Home Run, Strike Out, or Base Hit:
What is the Influence of Accelerators on Acquisition, Quitting, and VC Financing in New Ventures?

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Abstract

Increasingly, entrepreneurs in search of critical early stage resources face an evolving paradigm: the rise of accelerators that integrate small equity investments with an intensive, cohort-based mentoring experience. While the emergence of these accelerators is attracting substantial interest in the popular imagination, scholars know little about the overall influence of such accelerators on performance outcomes of new ventures. In this paper, we bring to bear a novel, hand-collected dataset of n= 614 startups and their founders that that comprise each cohort that has proceeded through two of the most established accelerators—Y Combinator and Tech Stars—from the period 2005-2011. We identify a matched sample of startups that instead receive their first formal financing from angel investor groups to address the counterfactual: what might have happened had the given startup not gone through the accelerator experience, i.e., had the startup instead pursued an alternative strategy for earliest financing? Specifically, in this paper we ask: *What is the impact of receiving financing from a top accelerator on subsequent outcomes- i.e., being acquired, deciding to quit, or obtaining follow-on funding from formal venture capitalists (VCs)?* We find that accelerators contribute to substantial differences in entrepreneurial outcomes relative to startups that receive formal angel group financing: participation in a top accelerator program increases the likelihood and speed of exit by acquisition as well as exit by quitting. In contrast, we find that receipt of follow-on funding from VCs occurs more slowly for startups participating in an accelerator relative to those with angel group financing. As well, we find that high status educational background increases the likelihood and time to exit by acquisition and exit by quitting, but with smaller magnitude than the effect of accelerator participation. In contrast, we find that educational background increases the likelihood and time to follow-on VC funding. Finally, we find that high status educational background in conjunction with accelerator participation diminishes the effect of being in an accelerator on the outcomes of interest, suggesting that accelerator participation and high status educational background may serve as substitutes.

"One of the companies in the room will be worth more than all of the others put together…. Ninety percent will ultimately fail. That makes for a very interesting game of trying to figure out who that one company is." (Paul Graham*,* quoted in *New York Times* (Rich, 2013)*)*

"There's so much luck involved with startups you increase your odds of success by swinging the bat multiple times. Each time you do something that isn't swinging the bat, you theoretically decrease your odds of success." (Harj Taggar, co-founder Auctomatic and partner in Y Combinator, quoted in Stross (2012))

1. Introduction

Increasingly, entrepreneurs in search of critical early stage resources face an evolving paradigm: the rise of accelerators that integrate small equity investments with an intensive, cohort-based mentoring experience. Anecdotes abound about the purported success of these accelerators in helping entrepreneurs to "do more faster" as one of the top accelerator programs proclaims. The emergence of these accelerators is attracting substantial interest in the popular imagination, in large part because of the potential to jumpstart new ventures with relatively small financial stakes but with significant potential exit outcomes (Carr, 2012, O'Brien, 2012, Stross, 2012). For example, DropBox, one of the early startups to go through Y Combinator in 2007, was by late 2013 seeking a $8 Billion valuation ahead of an anticipated initial public offering (Hardy and Gelles, 2013, Macmillan and Ante, 2013). However, notwithstanding attention in the popular press, relatively little scholarly attention has been devoted to understanding *what outcomes* accelerators may impact, whether they do it more *quickly*, and what the relevant *counterfactual* is: in other words, what role might accelerators play in the larger entrepreneurial ecosystem?

For entrepreneurs, initial accelerator backing presents several trajectories. Specifically, the entrepreneur may have exit options: a viable acquisition offer or an insight into quitting (Arora and Nandkumar, 2011). Likewise, the entrepreneur may attract follow-on funding from VCs, enabling the growth potential of the company but also curtailing the founders' rights (de Bettignies, 2008, Winton and Yerramilli, 2008). Alternatively, the company may simply plow forward at a steady rate (Åstebro and Winter, 2012). For entrepreneurs, each option carries distinct implications. In this paper, we ask: *What is the impact of receiving financing from a top accelerator on subsequent outcomes-i.e., being acquired, deciding to quit, or obtaining follow-on funding from formal venture capitalists (VCs)?*

In large part, the paucity of scholarly attention to the impact of accelerators on subsequent outcomes is a function of the novelty of the phenomenon: the most established accelerators are only starting to provide enough of a track record to identify distinct trajectories for the startups emerging from the accelerator experience.[1] In this paper, we bring to bear a completely novel, hand-collected dataset of

