen, 2010) and the evaluation of the viability of ideas (Lerner & Malmendier, 2013). At the same time, startups must differentiate themselves in order to obtain resources for survival and growth. This becomes harder to do as the relative similarity (or overlap) between them increases (Baum, Calabrese, & Silverman, 2000). Competition for scarce resources—such as the attention of venture capital investors or acquirers—becomes more predominant when groups are too similar to one another and occupy overlapping niches (Deepphouse, 1999; Podolny & Stuart, 1995). These tendencies may be exacerbated when companies share common relationships, such as the competition amongst startups within a venture capital portfolio (Fulghieri & Sevilir, 2009; Ozmel & Guler, 2014).

The literature on organizational learning and founding team demography points to initial diversity of functional experience within the founding team as shaping subsequent startup outcomes, such as receipt of VC investment (Beckman & Burton, 2008). More broadly, possession of different types of prior experience leads to distinct insights such as the viability of competing strategic choices (Fern, Cardinal, & O'Neill, 2012) or the recombination of different knowledge (Gruber, Harhoff, & Hoisl, 2012).

These tensions between learning and competition may be amplified in the context of an increasingly prominent feature of the entrepreneurial ecosystem: entrepreneurial accelerators. Recent work demonstrates that accelerators influence both the incidence and timing of entrepreneurial outcomes; specifically, founders going through top accelerators are more likely to exit—through acquisition or through quitting—than are comparable angel-group backed founders (Winston Smith & Hannigan, 2015). A distinctive feature of accelerators is the explicit design of cohorts, which are modeled to a large extent on the university experience (Graham, 2014). Accelerator cohorts represent short “boot camp” periods in which portfolio firms interact extensively with their peers—i.e., the other founders—as well as mentors.

Little is known, however, about the specifics of cohort effects. We posit that the microcosm of the cohort experience should amplify the mechanism for the transmission of both peer learning and direct competition. Further, we suggest that both of these facets—learning and competition—are fostered through the relative similarity between the prior experience of the founding team of a given startup and the distribution of prior experience within the broader cohort. In this paper, the relationship between the founding team and the accelerator cohort provides the focal point for our analysis. We ask: How do learning and competition amongst peer startups impact new venture trajectories?

To answer the question of how peer effects impact entrepreneurial outcomes in accelerators we leverage a novel, hand-collected dataset comprised of all startups that proceeded through 25 cohorts in two established accelerators in the U.S. over the period 2005-2011. We collect data at the founder and startup level on all of the 933 founders of 394 startups that were in 25 cohorts. We track a full range of trajectories that each startup

might follow through 2015: exit through acquisition; exit through quitting; continuation through VC investment; or remaining alive. Thus, we are able to identify outcomes without selecting on a given event (such as receipt of VC financing) having to occur. We distinguish two dimensions of founding team experience prior to entering the accelerator program: prior entrepreneurial/business experience, prior technical (coding and scientific) experience. These dimensions are similar to those the literature on functional experience, but are more finely honed for the parsimonious structure of nascent startups (Beckman & Burton, 2008).

From a research perspective, the composition of a given cohort is exogenous to the founding team. This arises from the specific nature of the top accelerators: partners invest funds in hopes of an outsized return, similar to venture capitalists. Partners in top accelerators also receive far more applications than spots available for any given cohort. In effect, the accelerator cohorts are thus assembled with an eye to the highest expected “successes” that is essentially agnostic as to the mix of companies that will comprise the cohort. We exploit the resulting heterogeneity within each cohort in our analysis.

Our findings point to a substantial role of peer effects that are external to the founding team in shaping the future trajectory of startups. The literature on peer effects suggest that entrepreneurial decisions may be heavily influenced by those imparting knowledge and experience in a cohort environment (Lerner & Malmendier, 2013). We provide evidence that these peer effects occur through both learning and competition amongst startups in a given accelerator cohort. Further, we are able to demonstrate that the relative demographic similarity between the prior experience of the founding team and the prior experience of the cohort as a whole guides the extent of learning and of

competition. To this end, we observe marked differences in trajectory as a function of each different type of experience. All else equal, startup teams with a high share of technical backgrounds in cohorts with a high share of founders with technical backgrounds are more likely to exit via quitting or acquisition, while technical teams in a cohort with a high share of entrepreneurial experience are also more likely to get VC funding. Similarly, startup teams with a high share of business backgrounds in cohort with a high share of founders with business backgrounds are less likely to get VC funding, while the same team in a technical cohort is more likely to get VC funding.

Our research makes several important contributions to the literature. First, by drilling down into the composition of each startup team in every cohort we “peer inside” a unique setting that provides a vantage point for examining a much broader question in the literature: how do peer effects impact entrepreneurs after the point of entry? Thus, we substantially extend the literature that has so far focused largely on the importance of peer effects in the individuals’ decision to become an entrepreneur (Kacperczyk, 2013; Lerner & Malmendier, 2013; Nanda & Sørensen, 2010). Second, our research contributes to the substantial literature on the importance of prior experience in shaping career paths and firm performance (Dencker, Gruber, & Shah, 2009; Gruber, MacMillan, & Thompson, 2008; Shane, 2000; Winston Smith & Shah, 2013). Our current paper adds a new lens on the differential role of distinct types of prior experience in shaping the earliest trajectories of new ventures. As well, we illuminate the role of organizational attributes in channeling collective experiences. Third, we contribute to the deeper scholarly quest to understand the determinants of entrepreneurial success and the strategic dimensions along which founders face opportunities and obstacles (Alvarez &

Barney, 2008; Campbell, Ganco, Franco, & Agarwal, 2012; Fern et al., 2012; Sørensen & Sharkey, 2014; Vissa & Chacar, 2009). In this work, we highlight the significance of the different types of knowledge— on the part of founding teams and their peers—in shaping the ability of startups to navigate critical early decisions regarding exit and financing outcomes. Finally, our paper points to normative solutions for policy makers. The research provides granular insights regarding the critical importance of entrepreneurship in relationship to the broader impact of investment in science, technology, and computer science related endeavors (National Research Council, 2014).

The rest of this paper proceeds as follows. The next section provides theoretical background and develops hypotheses. The following section describes our data, sample, and empirical methodology. We then present empirical results and discussion. The final section concludes.

Theoretical Background and Hypotheses

Peer Effects, Colocation, and Entrepreneurship

A substantial body of literature links social interactions to entrepreneurship. The occurrence of clusters of entrepreneurs in areas like Silicon Valley is tied to the underlying benefits from geographic proximity that facilitates connections between individuals (Saxenian, 1994). Individuals with entrepreneurial social peers are more likely to become entrepreneurs themselves even if the profits are lower and the job alternatives are better because their peers have increased the non-pecuniary benefits of entrepreneurship (Giannetti & Simonov, 2009). Likewise, university peers with prior founding experience transfer entrepreneurial behaviors, attitudes, and information that

reduce the uncertainty of founding a new venture (Kacperczyk, 2013). Overall, social interactions have been found to be salient in entry into an entrepreneurial career.

Peer effects provide a strong mechanism through which social interactions influence entrepreneurship. Studies consistently find that peer groups can be powerful reference points for an individual's behavior (Bandura, 1977). In general, social learning theory suggests that individuals model their behavior after similar others (Bandura, 1986). More specifically, peer groups influence the value of and attitudes toward a particular choice (Giannetti & Simonov, 2009; Sørensen, 2007). Importantly, peer effects broadly influence choices, even when the peers are randomly determined. Sacerdote (2001) finds that randomly assigned freshman year roommates affect not only student's GPA but also the probability of joining certain social groups and fraternities even after the two are no longer roommates.

The peer effects literature suggests that entrepreneurship is heavily shaped by colocation and direct peer interaction. An individual is more likely to take up a new activity with greater spatial and social proximity to his or her referent peers (Wright & Mischel, 1987). The intensity of the cohort experience provides founders with a group of peers going through a similar experience in the same time frame in a similar manner to cultural capital from social bonding and network formation in universities (Bourdieu, 1986). Recent studies suggest that the bonding ties from attending the same college at the same time influence subsequent economic and financial decisions, such as investment decisions regarding portfolio choice (Massa & Simonov, 2011). The accelerator cohorts are co-located and engaging in ongoing collaboration, such as weekly dinners in the Y

Combinator program (Stross, 2012). This type of cohort experience should lead to a strong and unique peer effect.

Prior Experience, Startup Team and Cohort Composition

Peer effects may impact outcomes through two mechanisms: mentoring and observational learning (Kocher, Sutter, & Wakolbinger, 2014). Receiving advice or mentoring forces decision-makers to think differently about a problem than they would have otherwise (Schotter, 2003), increases the depths of reasoning, and accelerates the learning process (Sbriglia, 2008). Participants in a beauty contest game who received advice had permanent positive effects on outcomes over participants who received no advice (Kocher et al., 2014). Peer effects may also be salient in cohorts because the spatial propinquity amongst founders allows for easy observability of peers (Kacperczyk, 2013). Beauty contest participants who learned from observing their peers also had positive effects on outcomes over participants who did not observe their peers (Kocher et al., 2014). Further, these effects may be particularly strong because peers in a cohort are competitors vying for the same resources and attention (Bothner, 2003). When peers occupy substitutable positions, they “locally monitor and affect each other’s choices” (Burt 1987, p. 1291; Bothner 2003, p.1176).

