Peering Inside: How do Peer Effects Impact Entrepreneurial Outcomes In Accelerators?

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Abstract

In this paper, we examine the influence of peer effects in entrepreneurial accelerators on performance outcomes of new ventures. Accelerators have been found to impact the trajectories of new ventures as well as entrepreneurial learning. However, little is known about the mechanisms through which this occurs. The unique features of accelerators may provide some clues. They include intensive mentoring and a cohort experience that mirrors that of educational institutions. We posit that the influence of networks formed within accelerator cohorts may extend beyond the intensive "boot camp" period of the program. We leverage a unique hand-collected dataset of startups and their founders that are funded by top entrepreneurial accelerators. Our results suggest a strong cohort effect in accelerators that confers signaling, networking, and advisory benefits to portfolio firms and influences the likelihood of entrepreneurial exit by quitting and acquisition.

Keywords: entrepreneurship; peer effects; founding teams; new venture growth; accelerators

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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 also 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 (Deephouse, 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 playing an important role in shaping subsequent startup outcomes, such as receipt of VC investment (Beckman & Burton, 2008; Beckman et al., 2007). More broadly, possession of different types of prior experience leads to distinct insights such as the viability of competing strategic choices (Fern et al., 2012) or the recombination of different knowledge (Gruber et al., 2012b).

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 has demonstrated 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. We hypothesize that peer effects may manifest through several levels: the diversity of prior experience of the founding team; the diversity of prior experience of founders of other startups in the cohort; and the relative similarity between the experience of the startup team and that of other founders in the cohort in which it is embedded. 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 trajctories?*

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 four distinct dimensions of founding team experience prior to entering the accelerator program: prior entrepreneurial experience, prior business and managerial experience, prior coding (computer programming) experience, and prior scientific and technical 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 and Malmandier, 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 founding teams *and* cohorts that have relatively concentrated shares of founders with technical and scientific backgrounds are more likely to exit via quitting and those with a higher share of prior coding experience are more likely to exit via acquisitions. In contrast, we find that concentrated teams and cohorts with prior entrepreneurship and business/managerial experience are more likely to receive a first round of 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 HYPOTHESIS DEVELOPMENT

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 and Simanov, 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 particularly 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, 1986). 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 (Sorenson, 2002; Giannetti and Simanov, 2009). 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 and 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 and 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 et al., 2014). Receiving advice or mentoring forces decision-makers to think differently about a problem than they would have otherwise (Schotter, 2003, p. 196), 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 and Ruef, 2006; Kacperczyk, 2013). Whether an individual has entrepreneurial role models greatly affects underlying attitudes about the desirability and legitimacy of becoming a founder (Stuart and Ding, 2006; Roach and Sauermann, 2013). 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 (Nanda and Sorenson, 2010; Kacperczyk, 2013), which in turn decreases the likelihood of venture failure (Cooper et al., 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, and Thompson, 2012), which contributes to both decreasing venture failure and increasing venture growth (Cooper et al., 1994).

Accelerator-based 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 et al., 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).

We expect that peer effects will be salient at both the team and cohort levels. Figure 1 depicts four combinations of the relative similarity of startup teams and cohorts. Entrepreneurial teams bring four significant types of prior experience to each accelerator-based cohort - entrepreneurial, coding, science and technology, and business experience – which should interact uniquely in each cohort-team fit to impact outcomes for new ventures.

Insert Figure 1 about here

A diverse team in a diverse cohort (quadrant I of Figure 1) has access to novel information and diverse perspectives within their team and within their cohort. Team diversity breeds more innovative ideas and more valuable new ventures (Beckman, 2006; Gruber, MacMillan, and Thompson, 2012). Yet, the weak ties that bind diverse teams do not encourage the transfer of tacit knowledge (Beckman, 2006) or the in-depth discussion that comes from shared language (Stasser et al., 1989; Rulke and Galaskiewicz, 2000). Team outcomes depend on the cognitive comprehensiveness that comes from the ability to exhaustively discuss problems (Chowdhury, 2005).