[1] To some extent, related forms of "early stage business incubation" (i.e., business incubators) have existed for a long time (see, for example, Amezcua et al. (2013)). However, there is growing recognition that accelerators are distinct from incubators along crucial dimensions: "Accelerators are slightly more formal than incubators, which operate as coworking spaces with some mentorship and classes. Incubators don't have regular cohorts of startups,

n=614 startups and their founders that that comprise each cohort that has proceeded through two of the most established accelerators—Y Combinator and Tech Stars—from the period 2005-2011. In order to test our hypotheses, we analyze the performance of founders and companies that participate in elite accelerator programs as a function of accelerator-specific, cohort-specific, and founder-specific characteristics.

A crucial issue in assessing the impact of accelerators on the startups that go through these programs is identifying the appropriate counterfactual against which any outcomes can be assessed. To do this, we ask: *had the entrepreneur not entered the accelerator program, what would have been the likely source of this first formal round of equity financing?* For entrepreneurs seeking seed-stage equity finance, applying to formal angel groups would be the closest counterfactual (Kerr et al., 2011). Thus, we identify a matched sample of startups that instead receive their first formal financing from 19 of the most active angel investing groups covering the similar range of industries and geographic locations as Y Combinator and TechStars over this time period. We further utilize the non-parametric Coarsened Exact Matching (CEM) approach to derive a more stringent matched sample (Azoulay et al., 2010, Iacus et al., 2012).

We find that accelerators contribute to substantial differences in entrepreneurial outcomes relative to startups that receive formal angel group financing. Specifically, we find that participation in a top accelerator program increases the likelihood of exit through multiple channels: accelerators increase the likelihood of exit by acquisition as well as exit by quitting. Second, we find that accelerator participation on its own does not have a statistically significant effect on the likelihood of attaining follow-on financing from formal venture capitalists. In parallel results we examine the effect of accelerator participation on the time to reaching each of these outcomes. We find that accelerator participation increases the time to exit through multiple channels, i.e. by acquisition and by quitting. In contrast, we find that receipt of follow-on funding from VCs occurs more slowly for startups participating in an accelerator relative to those with angel group financing.

One potential complication is that the role of the accelerator, *per se,* in helping entrepreneurs navigate early decisions and landmarks may be mixed with the role of status and signals coming from participation in a "top" accelerator. Both Y Combinator and Tech Stars are known for—and cultivate the appeal of—being highly selective, and coverage in the popular press emphasizes this element. For example, a managing director of TechStars noted *"We started this program in early January and received over 600 applications from start-ups that hope to build their company with our help,"* of which approximately "a dozen" were selected (Bilton, 2011). Likewise, Y Combinator is touted as the "Harvard

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and are more flexible about how long the startups stay." (Gruber et al., 2012, p. 14). As well, most elite accelerators also operate based on a small equity stake in the startup, which places them in line with other sources of early stage entrepreneurial finance, such as angel groups.

of Silicon Valley" (Rich, 2013, Wagner, 2011).

In our analysis, we seek to extricate the role of the accelerator from the potential signaling benefits that might arise from participation in a top program. First, this effect is partially mitigated by our comparison sample of startups at similar stages in similar industry and location that instead receive financing from the "top" angel groups (Kerr, Lerner and Schoar, 2011). Second, in keeping with the literature, we conjecture that status can be conveyed through multiple channels that might substitute for one another (Ozmel et al., 2012, Pollock et al., 2010). A strong signal available to a new entrepreneurs is the prestige of the educational institution from which she received her degrees (Burton et al., 2002). We use the role of the founders' educational backgrounds to disentangle the effect of status from the effect of the accelerator itself. We collect detailed data at the founder level on educational background, including institution(s) and degrees for all founders and incorporate this in our matching methodology. In doing so, we find evidence that the status of the founders' educational background and accelerator participation may partially substitute for one another in the early stage entrepreneurial ecosystem. However, even taking this into account, the role of the accelerator itself in promoting multiple outcomes remains highly robust and continues to provide the dominant effect.