The career arc of an entrepreneur relies on context (Aldrich & Ruef, 2006; Kacperczyk, 2013). Whether an individual has entrepreneurial role models greatly affects underlying attitudes about the desirability and legitimacy of becoming a founder (Roach & Sauermann, 2013; Stuart & Ding, 2006). Moreover, role models can impact entrepreneurial outcomes. Peer and familial role models with entrepreneurial experience

convey information about opportunities, transfer know-how, and facilitate access to resources (Kacperczyk, 2013; Nanda & Sørensen, 2010), which in turn decreases the likelihood of venture failure (Cooper, Gimeno-Gascon, & Woo, 1994). Similarly, having industry-specific knowledge, either directly or accessed through peers' knowledge, transfers information about market needs and facilitates the commercialization of the venture's technology (Gruber, MacMillan, & Thompson, 2012), which contributes to both decreasing venture failure and increasing venture growth (Cooper et al., 1994).

Accelerator cohorts provide a unique setting to uncover the mechanisms behind the effects of diversity of prior experience and entrepreneurial outcomes. Each cohort may be either diverse or concentrated in prior experience and will influence diverse and concentrated entrepreneurial teams differently. The context of peer influence in accelerator-based cohorts lies in the fit between the composition of the entrepreneurial team and the cohort. Prior founding team literature demonstrates the inherent struggle for balance between diversity and homophily in the background of founders (Ruef, Aldrich, & Carter, 2003). Founding teams with strong overlap in prior organizations tend to exploit their ideas faster while founding teams with weaker overlap tend to produce more valuable and innovative ideas (Beckman, 2006).

Founding teams bring two significant types of prior experience to each cohort – technical and business experience. We focus on these two dimensions of experience because human capital that supports technological development and growth in the market holds the greatest potential for providing resources that are important for new venture outcomes (Vandenbroucke, Knockaert, & Ucbasaran, 2016). We expect that peer effects of these experience dimensions will be salient at both the team and cohort levels.

Technical and Scientific Experience and New Venture Outcomes

In examining founding team composition, Eesley, Hsu, and Roberts (2014) point out that in high technology ventures, where technical issues are the greatest source of complexity, prior experience in technical fields is more important on the founding team. A greater concentration of technical experience within the team and the cohort will provide better knowledge and expertise regarding what technical or scientific innovations have been tried before. Additionally, a greater concentration of technical peers increases firms' connections to the external technical community, which can be helpful for providing information and overcoming technical challenges that would impede successful outcomes. Technical expertise provides the knowledge needed to solve detailed problems, which can reduce deficiencies in implementing technical ideas (Beckman, 2006).

Recent research supports these benefits of technical expertise. Specifically, studies have found that founding teams with technical backgrounds have a greater likelihood of exiting by IPO or acquisition (Eesley et al., 2014) and have higher performance and exit rates when they start a venture in their technical field of education (Braguinsky, Klepper, & Ohyama, 2012).

Prior Business Experience and New Venture Outcomes

Prior studies have highlighted the importance of prior business experience of founders for several reasons. Prior business-related experience, such as having held a prior managerial position, can aid in the learning activities new ventures, and subsequent survival (Dencker, Gruber & Shah, 2007). Founders take general human capital gained

from prior management experience and apply it directly to their new firm (Columbo & Grilli, 2005). Prior research has also shown that venture capitalists value prior management experience when evaluating proposals, increasing the likelihood of receiving VC funding (MacMillan et al., 1985).

Other types of business experience, such as having founded a prior venture, uniquely enable founders to be able to decide when to keep going and when to pull the plug (Arora & Nandkumar, 2011). Repeat entrepreneurs also have greater access to financing (Westhead & Wright, 1998) and knowledge of how to launch and commercialize ideas (Gruber, 2009). Wennberg et al. (2010) find that prior entrepreneurial experience increases the likelihood of an exit by acquisition over any other trajectory. Experienced entrepreneurs are also more likely to receive VC funding. Venture capitalists view prior entrepreneurial experience favorably because it signals a greater ability to build a high potential venture and a willingness to exit (Wennberg et al., 2010). In their study of new ventures in the information security industry, Arora and Nandkumar (2011) show that experienced founders cash out more quickly (favorable acquisition) but also fail faster.

While this literature clearly demonstrates that prior experience is salient in the outcome trajectory of the startup, startup teams are rarely insulated from the experiences of those around them. In fact, entrepreneurs rely heavily on their interpersonal networks and social environment to supplement their experience (McEvily & Zaheer, 1999; Baum, Calabrese & Silverman, 2000). The literature on the social influence of peers argues this perspective, finding that the experience of those around you affects behaviors and outcomes (Kacperczyk, 2013; Nanda & Sørensen, 2010). However, much less attention

has been paid to how peer knowledge interacts with an individual’s knowledge. For instance, does exposure to peers with entrepreneurial experience affect two people the same way when one already has prior entrepreneurial experience and the other does not?

The Interaction of Experience at the Startup and Cohort Levels

This paper opens this black box by separating experience into specific domains and examining the interaction of a startup team’s experience with the experience of their peers in the cohort. We examine the concentration of business and technical experience at the founding team level and the cohort level. Figure 5 depicts four possible combinations of the relative similarity of startup teams and cohorts.

		Cohort Concentration	
		Technical Experience	Business Experience
Team Concentration	Technical Experience	<ul style="list-style-type: none"> • Learning: all tech cohort, business weakness • Competition: no one stands out 	<ul style="list-style-type: none"> • Learning: peers advise on VCs and how to commercialize • Competition: tech teams stand out
	Business Experience	<ul style="list-style-type: none"> • Learning: peers add much needed technical advice • Competition: business teams stand out 	<ul style="list-style-type: none"> • Learning: all business, tech weakness • Competition: no one stands out

Figure 5. Startup Team-Cohort Experience Interaction

We expect that teams in dissimilarly experienced cohorts will have higher likelihoods of favorable outcomes while teams in similarly experienced cohorts will not. We expect this for two reasons. First, the literature on prior experience highlights the value of complementary knowledge and the pitfalls of substitutable knowledge to

founding teams. Receiving new knowledge from others has benefits for favorable firm outcomes while receiving redundant knowledge may impede them. Second, the literature on competition suggests that, in a struggle for resources, firms that differentiate from the pack will stand out more, increasing their chances of an acquisition.

Concentrated teams consist of similar founders that share a depth of understanding in their functional area as well as shared language and routines (Tsai and Ghoshal, 1998; Beckman, 2006). The strong ties amongst a concentrated team facilitate faster implementation of ideas (Beckman, 2006). Participation in a similarly concentrated cohort creates an even larger collective mind (Chowdhury, 2005) that will likely only marginally influence within-concentration activities. In fact, peers in similarly concentrated cohorts tend to communicate redundant knowledge (Beckman, 2006). As a result, concentrated teams are less likely to receive knowledge they lack from a similarly concentrated cohort of peers. Startups that lack access to complementary capabilities may face negative performance consequences. Beckman and Burton (2008) demonstrate that founding teams with narrow functional experience have difficulty adding experienced executives and are less likely to succeed than broadly experienced teams. Teams that lack complementary capabilities don't have the range of skills needed to grow and develop a venture, increasing the likelihood of quitting due to an inability to acquire the resources they need.

Technical teams in technical cohorts may be more likely to quit, relative to technical teams in business cohorts, because they lack knowledge of how to grow and develop business ideas (Colombo & Grilli, 2005). Colombo and Grilli (2005) argue that prior managerial experience in other firms helps new ventures to grow. Prior

management experience has been found to positively affect economic performance (Gimeno et al., 1997), preventing quitting due to low performance. Dencker, Gruber and Shah (2007) find that prior management experience helps firms survive by increasing the effectiveness of learning activities. Moreover, technical teams may have higher opportunity costs of entrepreneurship, which increases the likelihood of accepting greater risks of failure. Arora and Nandkumar (2011) show that human capital, particularly pre-entry experience of the founding team, increases the threshold of acceptable profitability of the venture. The authors point out that what drives this threshold higher is the quality of the entrepreneur and of the idea itself. Founding teams with technical experience tend to have better ideas because they have knowledge of what has been tried and what has succeeded and failed (Eesley, Hsu & Roberts, 2013). As a result, they are better able to discern when to keep going and when to pull the plug (Arora & Nandkumar, 2011). In this type of team-cohort interaction, technical teams are unable to gain complementary skills that support survival and growth, and are surrounded by technical peers whose expertise may encourage them to pull the plug rather than continue.

Business teams in business cohorts may also be more likely to quit, relative to business teams in technical cohorts. While these teams have the experience that supports growth and commercialization, they lack the complementary skills that prevent technical failure. Prior research shows that teams with technical experience have the expertise that may prevent failure from technical issues or complexity (Dencker, Gruber & Shah, 2009; Eesley, Hsu & Roberts, 2013). In this type of team-cohort interaction, business teams lack these complementary technical skills within their teams and are unable to gain them from social interaction with their cohort peers.

Hypothesis 1: The probability of quitting will be greater for teams in similarly experienced cohorts than for teams in dissimilarly experienced cohorts.

Teams with technical experience should also be more likely to exit by acquisition in a predominantly technical cohort, relative to technical teams in a dissimilar cohort. Because technical teams have high opportunity costs, they are more likely to exit by acquisition. Arora and Nandkumar (2011) find that high-opportunity-cost entrepreneurs will invest more aggressively, making them more impatient for success and increasing the chances of acquisitions. In their study of technically focused founding teams, Eesley, Hsu, and Roberts (2013) report that having greater expertise, more ties to the external technical community, and shared language and routines enable ventures to have better skills and coordination, which in turn enables new ventures to have more successful exits. Technical teams in technical cohorts may benefit from a depth of expertise and shared language that amplifies the effects of technical expertise within the startup team. In this type of team-cohort interaction, teams tend to have valuable, technically sound ideas, which attract acquisition offers, but lack the skills needed to fully commercialize and grow the ideas, increasing the probability of an exit by acquisition.