Diverse cohorts will complement the knowledge of a diverse team. Although prior experience is spread out over the team and the team doesn't overlap knowledge bases, prior experience is also spread out over the cohort. Team members will share language with cohort peers and will be able to utilize diverse information gained from diverse peers. Founders with prior entrepreneurial experience provide honest assessments of the viability of ideas, which can lead new ventures to continue to pursue their ideas or to quit before burning through resources on a less promising idea (Lerner and Malmendier, 2013). Prior coding and science and technology experience provides the knowledge needed to solve detailed problems, preventing failure from deficiencies in implementing technical ideas (Williams and O'Reilly, 1998; Beckman, 2006). Still, coding and technological experience may limit the ability to assessing the broader merits of ideas or feasibility of launching in the market. Similarly, founders with prior business experience share the knowledge required to launch and commercialize ideas (Gruber, 2009) but offer little influence on the technical development of the new venture. Hypothesis 1 follows:

Hypothesis 1: Greater concentration <u>of startup team members</u> within a particular experience domain at the <u>startup</u> team level will significantly effect exit and financing outcomes.

Furthermore, a diverse team can learn from the packaged knowledge of a concentrated cohort (quadrant II of Figure 1), but the extent of peer influence depends on the area of concentration within the cohort. For example, a high concentration of prior entrepreneurs will highlight the merits of some proposed ideas over others (Lerner and Malmendier, 2013) but will not be able to speed commercialization or solve detailed problems. A high concentration of peers with prior coding or technological experience will transfer the detailed technical knowledge (Beckman, 2006) but may be encouraging ideas that are less viable. Peers with business experience can aid in the launch of ideas (Gruber, 2009) but may be launching ideas with technical problems that are less viable. Hypothesis 2 follows:

Hypothesis 2: Greater concentration of <u>cohort members</u> within a particular experience domain at the <u>cohort level</u> will significantly effect exit and financing outcomes.

If both the team and the cohort are concentrated in composition (quadrant III of Figure 1), the effects of peer influence on outcomes may depend on whether the area of concentration is similar or dissimilar. Concentrated entrepreneurial 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 new and innovative ideas from a similarly concentrated cohort of peers. In short, concentrated teams in concentrated cohorts are too much of a good thing.

Cohorts of concentrated peers may introduce novel ideas and fresh perspectives to dissimilarly concentrated teams. Fresh perspectives can open up new market opportunities for (Gruber, MacMillan, and Thompson, 2012; Shane, 2000) and introduce distant knowledge that can lead to innovative recombination (Hargadon, 2003). Without common ground, however, distant knowledge may fall on deaf ears. For instance, a team of founders with business backgrounds may receive novel information from a cohort of computer programmers. With no background in computer science, the founders are unable to utilize that information. Because the team is concentrated in an area dissimilar from the cohort, the team has no prior related knowledge from which they can apply and commercialize the advice (Cohen & Levinthal, 1990).

Hypothesis 3: Greater concentration of startup team members and cohort members within the same experience domain will negatively moderate each other.

EMPIRICAL SETTING, DATA, AND METHODOLOGY

Institutional Setting: Entrepreneurial Accelerator Cohorts

We test our hypotheses in a setting that allows us to isolate the role of peer effects in shaping new ventures: founding teams and cohorts in top accelerators. In this paper, we leverage the context of accelerator cohorts to study the relationship between peer effects and startup trajectories. We focus on two channels through which a focal startup experiences peer effects: through learning from other startups in the cohort and through competition amongst the startups in the cohort for similar resources.

Accelerators pursue high levels of engagement with start-ups through a combination of equity financial capital and a structured development program involving a pre-determined cohort and length of time, e.g., three months. (Carr, 2012; O'Brien, 2012). . The top accelerators take a small equity stake in the startup in exchange for a fixed amount of capital (e.g., Y Combinator currently takes a 7% equity stake for a $120,00 investment per team and Techstars takes a 7-10% equity stake for a $118,000 investment per team). While the specific investment has fluctuated, these accelerators commit to roughly equivalent investments in all startups in a given cohort, in contrast to top angel groups.

Within an accelerator, cohorts proceed in tandem, creating a portfolio of companies that simultaneously learn from one another while also implicitly competing for scarce resources such as attention and follow-on investment funding.