Our contribution to the literature is three-fold. First, we make a substantial empirical contribution to the literature on strategic entrepreneurship and entrepreneurial finance. To the best of our knowledge, we provide the first large-scale, empirical analysis of the effect of accelerators on the full spectrum of entrepreneurial outcomes: acquisition, quitting, and subsequent VC financing. In doing so, we provide an empirical answer to the important question: *do accelerators accelerate the entrepreneurial process?* Second, we provide an important theoretical contribution to the literature on entrepreneurial finance and the importance of early resources in shaping young firm trajectories. We elucidate a theoretical underpinning for understanding why accelerators may accelerate exit outcomes— both acquisition and quitting—but not follow-on funding by looking to the incentives and motivations of top tier accelerators relative to those of top tier angel groups. We show that the earliest choice of equity finance—accelerator compared to angel groups—can have important consequences for the next stages in performance of the youngest innovation-focused firms. Third, we identify a tradeoff between the value of the accelerator and the value of high status educational background for the entrepreneur. We delineate several channels through which this tradeoff may occur: through potential redundancy of the signaling benefit accruing to both top-tier accelerator programs and to prestigious educational institutions as well as through the redundancy of peer effects in both. Taken together, we provide significant insights into an emerging paradigm for the earliest stages of entrepreneurial finance.

Finally, our work has important implications for practitioners and policy makers. In this paper, we provide evidence of important consequences to a growing and important phenomenon in the entrepreneurial ecosystem: the growth and proliferation early stage entrepreneurial accelerators as new sources of finance for startups. The growth of new firms serves as an engine for economic growth and innovation (Haltiwanger et al., 2013). We show that accelerators can contribute to this process through relatively small amounts of financial capital combined with intensive monitoring. Moreover, the clustering and cohort effects of accelerators in a range of geographic locations that includes both traditional top-tier entrepreneurial and VC hubs (e.g., Silicon Valley, Boston, etc.) as well as smaller or less traditionally entrepreneurial locations. This has important implications for the economic geography of entrepreneurship and innovation (Agrawal et al., 2011, Max, 2012).

2. Institutional Background: Entrepreneurial Accelerators and Angel Groups

2.1. Entrepreneurial Accelerators

Entrepreneurs and the ventures they seek to launch are often knowledge rich but resource constrained. The combination of constrained financial resources and knowledge richness—often tacit and embedded in the human capital—makes new firms with innovative ideas ripe for early stage equity financing to help the venture get out off the ground (Gompers and Lerner, 2001). Overall, firms in the earliest stages utilize capital from a variety of sources, but typically proceed from informal sources, e.g., family and friends, to more formal providers of financing, e.g., angel investors and VCs (Cassar, 2004, Robb and Robinson, 2012, Winston Smith, 2012).[3]

Early-stage entrepreneurial accelerators are emerging as a phenomenon that appears to be both distinct from traditional forms of angel investing and yet linked with the larger VC financing ecosystem. To be clear, accelerators--such as Y Combinator and Tech Stars --pursue high levels of engagement with start-ups combined with relatively small levels of initial financial capital and an intensive, typically cohort-based experience (O'Brien, 2012). Accelerators have a structured development program, with a pre-determined cohort and length of time, e.g., three months, in the case of Y Combinator, which may allow for a more efficient flow of resources available to start-ups that belong to the accelerator class (Carr, 2012). It is worth noting the distinction between accelerators and the less-defined concept of incubators. Incubators also exist to jump-start commercialization of a new innovation (Smilor and Gill Jr., 1986). However, they lack these definitive features that comprise the accelerator model.[4]

Accelerators typically bring start-ups together into cohorts for extensive training regimens, creating

[3] An extensive literature examines the role, structure, and importance of VC financing in young firms; however, such financing pertains to only a small fraction of early firms. For later stage firms, venture capitalists provide equity-based risk capital combined with guidance and monitoring (Gompers et al., 2010, Gompers and Lerner, 2006).

[4] As well, the literature on standalone incubators includes universities (Amezcua, Grimes, Bradley and Wiklund,

both a portfolio of companies competing for similar resources and a cohort of entrepreneurs who can learn in tandem from both mentors and each other (Cohen and Bingham, 2013). By contrast, start-ups in VC portfolios need to compete for attention and resources depending on the focus and size of the fund (Fulghieri and Sevilir, 2009). As well, the nature of the advice imparted through the accelerator may differ from the VC scenario. By engaging start-ups at a nascent stage of development, the envisioned technologies are often immature. Thus, as opposed to firms funded at the VC stage, accelerator-backed firms receive bets based more on the “jockey”, i.e., the founder, rather than the “horse”, i.e. the business idea (Kaplan et al., 2009).