Hypothesis 2: The probability of an exit by acquisition will be greater for teams with technical experience in a technical cohort than for teams in dissimilarly concentrated cohorts.

Cohorts of peers with dissimilar experience may introduce novel ideas and fresh perspectives to startup teams. Fresh perspectives can open up new market opportunities (Gruber, MacMillan & Thompson, 2012; Shane, 2000) and introduce distant knowledge that can lead to innovative recombination (Hargadon, 2003).

Teams with broad experience in multiple domains have the full range of capabilities needed to thrive, and tend to obtain VC funding more quickly (Beckman & Burton, 2008). In particular, the combination of market pioneering know-how and technological know-how has synergistic effects (Griffin & Hauser, 1996; Teece, 1986; Agarwal et al., 2004). Technical teams tend to have better ideas but lack commercialization skills. Business teams lack knowledge that prevents failure from technical deficiencies but have know-how of how to launch, commercialize, and bring those ideas to fruition. Colombo and Grilli (2005) show that there are gains from combining complementary capabilities of founders relating to technical and commercial experiences. The synergistic effects of complementary knowledge should increase the value of the idea. In a predominantly business cohort, technical teams can learn from their peers with business experience, gaining the complementary skills needed to commercialize and grow. As one of few in the cohort, technical teams will also be more likely to stand out amongst their peers and attract the attention of investors. Likewise, business teams can learn from their peers with technical experience, gaining the complementary knowledge needed to improve technical aspects of their venture. As one of few in the cohort, business teams will also be more likely to stand out amongst their technical peers and attract the attention of investors.

Hypothesis 3: The probability of receiving VC funding will be greater for teams in dissimilarly concentrated cohorts than for teams in similarly concentrated cohorts.

Data and Methodology

Sample Selection and Data Collection

We focus on two of the top-ranked and longest-operating accelerators in the U.S., Techstars and Y Combinator. Both are widely identified as leaders and pioneers in establishing this organizational form in the area of early stage venture financing (Geron, 2012; Gruber, 2011). As such, they have clear and reproducible routines for selecting startups and mentoring and monitoring the startups progress during the cohort period. We identified the full census of startups that passed through each program between 2005 and 2011, in a total of 25 distinct cohorts.

The focal unit of analysis is the individual startup and its founding team. We track exit and funding outcomes for all startups through 2015. VentureXpert was the core source of data for investment and acquisition outcomes. We use Crunchbase for additional data on investment and acquisition events, current status, and investor profiles. Finally, we searched SEC filings, databases of Forbes and BusinessWeek magazines, and websites of startups and investors for missing or incomplete information.

We collect data on each member of the founding team in our sample from multiple sources. We started with the websites provided by Techstars and Y Combinator, which list startups by cohort. We then scoured LinkedIn, Crunchbase, technology blogs, and the startups' websites for the complete founding team list. Our dataset examines founder characteristics and entrepreneurial outcomes experienced by the startup through 2015. The dataset captures information on the complete work and education histories of each founder involved in each startup. The final sample is a dataset of n=394 startups and n=933 founders.

The online database Crunchbase is an open and public source of startup information, and includes key event details that cover all the possible entrepreneurial outcomes, but is in itself not a complete source of data. We corroborated startup characteristics and event details by searching through SEC filings, and the popular business press.

The extent to which our data collection process relied on corroborating sources depended in some part on the nature of the firm, founder, and entrepreneurial outcome. For example, firms that are acquired generally announce the deal in the media and online. Crunchbase lists firms that are shut down but to carefully corroborate this data we developed a careful process of tracking firms' activities and matching them to founder backgrounds. Firms that updated websites regularly and continued to post to existing social media network profiles, such as Twitter and Facebook, were determined to be alive. However, a lapsed internet presence, coupled with a paucity of technology blog coverage and a change in career histories for all of the founders on LinkedIn or Crunchbase indicated that the firm had been shut down.

Crunchbase also has information that extends many of the details found in Venture Xpert, such as founder backgrounds, including education and work histories prior to and after moving through a top accelerator program. At a minimum, this data informed us who was on each founding team, and in many cases, these sources gave us complete career biographies of each founder. To complete this data collection process however, we supplemented the founder histories with extensive data from LinkedIn.com, the well-known publicly traded social media network designed to share career histories (NYSE: LNKD). For each founder, we collected data on each job held over the course of

their careers, including dates, job titles and descriptions, and employer characteristics. This data was corroborated using technology blogs, the popular business press, and founder profiles on other social media network platforms, such as Twitter and Github. By triangulating from a variety of sources, we were able to confirm existing details and fill in any gaps.

Each founder in our dataset has a record of work and education history. The structure of each record follows that of each LinkedIn profile. That is to say, each item of work or education history contains a title (ie. Program Manager, or Bachelor, Computer Science) as well as the name of the firm or institution at which it took place (i.e. Google, or Harvard University). Similarly, the record contains the relevant dates during which this experience took place. Key characteristics regarding the firm or institution make up the balance of the founder records on the work and educational dimensions.

Our primary interest is experience that took place prior to entering into an accelerator program. Consequently, for each experience field in each founder record, we compared the dates of work and education history with the entry date into the accelerator program. We include experience that occurred prior to the focal startup.

Measures

Dependent Variables

Our dependent variables consist of all the possible entrepreneurial outcomes that an early stage firm may experience: exit via acquisition, exit via quitting, receiving the first round of VC follow-on financing, receiving subsequent rounds of VC financing, and

simply remaining alive with just the initial accelerator funding.² Each of these outcomes is a discrete event for the firm, as measured at June 2013. This is not to suggest that a startup may not experience one or more event. For example, a startup that receives a first formal round of VC in 2010 and is acquired in 2011 is coded as having been acquired.

We identify two distinct exit outcomes. *ExitByAcquisition* is a dichotomous variable that is equal to 1 if the startup has been acquired. Similarly, *ExitByQuitting* is dichotomous variable that captures an event in which founders have quit and the startup no longer functions.

For startups that receive venture capital financing, we distinguish between receiving a first formal round and any subsequent rounds. The rationale for this distinction is simple: firms must first enter into the venture capital ecosystem which is in itself a difficult and potentially costly decision, given the equity demands of VCs (Hsu, 2004). Subsequent rounds indicate a commitment to the VC financing track and an indication of additional growth on the part of the startup. Therefore, *VC Round1* is a dichotomous variable representing a single round of VC financing, while *VC Round2+* indicates that the startup has received additional rounds.

Focal independent variables

To test the relative similarity between each founding team and its broader cohort, we first create variables characterizing the prior experience of each founding team. We

² A final outcome possibility in the entrepreneurial ecosystem is an initial public offering (IPO), but we did not observe any in our dataset. This is not surprising, given the age of the startups entering the accelerators; IPOs would be relatively unexpected Ritter, J. R. 2014. Initial Public Offerings: Updated Statistics. In University of Florida (Ed.), Ritter, J. R. 2014. Initial Public Offerings: Updated Statistics. In University of Florida (Ed.).

then do the same to characterize each cohort. Finally, we use these two variables to create the final variables that capture the interaction of experience between the team and cohort.

Creating founding team variables

In keeping with the peer effects literature, we have developed measures of prior founder experience that may influence other cohort members in different ways: prior industry experience and prior entrepreneurship experience. Prior experience may fall along different dimensions. As the literature has argued, learning from peers may serve as a strong influence on future decisions (Bandura, 1986). The social interactions between founders can be tied to education (Kacperczyk, 2013; Lerner & Malmendier, 2013), industry ties (Nanda & Sørensen, 2010), or simply shared connections on the basis of entrepreneurship itself (Saxenian, 1994).

Founders were coded as having prior experience in the areas of entrepreneurship/business or management fields, and technical programming/scientific fields. Experience that took place prior to entering into an accelerator program took on two dichotomous variables for each founder: PriorExp_Entrepreneurship, PriorExp_Coding, PriorExp_BusFunction, and PriorExp_SciTech. Constructing measures of work and entrepreneurial experience required in-depth text analysis of each founder's career history. The specifics of how each variable was coded are described below.

The literature has long argued that entrepreneurship is distinct from industry work. For instance, the status as a company founder places an individual clearly into the entrepreneurial space (Begley, 1995). Classifying "Founder" in the work experience data therefore served as a starting point in coding entrepreneurship experience. Other terms

included “entrepreneur” and similar terms, such as “founding partner”. Founders who possessed prior entrepreneurial experience according to these criteria were assigned a value of 1 for PriorExp_Entrepreneurship and 0 otherwise.

Industry work experience fell naturally into different categories. The nature of the accelerator model is to focus on nascent startups with scalable growth trajectories and low startup costs (Stross, 2012). Many of these firms come from software-based industries (Winston Smith & Hannigan, 2015). Therefore, it was not surprising to find that many founders have backgrounds in software coding and programming. Founders were classified as having coding/programming backgrounds if job titles included the following terms: programmer, developer, software, platform, architect, systems, digital product, designer, hacker, WebDev, or computer. Founders who possessed prior coding experience according to these criteria were assigned a value of 1 for PriorExp_Coding.