Importantly, the combination of "cohorting" culminating in a public Demo Day, in which the startups pitch to potential investors, distinguishes accelerators from other providers of similarly early-stage equity finance, such as top angel groups (Winston Smith & Hannigan, 2015). The pre-determined, relatively short, time frame for each cohort also separates accelerators from business incubators, which do not typically impose limited times on startups and rarely take equity stakes (Amezcua, Grimes, Bradley, & Wiklund, 2013; Gruber, Consalvo, Davis, & Newman, 2012a; Smilor & Gill Jr., 1986). Preparation for "Demo Day" shapes the startup experience from the first day in the program, in part because each startup expects that they will be directly compared to the other startups in the cohort (Carr, 2012; O'Brien, 2012).[1]

From a research perspective, accelerator cohorts provide an excellent lens through which to examine peer effects. Two major challenges confront researchers seeking to identify peer effects separately from confounding factors: the selection problem and the reflection problem— (see, e.g., Manski (1993), Ahern, Duchin, and Shumway (2014), and Shue (2013)). The *selection* problem refers to the tendency of individuals to form peer groups based on observable and unobservable preferences. The *reflection* problem refers to the issue that peers influence one another bi-directionally, making it hard to separate the directional effect of peer influence (Manski, 1993). To get around these problems, an increasing number of studies have focused on randomly assigned cohorts in elite MBA programs (Ahern et al., 2014; Lerner & Malmendier, 2013; Shue, 2013) or the assignment of roommates in colleges (Hasan & Bagde, 2015; Jain & Kapoor, 2014; Sacerdote, 2001; Zimmerman, 2003).

Accelerator cohorts are similar in many ways to these settings. Each cohort develops a distinct identity in which the startup founding team interacts frequently with other founding teams in structure and unstructured ways. Accelerator cohorts provide a solution along both selection and reflection dimensions. First, a focal startup thus has no control over which other startups are chosen for a given cohort, in other words, *selection* preferences are not at work. While founding teams most certainly reflect endogenous preferences of the founders, the other founding teams in the cohort are *exogenous* for any focal startup. This arises directly from the incentives and objectives of the accelerator to select startups that they hope, *ex ante*, are the most likely to “succeed” in terms of the financial return to the accelerator partners’ equity stake (CITES). Thus, top accelerators seek to assemble a cohort of startups that are most likely to succeed independent of the mix of experience and backgrounds of the cohort as a whole. Second, we are interested in the relationship between the experiences of the founders *prior* to entry in the accelerator, thus other founders can not mimic the preferences of the other startups after entry in the accelerator. Thus, the *reflection* problem is not a concern.

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

. 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.[1] 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

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 and Malmendier, 2013), industry ties (Nanda and Sorenson, 2010), or simply

[1] 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, 2014).

shared connections on the basis of entrepreneurship itself (Saxenian, 1994).

Founders were coded as having prior experience in the areas of entrepreneurship, coding and/or programming, scientific and technical fields, and business and/or management fields. Experience that took place prior to entering into an accelerator program took on four 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 and Hannigan, 2014). Therefore it was not surprising to find that many founders have backgrounds in software coding, programming, and development. Founders were classified as having coding/programming backgrounds if job titles included the following terms: programmer, developer, software, platform, architect, systems, digital product, designer, iOS, hacker, WebDev, or computer. Founders who possessed prior coding experience according to these criteria were assigned a value of 1 for *PriorExp_Coding* and 0 otherwise.

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 and 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 and 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*.

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.*

The share variables above were vital to our ability to test our three hypotheses. Hypothesis 1 explores the concentration of experience at the founding team level, which draws on the *FirmShare* variables. Similarly, Hypothesis 2 looks at the concentration of experience at the cohort level of analysis, and thus uses the CohortShare variables. Finally, Hypothesis 3 examines the differentials of concentration at the firm and cohort level. For this analysis, we created interaction terms of *FirmShare* and *Cohort Share* along each of the four experience dimensions, yielding the variables *CohortEnt_FirmEnt*, *CohortCoder_FirmCoder*, *CohortSciTech_FirmSciTech*, and *CohortBusFunction_FirmBusFunction*.

Founding team and cohort concentration similarity

A final aspect of our cohort based measures looked at the similarity of the firm to the cohort in composition and the concentration of the cohort overall. *CohortDistance* is a variable that is a vector of each firm's composition along the four experience dimensions relative to that of its constituent cohort. The greater the measure of distance, the greater the difference in team composition between startup and cohort. *CohortConcentration* is a variable that takes the Herfindahl Index of each constituent experience dimension across each cohort. A cohort with a *CohortConcentration* value of 1 would contain founders a singular background dimensions (ie. all founders within a cohort have prior coding experience, and only coding experience), while a *CohortConcentration* variable equal to 0 would indicate that no founders in the cohort had the same experiential background. (In reality, the range of concentration observed in the data spans from 0.52 to 0.97).