2.2. Angel Groups

Nascent startups require scalable capital, often subsist on relatively low financial resources, and possess few tangible milestones. Angel investors, like accelerators, provide early stage equity financing to relatively immature, yet promising firms that typically precedes VC investment (Freear et al., 1994, Freear and Wetzel, 1990). Traditional definitions of angel investors imply an informal market of individuals providing early stage funds at arm’s length to help start-ups get off the ground (Goldfarb et al., 2009, Wetzel, 1983, Wong et al., 2009). In contrast to VCs, angels rely more heavily on alternative forms of control, such as trust, rather than contractual control rights (Goldfarb, Hoberg, Kirsch and Triantis, 2009, Wong, 2002). Overall, angels and VCs differ in the size, structure, and stage of investment (Mason and Harrison, 2002), with angels investing at the earliest seed stage and in smaller amounts than VCs. Angel investors may be active or passive (Prowse, 1998). However, compared to VCs, angels provide substantially less mentoring and hands-on involvement in the startup. The latter is in particular contrast to accelerators.

Increasingly, the most professionalized angel investors are comprised of semi-formal networks as groups of high net worth individuals who co-invest in early stage ventures (DeGennaro and Dwyer, 2013, Kerr, Lerner and Schoar, 2011, Wiltbank and Boeker, 2007). Using a regression discontinuity analysis of funded and unfunded startups that seek investment from two of the top angel groups (Tech Coast Angels and CommonAngels) Kerr et al. (2011) find that financing by top angel groups increases survival and growth relative to new firms that do not receive angel group financing.

3. Theoretical Background and Development of Hypotheses

3.1. Expected differences associated with choice of accelerator versus angel group

3.1.1. Exit alternatives: Exit by acquisition and exit by quitting

Early stage investors in new ventures serve two critical roles: as providers of risk capital and as mentors who help guide the entrepreneur through early decisions and processes. Exit and continuation decisions are amongst the most important set of decisions faced by an entrepreneur. Entrepreneurs make important choices about continuation strategies such as whether to accept viable acquisition offers and whether to quit (de Bettignies, 2008, Winton and Yerramilli, 2008), and VCs often provide advice to portfolio firms (Puri and Zarutskie, 2012). An important difference between accelerators and angel groups is the formalized role of mentoring. While VCs are known to be active participants in the companies in which they invest, angel investors are less hands-on (Kerr, Lerner and Schoar, 2011). Accelerators, on the other hand, are highly involved with each cohort and depict themselves as providers of mentorship akin to that of VCs (Cohen and Feld, 2011, Cohen and Bingham, 2013, Stross, 2012).

Accelerators are more likely to advise entrepreneurs to accept acquisition offers rather than waiting for follow-on funding, relative to angel groups. We expect this for several reasons. First, angel groups receive returns when they exit the company, and thus angel contracts are written to facilitate subsequent VC investment (Ibrahim, 2008, Wiltbank and Boeker, 2007). In a related vein, angel groups—by nature of investing their own money in relatively few companies at a time— look for an "acceptable" return on each company (Ibrahim, 2008). Conversely, accelerators operate more like VC investors in that they seek an outsized return on just a few companies in any given portfolio, while expecting that most companies will bring far lesser returns. This greater tolerance for the entrepreneurs' trade-off when faced with an acquisition offer is evidenced below:

> *"If you take a large amount of money from an investor, you usually give up this option [to sell yourself when you're small for a few million, rather than take more funding and roll the dice again]. But we realize (having been there) that an early offer from an acquirer can be very tempting for a group of young hackers. So if you want to sell early, that's ok. We'd make more if you went for an IPO, but we're not going to force anyone to do anything they don't want to."*
> (Y Combinator, 2013)

The net result is that for any given company, accelerators' incentives are to focus on the entrepreneur while angel groups' incentives require a higher likelihood of return on the *given company.* Given the relative incentives of accelerators relative to angel investors, we expect the following:

> *Hypothesis 1a: Relative to startups receiving their first formal financing from angel investor groups, startups in entrepreneurial accelerators will be more likely to exit through acquisition.*

3.1.2. Exit by quitting

While the literature often focuses on successful outcomes, which for very young firms is typically follow-on rounds of funding or acquisition, exit by quitting can also be a beneficial outcome. Learning when to quit when an idea is not reaching fruition allows entrepreneurs to put their human capital and financial capital to alternative use. In other words, when the opportunity cost of continuing outweighs the benefits of waiting for a favorable acquisition opportunity, entrepreneurs should choose to quit. The choice to either quickly "cash out" or quickly "flame out" is most pronounced amongst those entrepreneurs with the highest opportunity costs (Arora and Nandkumar, 2011).