Business functions relate to the growth and ultimate organization of the nascent firm: these are vital success factors in the exploitation of novel ideas (Shane & Venkataraman, 2000). The constituent business functions that make up the organization: product management, accounting, sales, finance, marketing, etc. all comprise relevant points of experience for founders of nascent startups. Therefore, we identified founders as having business function experience if career histories included keywords related to the organizational elements of running a firm. Founders who possessed prior coding experience according to these criteria were assigned a value of 1 for PriorExp_BusFunction and 0 otherwise.

The final dimension of work history that we considered was scientific and technical experience. To the extent that entrepreneurship, coding/programming, and

business function jobs offer experience germane to the accelerator-backed startup's coalescence into developed organization, scientific and technical experience may be the key to growth (Colombo & Grilli, 2005). Within software driven startups, external knowledge and ideas may offer new applications and trajectories. Therefore, we identified founders as having prior scientific and technical experience if past employment data noted terms such as technical, scientist, biologist, chemist, or engineer. Founders who possessed prior coding experience according to these criteria were assigned a value of 1 for PriorExp_SciTech and 0 otherwise.

Founding team and cohort concentration by type of experience

Once founders were labeled individually, they were aggregated to the startup level along the four experience dimensions. This provided a count of the number of founders within each startup that had experience in entrepreneurship, coding/programming, and scientific/technical, and business function jobs prior to entering their respective accelerator programs. We also identified the total number of founders at the startup level, resulting in FounderCount, a simple count variable. We then used the counts of founders within the startup team that had specific type of experience as the numerator and FounderCount as the denominator to create measures of the share of each startup of that had those types of experience. This process ultimately yielded the variables FirmShare_Entrepreneur, FirmShare_Coder, FirmShare_SciTech, and FirmShare_BusFunction. We start with these four experience variables so that we are able to test the effects of each specific type of experience later. However, we combine these four variables into two: entrepreneurial/business and scientific/technical. Prior

studies show that entrepreneurial and business experience both contribute to startup activities related to commercializing and launching a venture, while coding and scientific experience both contribute to the development of the main technology or product (Vandenbroucke et al., 2016; Eesley et al., 2014; Agarwal et al., 2004). To create these two variables, we add the two partner FirmShare variables.

Startups that pass through accelerator programs do so in cohorts (Stross, 2012). We created variables that measure the size of individual cohorts, by firm (TotalFirmsPerCohort) and founder (TotalFoundersPerCohort). The latter variable served as the denominator to calculate the share of each cohort that contained our relevant experience metrics, generating the variables CohortShare_Entrepreneur, CohortShare_Coder, CohortShare_SciTech, and CohortShare_BusFunction. Similar to what we did for the firm share variables, we also create combined variables of entrepreneurial/business and coding/scientific experience at the cohort-level.

Creating Founding Team-Cohort Relative Experience Variables

Our hypotheses examine the differentials of concentration at the firm and cohort level. We created interaction terms of FirmShare and Cohort Share along both experience dimensions, yielding the variables FirmTech_CohortTech, FirmTech_CohortBus, FirmBus_CohortBus, FirmBus_CohortTech. For the variables that examine the same experience at the team and cohort level (FirmTech_CohortTech, FirmBus_CohortBus), a greater the value indicates a greater similarity between the team and cohort. For the variables that examine the opposite experience (FirmTech_CohortBus, FirmBus_CohortTech), a greater value indicates greater dissimilarity.

Controls

We control for a number of factors that might influence outcomes. Specifically, we include controls for the number of founders of the startup team, number of founders in the cohort, year of entry into the accelerator program, and age of the startup at entry. The latter two account for both the age of the startup entering into the accelerator program and capture any differential effects over time that stem from the evolution of the accelerator form of organization.

We include dummy variables for startup locations. The control variables tied to StartupHQ map the founding location of each startup. We clustered founding locations into six broad clusters: California, the western (i.e., Washington), northeastern, southeastern, and midwestern United States, as well as those outside of the U.S.

We also include dummy variables for industry level effects. For basic industry classifications, we relied on the industry tag assigned by Crunchbase and parsed the data into six distinct sub-industry clusters: Music, Gaming, and Media; Social Media, Location, and Mobile Apps; Payment and Commerce; Web Business; Underlying Technology, and Other Industry.

Empirical Strategy

In this paper, we seek to evaluate the peer effect dynamics within accelerator cohorts. These effects are posited to have an influence on entrepreneurial outcomes, each of which is a distinct state for the startup at the time of measurement. Because we are interested in the relative likelihoods of multiple outcomes we utilize a multinomial logit framework (Greene, 2008; Wooldridge, 2002). We consider the relative likelihood of

each outcome (measured as the final outcome as of June 2013): ExitByAcquisition, ExitByQuitting, VC Round2+ (which includes all further rounds of financing). We model these outcomes relative to the baseline outcome of remaining Alive, in which startups receive only the initial round of accelerator funding but do not yet receive additional investment from VCs and do not exit.

Multinomial logit models assume that the choice between alternative outcomes are not influenced by which alternatives are in the choice set (McFadden, 1974). However, since there may be correlation between outcomes that represent an “exit” choice (ExitByAcquisition and ExitByQuitting) and outcomes that represent a choice to not exit the venture (Alive and VC), we must first test the independence of irrelevant alternatives (IIA) assumption (McFadden, 1974). Results of the Hausman chi-squared tests of the IIA assumption showed that there is no evidence to reject the null hypothesis that our outcome alternatives are independent (Somaya, Kim, & Vonortas, 2011). Therefore, the results support the use of the multinomial logit model.

Each startup is characterized by a vector of covariates, X , and the coefficient vector β . The multinomial logit specification allows covariates to have different effects for each outcome. We estimate the likelihood of each of the alternative outcomes, $j=1, \dots, j$ using multinomial logit regression (Wooldridge, 2002, Ch. 15). For outcomes $j = 1, \dots, j$ we estimate:

$$\Pr(Y = j | x) = \exp(xb_j) / \left[1 + \sum_{h=1}^J \exp(xb_h) \right]$$

In multinomial logit estimation, the probability of all outcomes sums to unity. The baseline is outcome h , (Alive), where:

$$\Pr(Y = 0 | x) = 1 / \left[1 + \sum_{h=1}^J \exp(xb_h) \right]$$

Results

Univariate Statistics

The summary statistics of our sample can be found in Table 6. Both the firm and cohort share variables show that prior entrepreneurial experience is the most prevalent career history, followed by coding, scientific and technical, and business function. The average year of entry into an accelerator program was 2009, six months ahead of the average year of founding, which is consistent with trajectory of nascent firms receiving accelerator funding.

The statistics on outcomes show that startups exit via quitting slightly more often than they do via acquisition, with roughly one fifth of the sample each. 9% of startups receive just a first formal round of venture capital, while 6% get a second round or more. The remaining 46% of firms in the sample are classified as being alive, or having received the accelerator funding but not experienced any further entrepreneurial outcomes.

A correlation matrix can be found in Table 7. Cohorts vary from 8 to 42 startups. Within cohort correlations, such as that between entrepreneur and business function shares, are interesting, given that the distribution of founders and teams within a cohort is random (to the startup).

Multinomial Regression Analysis

Table 8 contains our full multinomial logit regressions. Each column of Table 8 shows the effect of the founding team and cohort composition on the three possible

Table 6. Summary Statistics

Variable	Mean	SD	Min	Max
Firm Share Entrepreneur	0.5746	0.3754	0	1
Firm Share Coder	0.3124	0.3270	0	1
Firm Share SciTech	0.2538	0.3171	0	1
Firm Share BusFunction	0.1549	0.2869	0	1
Cohort Share Entrepreneur	0.3720	0.195	0.0625	0.8500
Cohort Share Coder	0.1952	0.0741	0.0810	0.4000
Cohort Share SciTech	0.1562	0.0774	0.0405	0.4285
Cohort Share BusFunction	0.1028	0.0813	0	0.3043
Startup Team*Cohort Experience				
Tech Team in Bus Cohort	0.2638	0.3248	0	2.3
Tech Team in Tech Cohort	0.2088	0.2383	0	1.28
Bus Team in Tech Cohort	0.2706	0.2320	0	1.28
Bus Team in Bus Cohort	0.3929	0.4081	0	2.3
Controls				
Ln Founders Per Cohort	4.2325	0.8463	2.7080	5.2257
Ln Number Founders	1.1453	0.2366	0.6931	1.7917
Age at Enter	1.697	2.59	0	15.62
Year Enter	2009.3	1.6572	2005	2011

Table 6: (continued)

Variable	Mean	SD	Min	Max
IndustrySocialLocationMobile	0.2969	0.4574	0	1
IndustryPaymentCommerce	0.1852	0.3890	0	1
IndustryWebBusiness	0.1700	0.3761	0	1
IndustryUnderlyingTech	0.1598	0.3669	0	1
IndustryMediaMusicGaming	0.1345	0.3416	0	1
StartupHQCalifornia	0.5355	0.4993	0	1
StartupHQWest	0.1649	0.3716	0	1
StartupHQSouth	0.0203	0.1412	0	1
StartupHQNortheast	0.2081	0.4064	0	1
<hr/>				
Outcomes				
Quit	0.2258	0.4186	0	1
Acquired	0.1928	0.3950	0	1
Alive	0.4644	0.4993	0	1
VC	0.0939	0.2920	0	1

dependent variables: exit by quitting, exit by acquisition, and the receipt of follow-on VC funding. In H1, we predicted that the likelihood of an exit by quitting would be highest for teams in cohorts with similar experience (technical teams in technical cohorts and business teams in business cohorts). Column 1 shows that technical teams in technical cohorts are more likely to exit by quitting ($\beta=4.850$, $p<0.01$) than technical teams in a business cohort ($\beta=-3.110$, $p<0.01$). However, the coefficient on business teams in business cohorts is not significant. Taken together, this provides some support for H1.