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, date of entry into the accelerator program (*year_enter*), and year of founding (*year_founding*). 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 Round1,* and *VCRound2+* (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.

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, $j= 1,\ldots,J$ using multinomial logit regression (Wooldridge, 2002, Ch. 15). For outcomes $j = 1, \ldots, J$ we estimate :

$$\Pr(Y = j \mid x) = \exp(x\beta_j) / \left[1 + \sum_{h=1}^{J} \exp(x\beta_h) \right]$$

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

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

RESULTS

Univariate Statistics

The summary statistics of our sample can be found in **Table 1**. The first two variables, *CohortDistance* and *CohortConcentration,* show a significant range of profiles throughout the full cohort set. *CohortDistance* ranges from 0.0025 to 0.8498, while *CohortConcentration* has a minimum of 0.5238 and a maximum of 0.9680. Taken together, the cohort composition measures appear to indicate that many cohorts are different, but a substantial number are concentrated in their prior experience. 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 intro 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 2**. While the number of firms within a cohort can vary from 8 to 42, each startup team ultimately belongs to one. Therefore, the correlations between the firm and cohort share on an individual dimension are not entirely unexpected. However, within cohort correlations, such as that between entrepreneur and business function shares, are far more interesting. The clustering of founders and teams within cohorts is random (to the startup) and there appear to be some natural complementarities in the data.

Insert Table 1 about here

Insert Table 2 about here

Multinomial Regression Analysis

Table 3 contains our full multinomial logit regressions. We estimated three models, starting from baseline (Model 1, Columns 1-4), and adding the *Cohort Distance* (Model 2, Columns 5-8) and *Cohort Concentration* (Model 3, Columns 9-12) variables cumulatively. The results a presented with each possible entrepreneurial outcome, *ExitByQuitting*, *ExitByAcquisition*, *VCRound1*, and *VCRound2+* listed sequentially.

Overall, our results show strong support for our three hypotheses. The peer effects at the firm level show statistically significant effects on the likelihood of various outcomes. The results at the cohort level are more telling, and show nearly identical results, but mostly greater in magnitude. When the firm and cohort shares are interacted along the four experience dimensions, we observe a negating effect. When firms are concentrated upon the same dimensions are their cohorts, the likelihood of outcomes falls. The addition of the *CohortDistance* measure does not impact the results (Columns 5-8). However, *CohortConcentration*, a broad measure of the concentration of a particular experience area within the cohort, decreases the likelihood of *ExitByQuitting*, but increases the likelihood of *VCRound2+* (Columns 9-12).

We focus our analysis on the full model (Columns 9-12). Hypothesis 1 posited that team concentration in an area of prior experience would impact entrepreneurial outcomes. The results in the full model lend strong support to this hypothesis. We find that a higher share of prior entrepreneurs on the founding team leads to a greater likelihood of receiving a first formal round of venture capital (Column 11, $p < 0.05$). Similarly, teams with a high concentration of coders are more likely to be acquired (Column 10, $p < 0.10$). Startups with a high share of scientific or technical backgrounds are likely to quit (Column 9, $p < 0.01$) as well as be acquired (Column 10, $p < 0.10$) *and* receive a second round of VC or more (Column 12, $p < 0.01$). Taken together, our results at the startup level show that not only does the concentration of founder experience matter at the firm level, but it may be highly contextual to the specific outcomes.

Hypothesis 2 suggested that the concentration of founder experience measures at the cohort level would impact exit and financing outcomes. Our results show strong support for this hypothesis. Many of the results mirror what we observed at the startup share level of analysis, however the cohort measures appear to be stronger in magnitude. For cohorts with higher shares of prior entrepreneurs, constituent startups are more likely to receive a first formal round of VC financing (Column 11, $p < 0.01$). The cohort effect also carries over to the science and technology dimension and receiving a second VC round (Column 12, $p < 0.05$). Business function experience also carries an influence at the cohort level, giving constituent startups a higher likelihood of exit by acquisition (Column 10, $p < 0.1$). As with the startup team share of each dimension, the outcome effect is fundamentally tied to the nature of the experience.