Two features of the accelerator model stand to accentuate the likelihood of learning to quit. First, the intensive mentoring experience draws on successful serial entrepreneurs who themselves have often "failed" at one or more startups and willingly share these lessons with the founders (Cohen and Feld, 2011). Individually, entrepreneurs tend to be overoptimistic about the prospects of success (Lowe and Ziedonis, 2006). However, the founders of the accelerators have their own war stories to share to encourage insight into the value of quitting; as Brad Feld co-founder of TechStars, notes (Feld, 2013): *"I strongly believe that there are times you should call it quits on a business. Not everything works. And — even after trying incredibly hard, and for a long period of time — failure is sometimes the best option. An entrepreneur shouldn't view their entrepreneur arc as being linked to a single company, and having a lifetime perspective around entrepreneurship helps put the notion of failure into perspective."* The importance of failing quickly is baked into the mentoring model. As one of the founders of a TechStars backed startup observed (Cohen and Feld, 2011): *"We didn't focus on learning and failing fast until it was too late."*

Second, peer effects embedded in the cohort-based experience of the accelerator model may further facilitate learning to quit. The intensity of the cohort experience provides founders with a group of peers going through a similar experience in the same time frame. For example, within the accelerator, each cohort is seen as a "class" and entrepreneurs who go through a specific program are referred to as "alumni" and a network develops amongst companies that have gone through the same accelerator program in different cohorts (Cohen and Feld, 2011, Stross, 2012). This structure mirrors the formation of cultural capital in the context of university or professional school social bonding and network formation (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, to a greater extent than other aspects of college imprinting, including prestige (Massa and Simonov, 2011).

Importantly, peer effects may be particularly salient in recognizing when ideas might fail and thus highlighting the value of quitting. For example, strong peer effects contribute to learning when to quit unsuccessful ventures, as found in the Lerner and Malmendier (2013) study of cohorts of Harvard Business School graduates. Likewise, peer effects more generally influence the perception of the viability of an entrepreneurial career option (Kacperczyk, 2013, Stuart and Ding, 2006). Thus, the peer effects associated with accelerator participation may enable entrepreneurs to more clearly and realistically evaluate the relative chance of success and hence the value of quitting rather than continuing to burn through resources.

Given the above reasoning, Hypothesis 1b follows:

> *Hypothesis 1b: Relative to startups receiving their first formal financing from angel investor groups, startups in entrepreneurial accelerators will be more likely to exit through quitting.*

3.1.3. Follow-on funding from venture capitalists

Predictions about follow-on funding from VCs require understanding the motivations of founders as well as the incentives of the earliest (i.e., accelerator or angel group) investors. Founders often view obtaining follow-on funding (post-accelerator or angel round) as tantamount to the "holy grail" (Stross, 2012). However, while founders may initially see the successful quest for VC funding as a "badge of honor", more seasoned entrepreneurs recognize that accepting VC financing requires giving up control rights (Kaplan and Stromberg, 2004). A substantial literature reinforces the intuition that entrepreneurs seek to retain control rights when evaluating competing financing choices (de Bettignies, 2008, Ibrahim, 2010, Winton and Yerramilli, 2008).

In addition to the general concern of ceding control rights, the decision to accept VC financing effectively limits subsequent options. VC fundraising is a time-consuming process, and thus seeking and closing a VC deal prevents founders from devoting full attention to developing the product and idea behind the startup (Graham, 2007). As Paul Graham, founder of Y Combinator, notes *(Graham, 2007)*: "*If you take VC money, you have to mean it, because the structure of VC deals precludes early acquisitions.*"[5] Angel groups and accelerators possess substantially different views and incentives with respect to VC finance. While top accelerators actively caution founders against naively accepting VC finance, angel groups require exit strategies for startups in which they invest that will result in an acceptable return in the relatively near term (Wiltbank and Boeker, 2007, Wong, Bhatia and Freeman, 2009).