Table 7. Correlation Matrix

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)
FirmShareTechExp	1.00								
FirmShareBusExp	0.002	1.00							
CohortShareTechExp	0.13*	0.22*	1.00						
CohortShareBusExp	-0.03	0.35*	0.70*	1.00					
NumFounders	-0.02	-0.17*	-0.12*	-0.14*	1.00				
Age	-0.05	0.15*	0.08	0.21*	-0.08	1.00			
CohortSize	0.15*	-0.07	-0.36*	-0.61*	0.16*	-0.13*	1.00		
Silicon Valley	0.11*	-0.17*	-0.33*	-0.63*	0.12*	-0.15*	0.72*	1.00	
Serial Entr	0.06	0.12*	0.05	0.04	0.12*	0.01	0.06	-0.01	1.00

*p<0.05

Table 8. Multinomial Logistic Regressions

VARIABLES	(1) Quit	(2) Acquired	(3) VC
<i>Technical Teams</i>			
Tech Teams in Tech Cohorts	4.850*** (1.154)	2.409** (1.096)	0.301 (1.391)
Bus Teams in Bus Cohorts	-0.740 (0.955)	-1.150 (1.081)	0.811 (0.847)
<i>Business Teams</i>			
Bus Teams in Tech Cohorts	-0.688 (1.549)	0.330 (1.882)	-1.748 (1.771)
Tech Teams in Bus Cohorts	-3.110*** (0.931)	-1.736** (0.790)	0.287 (0.801)
<i>Firm & Cohort Controls</i>			
NumFounders	0.110 (0.277)	0.677** (0.282)	0.381 (0.326)
Age	-0.0905** (0.0437)	-0.186** (0.0749)	-0.00617 (0.0409)
Cohort Size	-0.861*** (0.334)	-0.985*** (0.274)	-0.0774 (0.301)
Silicon Valley	0.0573 (0.547)	0.328 (0.414)	-0.123 (0.404)
Serial Entr	-0.603* (0.338)	0.108 (0.296)	0.589** (0.244)
Constant	3.111*** (0.987)	2.377*** (0.894)	-1.044 (1.061)
Year & Industry Dummies	Yes	Yes	Yes
Observations	394	394	394

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 9 shows the results when we separate business and entrepreneurial experience. It may be that the insignificant results are due to the fact that these two types of experience are quite distinct. Column 1 provides some additional insight into H1. The signs on business experience are in the predicted directions but are insignificant. Interestingly, entrepreneurial experience seems to have the opposite effect.

Table 9. Regressions Separating Business and Entrepreneurial Experience

VARIABLES	(1) Quit	(2) Acquired	(3) VC_
<i>Technical Teams</i>			
Tech Teams in Tech Cohorts	3.566*** (0.907)	1.598** (0.708)	0.430 (0.669)
Tech Teams in Bus Cohorts	-4.089*** (1.000)	-2.140*** (0.745)	-0.590 (0.649)
Tech Teams in Entr Cohorts	3.533*** (0.807)	1.494** (0.739)	1.578** (0.621)
<i>Business Teams</i>			
Bus Teams in Bus Cohorts	1.839 (1.701)	-3.356 (2.797)	-5.381** (2.646)
Bus Teams in Tech Cohorts	-2.124 (2.547)	4.761 (3.577)	4.690* (2.640)
<i>Entrepreneurial Teams</i>			
Entr Teams in Entr Cohorts	3.258 (3.183)	3.894 (2.951)	6.384** (3.179)
Entr Teams in Tech Cohorts	-2.178* (1.308)	-3.266** (1.572)	-2.978* (1.803)
<i>Firm & Cohort Controls</i>			
NumFounders	0.510 (0.352)	1.079** (0.445)	0.413 (0.641)
Age	-0.113 (0.0740)	-0.253** (0.111)	-0.0577 (0.0590)
Cohort Size	-1.290*** (0.371)	-1.264*** (0.383)	-0.742* (0.405)
Silicon Valley	0.277 (0.574)	0.353 (0.544)	0.454 (0.632)
Serial Entr	-1.214** (0.565)	-0.0567 (0.444)	0.674** (0.311)
Constant	3.267*** (1.103)	2.529** (1.178)	0.372 (1.795)
Industry & Year Dummies	Yes	Yes	Yes
Observations	336	336	336

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

That is, entrepreneurial teams in technical cohorts are more likely to quit ($\beta = 5.6$, $p < 0.05$), while entrepreneurial teams in similarly concentrated cohorts are less likely to quit ($\beta = -5$, $p < 0.1$). This suggests that highly concentrated cohorts of entrepreneurial peers may be helping each other improve their ideas, preventing failure. On the other hand, entrepreneurial teams in dissimilarly concentrated cohorts may be learning from peers with fresh perspectives that may expose technical flaws in their ideas.

In hypothesis 2, we predicted that the probability that a venture would exit by acquisition would be greatest for technical teams in technical cohorts than for technical teams in business cohorts. Column 2 of Table 8 shows a positive and significant coefficient for technical teams in technical cohorts ($\beta = 4.9$, $p < 0.01$) and a negative and significant coefficient for technical teams in a business cohort ($\beta = -2.7$, $p < 0.05$), providing support for hypothesis 2.

Finally, we predicted that the probability of receiving VC funding would be greatest for teams in cohorts with dissimilar experience (technical teams in business cohorts and business teams in technical cohorts) than for teams in cohorts with similar experience. Column 3 of Table 8 shows that none of the combinations of team-cohort interactions are significantly more or less likely to get VC funding. However, when we examine the business and entrepreneurial experience separately again, we find some support for hypothesis 3. Column 3 of Table 9 shows that business teams in business cohorts have a negative probability of getting funding ($\beta = -5.381$, $p < 0.05$), while business teams in technical cohorts have a positive and significant probability of getting funding ($\beta = 4.690$, $p < 0.1$). This suggests that too much of the same business experience may negatively impact outcomes. Business teams in business cohorts are likely receiving

redundant information. Further, because all teams are similarly concentrated, startup teams are not standing out amongst their peers but rather blending in, which negatively impacts funding. Technical teams in entrepreneurial cohorts are also more likely to get funding ($\beta = 1.578$, $p < 0.05$) than technical teams in technical cohorts. These results suggest that for teams in cohorts of similar concentrations, learning and competitiveness may be dampened because of too much similarity.

On the other hand, entrepreneurial teams in entrepreneurial cohorts are the most likely to get funding ($\beta = 4.5$, $p < 0.05$). This echoes prior research that shows that VCs like to fund experienced entrepreneurs. In addition, we show that experienced entrepreneurs can also benefit from similarly concentrated peers. For example, an entrepreneurial team in a very dissimilar tech-heavy cohort has a negative and significant probability of getting VC funding, while an entrepreneurial team in a very similar cohort has a positive and significant probability of getting VC funding. This type of experience does not appear to be redundant. This suggests that each individual's entrepreneurial experience may be different enough that startups can still learn and benefit from being in similarly concentrated cohorts. However, in a tech-heavy cohort, entrepreneurial teams may have difficulty standing out more to investors.

Conclusion

In this paper, we highlight the role of a peer effects in an emerging organizational form of early stage entrepreneurship: the accelerator. At the outset, we asked: How do peer effects impact entrepreneurial outcomes in accelerators? Our analysis supports our hypotheses that peer effects manifest through the relative similarity between the experience of the startup team and that of other founders in the cohort in which it is

embedded. We focused on two distinct dimensions of founder experience prior to entering the accelerator program: prior business experience and prior scientific and technical experience. We found that the composition of the startup team and the cohort matters along both dimensions. Startup teams with a high share of technical backgrounds in cohorts with a high share of founders with technical backgrounds are more likely to exit via quitting or acquisition, while technical teams in a cohort with a high share of business experience are also more likely to get funding. Similarly, a startup team with a high share of business backgrounds in cohort with a high share of founders with business backgrounds is less likely to get VC funding, while the same team in a technical cohort is more likely to get VC funding.

Overall, we demonstrate a potentially important role for peer effects in top accelerators in shaping the trajectory of startups through early stages of the entrepreneurial landscape. To be clear, there are a number of accelerators, many of which are trying to emulate the relatively senior models of Y Combinator and Techstars (e.g, 500 Startups, Dreamit Ventures, etc. to name just a few). However, scholars and practitioners alike have lacked sufficient data on the actual outcomes of even the more established accelerators. In this paper, we provide compelling evidence that peer effects in top accelerators have demonstrably distinct impacts on a multitude of entrepreneurial trajectories.

Our study, of course, is not without its limitations. Foremost, we have intentionally studied two of the most well-known and longest established accelerators. However, our study does not include the many other accelerators that are in existence. Our results suggest that peer effects in top accelerators influence the trajectory and

outcomes of the entrepreneurs and startups whom they mentor/select to work with.

However, to the extent that these top accelerators represent the frontier of best practices, these results should provide guidance and insights that are more broadly applicable.