Finally, Hypothesis 3 explored the match of concentration on each dimension. It posited that when startups and cohorts were concentrated on the same experience dimension, it would negatively moderate the peer effect on exit and financing outcomes. Our results support this hypothesis. We observe that many of the interactions between startup and cohort share of experience resulted in a negative effect on outcomes – many of the same outcomes that showed a positive effect individually. Our intermediate model (Model 2) shows a negative effect of high concentration of prior entrepreneurs in startups *and* cohorts on receiving VC Round 1 (Column

7, -27.588, p <0.01). Similar results follow for the coding dimension (Column 6, -17.152, p<0.01) and scientific and technical experience (Column 5, -11.838, p <0.01). This result diminishes somewhat in our final model with the addition of the broader concentration model, which suggests that context may not be the sole contributor to the startup-cohort peer effect dynamic.

Insert Table 3 about here

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 may manifest through several levels: the relative concentration of prior experience of the team; the relative concentration of prior experience in the cohort; and 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 four distinct dimensions of founder experience prior to entering the accelerator program: prior entrepreneurial experience, prior business and managerial experience, prior coding (computer programming) experience, and prior scientific and technical experience. We found that the composition of the startup team and the cohort matters along all four dimensions. Startup teams *and* cohorts with a high share of founders with technical and scientific backgrounds are more likely to exit via quitting, or received two or more formal rounds of venture capital funding. Teams with a higher share of prior coding experience are more likely to exit via acquisitions, while those with prior entrepreneurship and business/managerial experience are more likely to settle on a first round of VC funding. Our results at the cohort level suggest that, controlling for the distance in team/cohort composition, cohort effects appear to mirror, and in some cases, dominate the team experience effects. However, when startup teams and cohorts are too closely matched they negatively moderate one another.

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.

Figure 1.

Composition		Cohort: Diverse	Cohort: Concentrated
Team	**Diverse**	Lack of shared knowledge Complementarities are too diffuse to make up for substantial knowledge gaps	**Entrepreneurs advise VC** Coders impart tech know-how Science/Tech introduces outsider knowledge Business Function aids launch
	Concentrated	Entrepreneurs know VC Coders are “acqui-hired” Science/Tech brings outside knowledge Business Function demonstrates routines, signals investors	All entrepreneurs: no complementarity All coders: no distinction, likely acqui-hires All Science/Tech: groupthink All Business: lacks skills

Table 1. Summary Statistics

Variable	Mean	SD	Min	Max
Startup team experience				
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 experience				
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				
CohortEntr_FirmEntr	0.2362	0.2157	0	0.8500
CohortCoder_FirmCoder	0.0630	0.0736	0	0.4000
CohortBusiness_FirmBusiness	0.0225	0.0529	0	0.3043
CohortSciTech_FirmSciTech	0.0453	0.0695	0	0.4285
Controls				
Cohort Distance	0.1869	0.1713	0.0025	0.8498
Cohort Concentration	0.8301	0.1241	0.5238	0.9680
Ln Founders Per Cohort	4.2325	0.8463	2.7080	5.2257
Ln Number Founders	1.1453	0.2366	0.6931	1.7917
Year Founding	2008.8	1.7113	2003	2011
Year Enter	2009.3	1.6572	2005	2011

Table 1. (cont'd)

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
Outcomes				
Fail	0.2258	0.4186	0	1
Exit	0.1928	0.3950	0	1
Alive	0.4644	0.4993	0	1
1st Round VC	0.0939	0.2920	0	1
2nd Round + VC	0.0609	0.2394	0	1