Finally, for young firms, VC financing is costly to acquire and hard to obtain (Hsu, 2004). Thus, at the earliest stages, initial support may serve as a signal of quality to follow-on investors (Spence, 1973). Similarly, the selectivity of the accelerator potentially could serve as a certification mechanism for follow-on VC investors (Alden, 2013, Rich, 2013). However, accelerators also face incentives to reveal only positive signals about their portfolio companies in order to continue to attract investors (Kim and Wagman, 2013). On balance, the signaling value of the prestigious accelerator may be muted.

Taken together, the arguments above suggest Hypothesis 1c:

> *Hypothesis 1c: Relative to startups receiving their first formal financing from angel investor groups, startups in entrepreneurial accelerators will be less likely to receive subsequent funding from VC investors.*

[5] This arises from two combined facets of VC investment: 1) Going public (IPO) will yield a greater return multiple for VCs than acquisition; and 2) VCs maximize the returns to their entire portfolio. Thus, VCs will prefer a riskier strategy for a given startup that has a small chance of a big return (IPO) because they have an entire portfolio of companies, only one of which needs to generate outsized returns. For the entrepreneur, however, an early acquisition offer—even if lower than a future acquisition or IPO—may be an attractive option.

3.2. Educational Prestige and Outcomes

Educational background might provide an outsized role in the earliest stages because the educational background and pedigree of the founder is readily observable to follow-on investors. At the outset, entrepreneurs face the substantial liability of being unknown entities, i.e., the liability of newness (Stinchcombe, 1965). Thus, potential acquirers or follow-on investors must rely on signals of promise when deciding to make an offer to new entrepreneurs. Overall, the evidence from the VC literature suggests that the pedigree of the founder facilitates the process of taking a new company though the early stages of growth and seeking out financing (Burton, Sørensen and Beckman, 2002, Hallen, 2008, Shane and Stuart, 2002).

Given high levels of uncertainty during the early stages of the startup's growth, signaling plays an important role in resolving issues of information asymmetry with external financing partners (Spence, 1973). For example, entrepreneurs may reveal their quality characteristics through the type of contractual rights and staging of funding agreed to with VCs (Gompers and Lerner, 2001) or through strategic use of patenting (Conti et al., 2011). However, these signally tools are likely unavailable at the nascent stages of company development. The sociology literature has shown that status influences publication outcomes (Simcoe and Waguespack, 2011) and that "coming from good stock" is a strong predictor of subsequent venture growth and performance (Burton, Sørensen and Beckman, 2002). Higher educational status acts as a signal of quality. Educational prestige, in particular, has been shown to be highly sticky, e.g., conferring financial benefits through better employment outcomes (Burris, 2004). Given the significant ambiguity regarding likely outcomes for very early stage investors as well as potential acquirers, educational pedigree may serve to reduce this ambiguity by acting as a harbinger of positive outcomes in the future. This, in turn, leads to greater likelihood of achievement of these expected outcomes (Butts, 2003, Krackhardt, 1987).

Higher educational status should also be associated with greater outside options, thereby facilitating the decision to exit by quitting. The entrepreneurship and labor economics literature show that the entrepreneurs with higher outside options are more likely to quit than persist in an unsuccessful venture (Arora and Nandkumar, 2011). As well, higher status educational background confers employment advantages for graduates of these institutions (Burris, 2004). Thus, entrepreneurs with higher prestige educational backgrounds enjoy greater outside options than those from other institutions.

Because higher prestige educational status of the founders' signals quality to outsiders and also increases employment options, we expect, *ceteris paribus*, that educational prestige will positively influence the likelihood of exit by acquisition and of follow-on funding. Taken together, the above arguments suggest the following hypothesis:

Hypothesis 2: Startups with founders possessing degrees from higher status educational *institutions will be more likely to exit by acquisition, exit by quitting, and receive follow-on funding from venture capital investors, relative to startups whose founders possess lower status degrees.*

3.3. Interaction of accelerator and educational prestige effects

"… [Harj Taggar, founder of Auctomatic] compared the experience with what he had found when he'd first arrived at Oxford and made the uncomfortable discovery that he was no longer the smartest student. So too at Y Combinator…. In the UK, he realized, he and his cousin had received attention in national media just because of the novelty of young founders starting a startup. … At Y Combinator, they were just one of many young teams of founders."(Stross, 2012)