CHAPTER 3: UNCOVERING THE EVOLUTION OF CONNECTIONS AND EXPERIENCE OF BOARD DIRECTORS IN EARLY STAGE VENTURES

Introduction

Scholars have long noted the entrepreneurial conundrum of how a new venture begins with zero resources and must collect and accumulate an entire arsenal of knowledge, skills and social capital (West & Noel, 2009; West III & DeCastro, 2001). The acquisition of these resources is crucial to performance and survival. Having the right mix of human capital, financial capital, and social capital is positively associated with successful outcomes like IPOs and venture capital funding (Beckman et al., 2007).

What remains understudied is how and when new ventures acquire the resources they need. Despite all we know about the association between financial and human capital resources and new venture performance, West and Noel (2009) note that previous research pays little attention to “how or where ...resource positions were developed” (p.4). In general, researchers in this area are limited due to the lack of quantitative data on early-stage startups. As new ventures face pressures to rapidly learn and evolve, it must be the case that they seek out different types of expertise along the way. But we have no systematic evidence of the mechanisms through which this occurs.

I seek to advance research in this area by examining how the resources brought in by the early board of directors of new ventures evolve over time. As a venture matures and changes and key personnel come and go, the resource composition of the venture’s networks will change and reflect different stages of venture development.

I conduct an exploratory analysis of the human and social capital of board members in 1,200 new ventures in the Computer Software industry between 2000 and

2014 guided by two overarching questions: 1) Who do founders first appoint to the board, and how do these appointments differ across experienced and novice entrepreneurs? 2) What systematic patterns do we observe in the evolution of experience on the board over time?

This research will make several important contributions. First, I hope to shed light on the mechanisms and strategies new ventures use to build and adapt resources. Having the right knowledge, skills and experience and the ability to acquire new resources as conditions change are likely to be crucial to the success of new ventures. My research will enhance our understanding of the mechanisms through which resources are acquired and adapted. Second, my research will focus on how startups grow and the stages in the growth process where new resources are most crucial. There has been no previous systematic research on this issue. It is my hope that a better understanding of the resource acquisition processes in new ventures will contribute to our knowledge of why some ventures survive and thrive despite strong odds against them. Finally, my research will contribute to our understanding of the importance of human and social capital networks to the behavior and performance of new ventures. Previous research shows that networks can provide new ventures with useful knowledge and connections. I aim to show that as new ventures' resource needs evolve, we will see systematic changes in the composition of their networks over time.

Literature

A growing stream of literature focuses on boards in new ventures. Barrow (2001) points out a changing paradigm, that boards in private, entrepreneurial firms were previously regarded as a mandate from venture capital firms. However, scholars observe

that many startups appoint boards prior to their first formal funding event (Deakins, O'Neill, & Mileham, 2000; Lynall, Golden, & Hillman, 2003). In a survey of why entrepreneurs appoint directors, Deakins, O'Neill and Mileham (2000) find that the top reason why directors were appointed was because of a perceived need for additional skills and expertise. Further, studies show that whether a director is appointed with or without venture capital funding, directors in new ventures carry out similar roles and responsibilities (Rosenstein, Bruno, Bygrave, & Taylor, 1993).

While studies on the board of directors are predominantly guided by agency theory, studies focused on boards in new ventures are skewed towards resource dependence theories (RDT) (Garg & Furr, 2017). This is unsurprising given that the acquisition of resources is crucial for long-term success and poses a major strategic challenge for nascent firms (Garg & Furr, 2017; Lichtenstein & Brush, 2001). In RDT studies, directors are conceptualized as providers of key resources (Hillman, Withers, & Collins, 2009), and their provision of resources can impact several important venture outcomes (see review by Garg & Furr, 2017). For instance, directors can provide key social connections that affect the speed at which ventures develop alliance portfolios, which in turn affects the speed at which the venture hits revenue milestones (Beckman, Schoonhoven, Rottner, & Kim, 2014). Directors can also provide prestige or legitimacy to a new venture (Chen, Hambrick, & Pollock, 2008) that can enhance IPO performance (Certo, 2003; Pollock, Chen, Jackson, & Hambrick, 2010).

Yet, the boards' role as resource providers changes over time, adapting to the needs of the firm (Huse & Zattoni, 2008; Lichtenstein & Brush, 2001). As firms face changing organizational problems and challenges, the board evolves from legitimacy-

seeking tasks in startup phases, to advisory tasks in growth phases, and control tasks in crisis phases (Huse & Zattoni, 2008). As organizations change, so too does the optimal set of resources needed (Lichtenstein & Brush, 2001), and the type of experience needed on boards. For instance, technical and sales knowledge on the board is important to high-technology new ventures because new ventures are primarily concerned with technical complexities related to their products and how to commercialize them (Vandenbroucke et al., 2016). Similarly, Huse and Zattoni (2008) show that early-stage firms draw heavily on the board's legitimacy resources while growth-stage firms draw more on the board's specialist knowledge. In this paper, I take this line of inquiry further by exploring systematic patterns in the networks and experience of directors in new ventures over time.

Methods and Sample Construction

Given this paper's focus on examining boards and founders in early stage entrepreneurial firms, it was important that the data contain comprehensive human and social capital information on all directors that were current during the sample period. Incomplete coverage of directors would compromise the aim of this study. In constructing a sample that meets these needs, I turned to a database that contains comprehensive information on the complete education, work, and service history of boards, BoardEx.

Boardex is a dataset compiled by a private research company specializing in the "Relational Capital" of public and private firms around the world. Boardex compiles available data from detailed resumes of directors and senior managers associated with over 800,000 organizations worldwide. Engelberg, Gao, and Parsons (2013) describe the

data as a “time series of hypertext-linked individual curriculum vitae” (p.87). These curriculum vitae contain information on college and graduate education, current and past work experience, current and past directorships, and social activities including service to universities and NGOs; awards and club memberships. To date, this type of rich, large-scale data on boards and top managers has not been used to study resource evolution in new ventures.

From there, I identified the industries in the database with comprehensive coverage of new ventures. This process left me with the U.S. Computer Software and Information Technology industries that contained over 1,200 new ventures. I restricted the sample to define new ventures as firms that are age 10 or less. I determine firm age from self-reported founding dates on firm websites, Crunchbase and VentureXpert. I was then able to supplement that with founder and funding data from Crunchbase and LinkedIn. Out of the total number of new ventures in the sample, I had to exclude those that had no coverage on any supplemental source (Crunchbase, VentureXpert, LinkedIn, or popular press articles). About 80% of the new ventures from the target industries were covered. The final sample includes 443 new ventures and n=1781 firm-year observations.

Constructing a Panel

I began assembling a panel dataset from the hyperlinked CVs of all directors to map what a firm’s resources looked like each year. First, I took every line item of a directors’ CV and determined which were current (occurred in a year when the director was on the board of the focal firm) and which were historic (occurred prior to board appointment). From there, I sorted each line item into year files. Each directors’ activity

prior to the year they entered the focal firm would appear in every year in which they served on the focal firm's board. For instance, if Director A was a director of Startup X in 2002 and 2003, all of Director A's prior employment and activity would be in the prior experience file for 2002 and 2003. But if Director A was no longer a current director in 2004, their prior experience would no longer be counted in the file for 2004 and later. I then was able to create variables to describe the prior experience of all directors that were on the board in each observation year.

Variables

Board experience

I examine board experience in the following functional domains: technical, entrepreneurial, management, finance, and director/advisor. Using BoardEx's role titles for each CV item, I code prior experience roles as being a functional role using keywords (i.e. "Engineer", "Technical Lead", "R&D", etc for technical roles). I measure functional experience as a proportion. For each dimension of functional experience, degree of experience is measured as the amount of collective years of technical experience on the board to all prior experience of the board's current members.

Board industry experience

To calculate industry experience of the board, I first determine the industry of the focal firm and the industries of all prior employment firms of each director. BoardEx classifies all firms into broad industry categories (i.e. Computer Software and Information Technology Services). I first match industries using their industry

classification categories. For instance, BoardEx classifies Zendesk and Symplified as a firm in the Computer Software industry. If a director at Zendesk was a director at Symplified in the past, I code this relationship as being industry experience and count the number of years that director served on Symplified's board. From there, I compute the measure for industry experience in two ways. Proportion of industry experience is measured as the amount of collective years of industry experience on the board to all prior experience of the board's current members.

Board characteristics

I measure the following descriptive characteristics of boards: board size, director age, number of past boards, number of current boards, and director network size.

Founding Team Experience

Founder prior experience is measured in two domains: prior entrepreneurial experience and diversity of prior experience. Using the same coding method as I did for board experience, I code founding team prior experience in two ways. First, I count the number of years a founder worked at a company within the same industry as the focal venture. I sum this number for all founders of a venture. Degree of founding team industry experience is computed as the cumulative number of years working within the focal industry for all founders divided by the total number of prior experience years of all founders. Degree of founding team technical experience is computed as the cumulative number of years working in a technical role for all founders divided by the total number of prior experience years of all founders.

Table 10 provides descriptive statistics for all variables. The average director is currently networked through other board appointments to around 572 executives and directors, and connects the focal firm to around 4 other firms. Of the proportion of prior experience on the board, the most common type of experience is prior management and director experience. The average director age is around 53 years, with a range from 28 to 77. Most directors that were under 35 were the founder or founding team members. These directors are excluded in the analysis of board composition, as I am interested in the experience of the directors they appoint.