Table 2. Correlation Matrix

Variable		(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)	(m)	(n)	(o)	(p)
Cohort Distance	(a)	1.00															
Cohort Concentration	(b)	0.02	1.00														
FirmShareEntrepreneur	(c)	-0.63	-0.11	1.00													
FirmShareCoder	(d)	-0.25	0.10	0.00	1.00												
FirmShareSciTech	(e)	-0.16	0.08	-0.00	0.49	1.00											
FirmShareBusFunction	(f)	0.27	-0.13	-0.01	-0.13	-0.13	1.00										
CohortShareEntrepreneur	(g)	-0.09	-0.81	0.25	-0.10	-0.04	0.17	1.00									
CohortShareCoder	(h)	-0.07	-0.57	0.11	0.06	0.00	0.08	0.64	1.00								
CohortShareSciTech	(i)	-0.05	-0.38	0.13	-0.00	0.21	0.04	0.53	0.51	1.00							
CohortShareBusiness	(j)	-0.03	-0.74	0.17	-0.10	-0.08	0.27	0.84	0.59	0.35	1.00						
CohortEnt_FirmEnt	(k)	-0.46	-0.55	0.76	-0.05	-0.04	0.11	0.73	0.42	0.40	0.60	1.00					
CohortBus_FirmBus	(l)	0.12	-0.31	0.06	-0.14	-0.13	0.84	0.36	0.23	0.11	0.49	0.28	1.00				
CohortSciTech_FirmSciTech	(m)	-0.15	-0.06	0.03	0.38	0.86	-0.07	0.12	0.14	0.49	0.06	0.08	-0.06	1.00			
CohortCoder_FirmCoder	(n)	-0.26	-0.10	0.02	0.88	0.43	-0.07	0.12	0.39	0.15	0.10	0.07	-0.05	0.41	1.00		
Ln Founders Per Cohort	(o)	-0.04	0.79	-0.01	0.12	0.14	-0.17	-0.60	-0.38	-0.17	-0.72	-0.41	-0.35	0.02	-0.02	1.00	
Ln Num Founders	(p)	-0.14	0.15	-0.20	-0.04	-0.10	-0.15	-0.17	-0.11	-0.12	-0.20	-0.22	-0.20	-0.13	-0.04	0.17	1.00

Table 3. Multinomial logit regressions on exit and financing outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	Exit By Quitting	Exit By Acquire	1st Round VC	2nd+ Round VC	Exit By Quitting	Exit By Acquire	1st Round VC	2nd+ Round VC	Exit By Quitting	Exit By Acquire	1st Round VC	2nd+ Round VC
Startup team experience												
Firm Share Entrepreneur	-0.668	-0.539	2.967**	2.362	-0.677	0.145	4.735***	3.701	-0.853	0.080	5.315***	4.013
	(-0.76)	(-0.48)	(1.98)	(1.12)	(-0.62)	(0.09)	(2.85)	(1.57)	(-0.82)	(0.05)	(2.99)	(1.54)
Firm Share Coder	0.296	3.138*	0.532	-1.227	0.113	4.263**	-0.941	-3.500	0.124	4.328**	-0.749	-4.601
	(0.19)	(1.84)	(0.31)	(-0.34)	(0.06)	(2.09)	(-0.32)	(-1.12)	(0.06)	(2.07)	(-0.21)	(-1.30)
Firm Share SciTech	2.681***	1.959*	-0.483	4.279***	3.511***	1.651	-0.188	5.521***	3.532***	1.677	-0.866	6.028***
	(3.07)	(1.87)	(-0.31)	(3.55)	(3.30)	(1.30)	(-0.09)	(3.96)	(3.24)	(1.28)	(-0.39)	(3.77)
Firm Share BusFunction	1.049	1.390	1.358	-3.263	1.371	1.391	2.864***	-4.642	1.472	1.367	3.101***	-4.167
	(1.05)	(1.03)	(1.31)	(-1.28)	(1.04)	(0.77)	(2.84)	(-1.11)	(1.08)	(0.75)	(3.13)	(-1.09)
Cohort experience												
Cohort Share Entrepreneur	-0.106	-1.524	10.462***	3.761	-1.661	0.047	12.627***	6.938	-4.015	-0.993	10.912***	17.934**
	(-0.04)	(-0.56)	(3.11)	(0.84)	(-0.55)	(0.01)	(3.17)	(1.08)	(-1.40)	(-0.23)	(2.64)	(2.22)
Cohort Share Coder	-3.794	0.952	-9.622	-11.327	-4.646	2.290	-12.606	-21.891**	-4.127	2.425	-17.837	-22.510**
	(-0.96)	(0.27)	(-1.44)	(-1.49)	(-1.11)	(0.58)	(-1.45)	(-2.27)	(-1.02)	(0.60)	(-1.56)	(-2.39)
Cohort Share SciTech	1.677	3.040	-6.536	8.647**	7.132**	4.882	-3.581	13.953***	7.805**	4.939	-2.030	15.342***
	(0.35)	(0.72)	(-1.14)	(2.09)	(2.13)	(1.03)	(-0.58)	(3.02)	(2.25)	(1.04)	(-0.28)	(3.17)
Cohort Share BusFunction	-3.285	10.257*	10.709	-0.623	-7.981	12.157*	18.204	-0.759	-8.148	12.610*	33.074*	-3.868
	(-0.60)	(1.75)	(1.25)	(-0.07)	(-1.30)	(1.79)	(1.38)	(-0.06)	(-1.33)	(1.81)	(1.80)	(-0.39)
Startup Team*Cohort Experience												
CohortEnt_FirmEnt	-0.289	-0.139	-6.522**	-4.953	1.032	-1.926	-11.694***	-10.415	1.716	-1.591	-13.096***	-12.148*
	(-0.13)	(-0.05)	(-2.17)	(-0.91)	(0.46)	(-0.53)	(-4.04)	(-1.57)	(0.84)	(-0.43)	(-3.53)	(-1.84)
CohortBus_FirmBus	-3.859	-8.454	-14.691*	21.142	-2.074	-10.602	-27.588***	34.998**	-2.171	-10.137	-27.567***	34.157**
	(-0.76)	(-1.19)	(-1.72)	(1.59)	(-0.28)	(-0.98)	(-2.95)	(2.09)	(-0.29)	(-0.93)	(-2.76)	(2.06)
CohortSciTech_FirmSciTech	-6.831	-6.512	11.062	-8.828	-11.838***	-5.519	8.785	-18.571**	-12.061***	-5.865	11.422	-21.368**
	(-1.51)	(-1.23)	(1.17)	(-1.29)	(-2.68)	(-0.99)	(0.83)	(-2.52)	(-2.70)	(-1.04)	(0.97)	(-2.56)
CohortCoder_FirmCoder	2.410	-13.021*	-7.781	-7.842	6.696	-17.152**	-3.803	9.045	7.074	-17.250**	-4.087	15.632
	(0.41)	(-1.86)	(-0.73)	(-0.35)	(0.98)	(-2.06)	(-0.27)	(0.49)	(0.99)	(-2.00)	(-0.24)	(0.77)