Accelerator participation and educational prestige are likely to serve as substitutes for two reasons. First, the value of a signal depends upon the extent to which it reduces information asymmetries and decreases uncertainty about underlying quality, and thus each subsequent signal reduces the value of that information. Multiple signals of quality result in diminished benefits to either signal (Ozmel, Reuer and Gulati, 2012, Pollock, Chen, Jackson and Hambrick, 2010). According to signaling theory, a signal confers valuable information about quality when it is both hard to achieve, e.g., acceptance into a top accelerator or degrees from prestigious institutions, and when it is costly to attain, e.g., accelerator programs require that the entrepreneur dedicate substantial time exclusively to the startup and degrees from prestigious institutions are generally expensive in actual cost and often the opportunity cost of earning a salary (Spence, 1973). Both accelerator participation and high prestige educational degrees signal to potential acquirers and VC investors that the startup is of high quality. Thus, the combination of accelerator participation and prestigious education may substitute for one another in signaling value to potential acquirers or follow-on VCs.

Second, peer effects would be expected to act in a similar fashion in the accelerator cohort context as in the context of prestigious educational institutions. In both cases, peers—either the accelerator or educational institution—would provide a similar frame of reference against which entrepreneurs can evaluate the likelihood and desirability of distinct outcomes.

Taken together, the arguments above suggest that accelerator financing and higher educational prestige may act as substitutes for one another. Hypothesis 3 follows:

Hypothesis 3: Higher status educational pedigrees will negatively moderate the impact of accelerators with respect to exit by acquisition, exit by quitting, and follow-on VC funding.

4. Sample and Data Collection

Our analysis is based on a unique, hand-collected dataset comprising a census of all startups that receive their first round of financing through from Y Combinator and TechStars over the period 2005-2011. We cover all cohorts of these two accelerators over the time period and trace outcomes through June 2013. We then create a matched sample of startups that instead receive their first round of financing from 19 top angel groups over the same time period. The resulting dataset provides a full picture of startups financed through two distinct early-stage financing routes: accelerators and angel investors. The final sample of accelerator-backed startups consists of 389 observations, while the angel group sample is made up of 225 startups (total sample of n=614). Our data includes the date of founding and entry into either the accelerator or angel group for first round of funding, the timing and amounts of subsequent rounds, and other key outcomes, such as exit via acquisition or by quitting. For each round of funding, we identify the participants and identify the presence of VC investors. At the startup level, the data include geographic location at time of founding, industry, and educational attributes of all members of the founding team. We provide details of our sample selection process, data collection and matching methodology, and construction of our measures below.

4.1. Accelerator Sample Selection and Data Collection

We started by identifying our accelerator sample as the full census of startups that were accepted into and received financing from two of the most established accelerators in the U.S.: Y Combinator (founded in 2005) and TechStars (founded in 2006). We intentionally focus on these two programs for several distinct reasons. First and foremost, our goal is to identify the potential impact of accelerators on the outcomes of new ventures; to do so, we focus on two of the most prominent programs with established track records and formal, reproducible criteria. Indeed, Y Combinator and TechStars are widely and consistently ranked as the top accelerators (Geron, 2012, Gruber, 2011). Second, in creating a comprehensive census of the startups that moved through these programs over a period of six years we are able to create a matched sample that proceed instead with financing from elite angel groups, and thus we are able to isolate the impact of the "top" accelerators with the "top" angel groups (see below). Thus, while this does not cover the universe of accelerator programs that are springing up (see, e.g., Lennon (2013)), it allows us to isolate the effects most clearly in the circumstances that are held out as the industry standard.

To construct the population of startups funded by our entrepreneurial accelerators, we started with the websites of those accelerators. Y Combinator allows technology writers and blogs to access its "Demo Day", during which all startups within a cohort make a presentation. We accessed these sources to construct our Y Combinator cohort lists and corroborated with various online accounts. For TechStars, the full list of all cohorts was available on their website[6.] We derive our TechStars list from this and then check against other sources.

We turned to the online database *Crunchbase* for additional data. *Crunchbase* is affiliated with the blog Techcrunch.com and owned by the AOL media group. *Crunchbase* is an open and public database maintained by people involved in the entrepreneurial ecosystem of technology startups, and scholars have

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[6] TechStars Portfolio List. Accessed at http://www.techstars.com/companies/all/ from June 2012-June 2013.

begun to use *Crunchbase* as a data source, e.g., as a predictive tool for mergers and acquisitions (Xiang et al., 2012). The structure of the data within *Crunchbase* is similar to that of *VentureXpert*: founding firms, dates, firm status, founder profiles, investor profiles, and firm outcomes.