Table 10. New Venture Boards Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Avg Director Age	1,678	52.7	6.2	28	77
Avg Dir Network Size	1,781	572	370	0	2322
Total Current Interlocks	1,781	3.8	4	0	31
Total Board Exp	1,781	8	8.9	0	58
Venture Age	1,781	6.5	2.5	0	10
<i>Board Experience</i>					
Proportion Board TechSci	1,781	.12	.18	0	1
Proportion Board Mgt	1,781	.68	.23	0	1
Proportion Board Entr	1,781	.04	.1	0	.75
Proportion Board Dir Exp	1,781	.67	.25	0	1
Proportion Board Finance	1,781	.09	.15	0	1
Proportion Board Industry	1,781	.24	.18	0	1

Analysis

To explore how board appointments differ across experienced and novice entrepreneurs, we examine a small subsample of ventures who have documented board appointments prior to receiving a formal funding event. Twenty-nine ventures formed

boards before receiving their first round of formal financing. Out of those twenty-nine ventures, nine had founders who previously founded a venture. Though our dataset captures ventures from 2000 to 2014, the ventures that had appointments prior to funding were all founded after 2008. These pre-funding appointments occurred predominantly between 2009 and 2011. After splitting this subsample into experienced and novice entrepreneurs, we summarize the prior experience and network connections of directors and compare between groups.

Our second question asks: what systematic patterns do we observe in the evolution of experience on the board over time? Using the key experience and network variables described above and the full sample of ventures, we characterize the experience and networks of boards by venture age.

The Assembly of Early Boards

Among ventures that appoint directors prior to receiving any formal external financing, there are differences in appointments between experienced entrepreneurs and novice entrepreneurs. Table 11 summarizes these differences. Experienced entrepreneurs tend to appoint directors with more technical experience and appoint about three times the entrepreneurship experience than novice entrepreneurs. Experienced entrepreneurs tend to appoint boards that create more than twice the amount of interlocks for their firm and create more within the focal industry. Experienced entrepreneurs tend to appoint boards with more industry experience, more management experience, and two times more marketing/sales experience. However, novice entrepreneurs tend to appoint directors with more finance experience than do experienced entrepreneurs.

Stylized Finding 1: Prior to a venture's first formal funding event, there are differences in board experience appointments between experienced and novice entrepreneurs. Relative to novice entrepreneurs, experienced entrepreneurs tend to appoint boards with greater experience and connections. Relative to experienced entrepreneurs, novice tend to appoint boards with more finance experience.

Entrepreneurship research has identified differences between first-time, novice entrepreneurs and experienced entrepreneurs (serial and portfolio) that may account for these differences in board appointments. One explanation is that prior founding

Table 11. Experience and Connection of New Board Appointments by Entrepreneur Experience (Proportion of all experience/ties)

Prior Experience of Directors Appointed	Experienced Entrepreneur	Novice Entrepreneur
Technical	12.7%	8%
Entrepreneurial	10%	3%
Management	71%	62%
Marketing/Sales	18%	9%
Industry	24.5%	21.2%
Finance	0%	10%
Interlocks Total	5.8	2.8
Interlocks to Industry Firms	16.2%	10.3%

experience adds managerial and technical skills, as well as new contacts that entrepreneurs can carry over into subsequent ventures (Hsu, 2007; Westhead et al., 2005b). Thus, ventures founded by experienced entrepreneurs will be more like to have enhanced human capital and networks to attract and appoint more experienced directors.

Another explanation is that experienced entrepreneurs are more likely to engage in effectual reasoning than novices (Politis, 2008). Instead of choosing one outcome and focusing on which means get them there, effectual reasoners focus on the means and visualize all possible outcomes that can be created with them (Sarasvathy, 2001). Effectual reasoning may also be applied to how entrepreneurs form early boards of directors. If experienced entrepreneurs foresee multiple future possibilities, they may stack the board with diverse, experienced directors that could benefit the venture in all possible scenarios. Thus, experienced entrepreneurs may appoint more connected, experienced directors to cover their bases to account for whatever outcomes or problems arise.

Prior research has also pointed to differences in how entrepreneurs collect and process information. Westhead et al. (2005) find that novice entrepreneurs used significantly fewer sources of information in the opportunity identification process. These inexperienced entrepreneurs lack frameworks for processing information and may be overwhelmed by too much information (Westhead, Ucbasaran, & Wright, 2005a). Thus, novices may focus on a narrower range of problems. The differences we find in board experience may reflect a novice focus on securing financing.

The Evolution of Board Experience Over Time

During the ten-year sample window, the ventures displayed several distinct patterns in the types of functional expertise brought in by the board. Technical/scientific and entrepreneurial experience increased from year one to year four, followed by a gradual and steady decrease from years four through ten (Figures 6 and 7). Industry experience followed a similar pattern. It rose sharply from year one to year four, followed

by a gradual and steady decrease from years four through ten (Figure 8). Director and managerial experience increased steadily from year one to year ten (Figures 9 and 10). Prior research on stages of venture development and qualitative interviews with founders provide insight into the problems faced, firm activities, and resources needed as firm went through these changes in board experience (Table 12).

Table 12. Resource Needs, Activities and Problems by Venture Stage

STAGE 1: STARTUP	STAGE 2: GROWTH
(Quinn & Cameron, 1983) <ul style="list-style-type: none"> • Marshalling of resources • Lots of ideas • No or little formal planning and coordination • Entrepreneurial Activities (Kazanjian, 1988) <ul style="list-style-type: none"> • Primary focus on technology/product development • Secondary focus on selling the idea/funding 	(Quinn & Cameron, 1983) <ul style="list-style-type: none"> • Goal-setting and planning • Formalization of rules • Systematic control (Kazanjian, 1988) <ul style="list-style-type: none"> • Sales/growth oriented • Organizational issues • Formal structures, task systems
Problems and resource needs: <ul style="list-style-type: none"> • Pitching the idea to get enough funding to finance tech needs • A foot in the door with customers 	Problems and resource needs: <ul style="list-style-type: none"> • Need to add a lot of new people, need to manage all of them