Table 3 (cont'd).

Controls												
Cohort Distance					0.946	0.748	-1.943	0.385	1.111	0.841	-2.013	-0.133
					(0.47)	(0.36)	(-1.34)	(0.11)	(0.53)	(0.40)	(-1.43)	(-0.04)
Cohort Concentration									-4.402**	-2.187	-8.231	16.719*
									(-2.09)	(-0.54)	(-1.50)	(1.71)
Total Firms Per Cohort									-0.031	-0.003	-0.070	0.028
									(-1.23)	(-0.14)	(-1.51)	(0.59)
Ln Founders Per Cohort	-0.736*	-0.271	1.068	-1.160	-0.977**	0.011	1.109	-1.706	0.068	0.317	5.030**	-3.023
	(-1.67)	(-0.50)	(1.51)	(-0.94)	(-2.46)	(0.02)	(1.36)	(-1.13)	(0.09)	(0.30)	(1.98)	(-1.52)
Ln Num Founders	0.268	1.637**	0.606	2.381*	0.948	2.074**	0.514	2.464	0.906	2.081**	0.459	2.337
	(0.37)	(2.11)	(0.68)	(1.83)	(1.07)	(2.16)	(0.45)	(1.64)	(1.05)	(2.19)	(0.39)	(1.54)
Year Founding	0.329	0.283	0.585**	-0.385	0.320	0.417	0.784**	-0.332	0.281	0.397	0.825**	-0.441
	(1.28)	(1.13)	(2.19)	(-1.43)	(0.98)	(1.47)	(2.33)	(-0.90)	(0.95)	(1.49)	(2.27)	(-1.00)
Year Enter	-0.838***	-1.063***	-0.747**	0.075	-0.908**	-1.371***	-0.935**	0.164	-0.727**	-1.322***	-0.927**	-0.227
	(-2.65)	(-3.45)	(-2.26)	(0.20)	(-2.46)	(-3.56)	(-2.08)	(0.35)	(-2.13)	(-3.62)	(-2.04)	(-0.30)
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	394	394	394	394	336	336	336	336	336	336	336	336
log pseudolikelihood	-421.5	-421.5	-421.5	-421.5	-336.6	-336.6	-336.6	-336.6	-332.3	-332.3	-332.3	-332.3

Robust z-statistics in parentheses, standard errors are clustered by cohort

*** $p<0.01$, ** $p<0.05$, * $p<0.10$

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