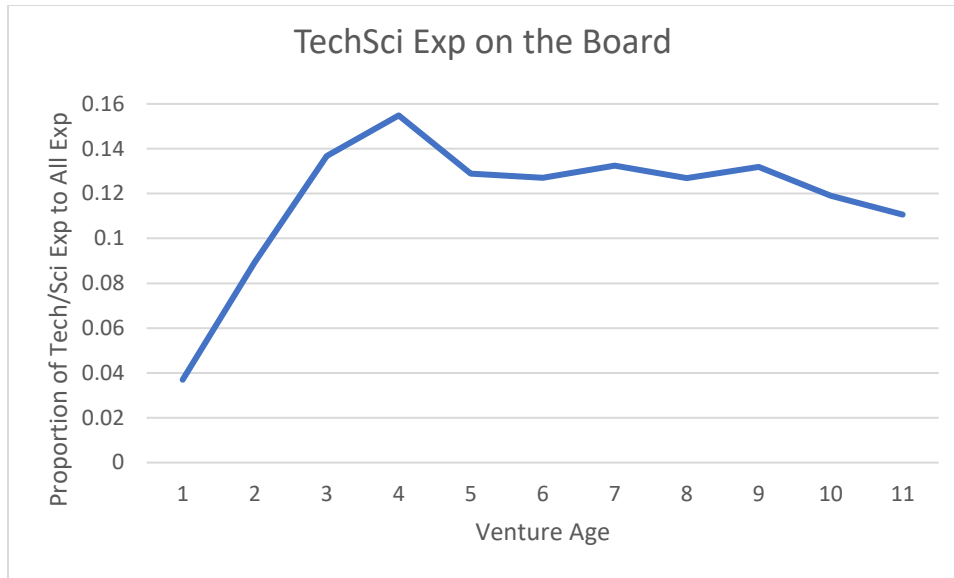


Figure 6. Proportion of Technical/Scientific Experience on the Board Over Time

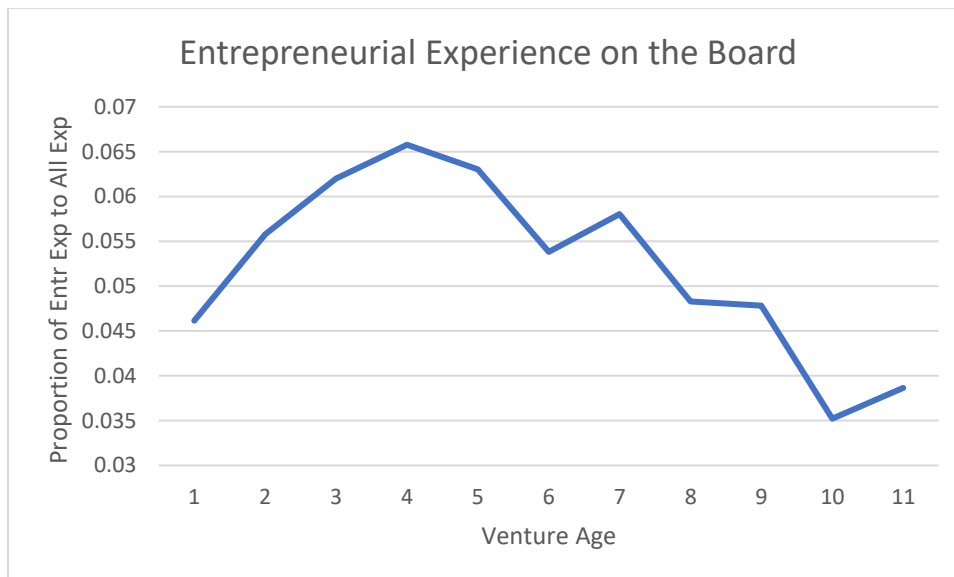


Figure 7. Proportion of Entrepreneurial Experience on the Board Over Time

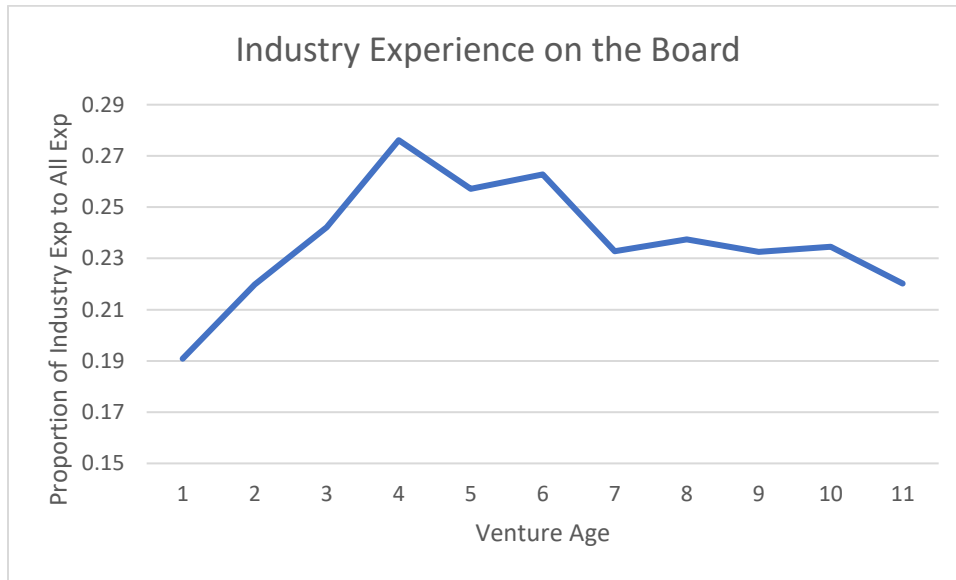


Figure 8. Proportion of Industry Experience on the Board Over Time

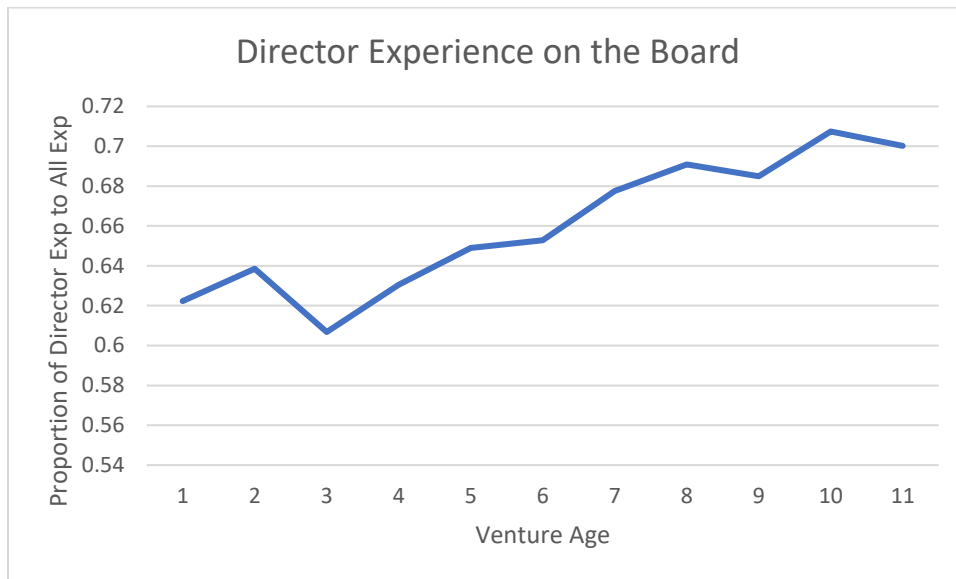


Figure 9. Proportion of Prior Director Experience on the Board Over Time

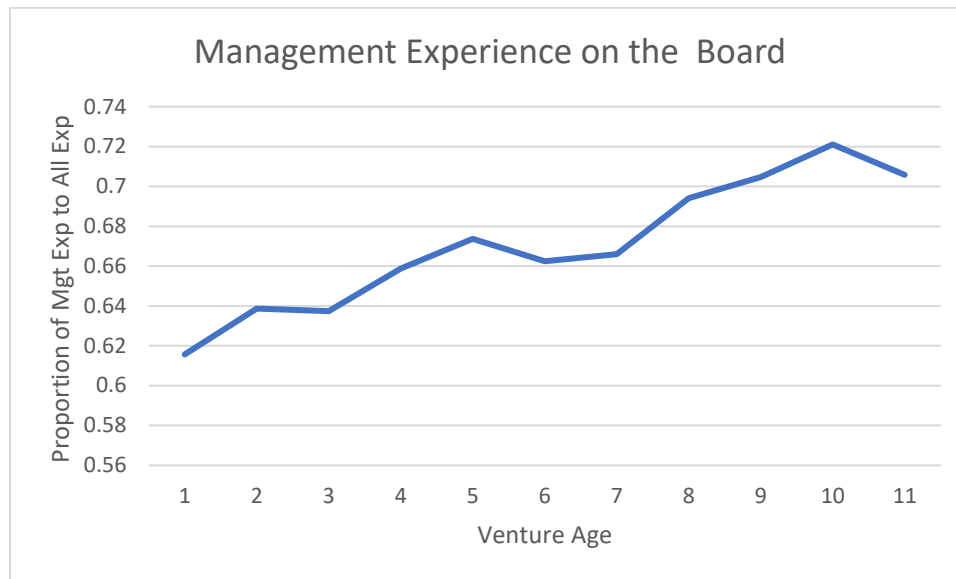


Figure 10. Proportion of Management Experience on the Board Over Time

Stylized Finding 2: Technical and entrepreneurial experience on the board increase in the first stage (startup) and decrease steadily in the second stage (growth).

Stylized Finding 3: Director and management experience on the board increases steadily over the startup and growth stages.

Stylized Finding 4: Industry experience on the board increases in the first stage (startup) and decreases steadily in the second stage (growth).

In the life cycle of the firm, the first stage is a startup stage characterized by informal entrepreneurial activities and the marshalling of resources (Quinn & Cameron, 1983). The firm's primary focus is developing the technology or the product and the secondary focus is selling the technology or product (Kazanjian, 1988). In this stage, the primary resource needs are technical experience to help build the prototype and startup

experience to help commercialize or fund the product. I find that the systematic patterns in experience on the board does indeed reflect that need. In the first few years of the ventures, directors who were appointed had predominantly technical, entrepreneurial, and industry experience. According to the interviews conducted with founders, the industry insiders were appointed to help ventures get a foot in the door with customers. They had experience and existing connections to the right customer base and the right network of suppliers. Founders also expressed a secondary need for help pitching the idea to finance their technical needs. Appointing entrepreneurs that had gone through the venture capital process was crucial in this stage.

The second stage of venture development is characterized by growth and occurred after the goals of the first stage had been met. Ventures entered this stage after obtaining funding, after developing the product, and when they had begun operating and selling their product. At this point, ventures were now focused on filling out the structure of the firm. Quinn & Cameron (1983) describe this stage as having a focus on formalization and planning. The issues firms face in the growth stage are concerned with more inward-facing organizational issues, such as establishing formal systems and structures (Kazanjian, 1988). Founders expressed a “need to add a lot of new people” and a “need to manage all of them.” These changes are reflected in the patterns found. During this second stage, ventures decreased the amount of technical, entrepreneurial, and industry experience, and increased the amount of management and director experience. The composition of the venture’s board changed in two distinct ways. Some ventures added several new directors without removing the startup stage directors, while other ventures removed those directors and appointed new professional directors.

These patterns suggest that resource provision is the dominant board function in the startup phase while monitoring becomes the dominant function in the growth phase. While this analysis finds that monitoring may be less important to entrepreneurs in the startup phase, it does not suggest it is less important. An interesting avenue for future research would be to examine the trade-offs and performance implications for startup-phase venture boards that favor resource provision over monitoring. As Garg and Furr (2017) point out, the recent scandals of Uber's misconduct and Theranos' fraudulent product claims suggest that the monitoring function of early venture boards may be as important as resource provision.

Conclusions and Implications

In this paper, I examine the development of boards in new ventures over the first 10 years of the venture's existence. I ask: Who do founders first appoint to the board, and how do these appointments differ across experienced and novice entrepreneurs? And, what systematic patterns do we observe in the evolution of experience on the board over time? My exploratory analysis supports the main prediction that, as a venture matures and changes and key personnel come and go, the resource composition of the venture's networks will change and reflect different stages of venture development.

My stylized findings on early appointments point to key differences in how experienced and novice entrepreneurs use board appointments. Overall, experienced entrepreneurs appoint more connected and experienced directors than novices. This suggests that experience as an entrepreneur may help attract more experienced and high-status directors, may build connections that introduce or provide access to these directors, or may teach founders the importance of appointing directors with only the greatest

experience and networks. An interesting avenue for future research would be to parse out the mechanism through which this occurs.

The systematic patterns found in how directors change over time also provide insights into how the importance of the four main board roles change as ventures face different challenges at different stages of development. My exploratory analysis demonstrates that in the startup stage, ventures appoint primarily technical, entrepreneurial, and industry expert directors. Over time, ventures replace those startup-phase directors with professional directors. While it's not surprising that boards professionalize over time, it is interesting and important to understand the impetus for those changes.

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