One of the benefits of the *Crunchbase* data is that it also includes founder backgrounds, including education and work history. However, some of this data was also incomplete. As such, we looked to *LinkedIn.com*, a publicly traded social media network for professionals (NYSE: LNKD). Because our previous two sources already indicated who the founders of each firm were, LinkedIn allowed us to retrieve founder backgrounds. In the event that our primary and secondary sources of data were incomplete, we relied on SEC filings, databases of *Forbes* and *BusinessWeek* magazines, and websites of startups and investors.

4.2. Angel sample and data collection

The use of a matched sample methodology seeks to establish the counterfactual path for the treatment group relative to the control group (Jain and Kini, 1995, Kerr, Lerner and Schoar, 2011, Megginson and Weiss, 1991). The ideal way to test the counterfactual is a randomized control experiment (RCE), or failing that, a natural experiment. Unfortunately, our treatment effect and counterfactual do not lend themselves to this approach. Rather, we created a carefully matched sample to evaluate the effect of the treatment, i.e., receiving financing through a top accelerator program, relative to the control, i.e. receiving financing from at top angel investor group. We explicitly matched our sample based on the geography, stage, the calendar date of first "treatment", i.e. receipt of the first round of financing from either the accelerator or the angel group, and the industry in which the startup operates.

As noted above, akin to accelerators, angel groups interface with startups at a stage of funding between personal funds and venture capital (Wong, Bhatia and Freeman, 2009). We selected startups that received financing from angel groups in their first formal funding round, just as accelerators are the first form of outside financing for the accelerator sample. Our assumption is that firms in both samples of are similar and high quality. Therefore, the baseline against which we compare outcomes of startups going through accelerator programs is to outcomes for startups that instead receive their first formal financing from angel groups.

We focus on startups in a defined number of industries and locations in which the accelerators are active. These are largely industries with relatively low startup costs, such as software technology firms.[7] We excluded firms in areas with high startup costs, such as technology hardware, biotechnology, and energy. Finally, we matched angel groups to a national geographic footprint across the United States that

[7] The industries included fall in the general categories of: Music, Gaming, and Media; Social Media, Location, and Mobile Apps; Payment and Commerce; Web Business; and Underlying Technology.

parallels the accelerator sample. Important to note however, is that we select our sample on the basis of startup properties, not those of founders.

As our focus is on the top angel groups as the relevant comparison to top accelerators, our primary data source for angel groups is Thomson One's *VentureXpert*. *VentureXpert* contains data on the firms on both sides of private equity (investors and start-ups), as well as venture outcomes and financing amounts. It has been used in numerous studies of entrepreneurial finance (Goldfarb, Hoberg, Kirsch and Triantis, 2009, Hellmann et al., 2013). We identified the top angel groups by number of deals and sought to match the geographic breadth and industry representation to those included in Y Combinator and TechStars cohorts. Our final sample of angel-group backed startups consists of the top 19 angel groups. (**Appendix Table 2** provides the full list). The groups have a national footprint, but similar to the accelerators, they often engage with firms in the Silicon Valley, Boston, and New York City clusters. These angel investors are prominent in the entrepreneurial finance space, and some have been studied in prior scholarly work (DeGennaro and Dwyer, 2013, Kerr, Lerner and Schoar, 2011).

VentureXpert is often incomplete at early stages of venture funding. We thus turn to the investment portfolios posted on angel group websites to obtain further details on portfolio companies. We further buttress our data from the same internet-based sources used in our accelerator sample (detailed above). This practice is consistent with other studies (Katila et al., 2008).

4.3. Coarsened Exact Matching (CEM)

As a more stringent matching procedure, we further use Coarsened Exact Matching (CEM) to balance the treatment and control groups in our sample. CEM is a non-parametric approach that is well-suited to facilitating causal inference from observational data by creating a balanced sample of treated and control group observations based on *a priori* specification of degree of desired matching (Blackwell et al., 2009, Iacus, King and Porro, 2012). Increasingly, CEM is viewed as an advantageous method for matching samples without imposing undue balance restrictions and has been applied to observational data in the management and political science arenas (Azoulay, Graff Zivin and Wang, 2010, Singh and Agrawal, 2011, Younge et al., 2012). In this vein, within the relative infancy of the literature on accelerators in a related paper, Cohen et al. compare a sample of accelerator backed startups that ultimately receive VC financing with a CEM matched sample on non-accelerator backed companies (Cohen et al., 2013).We used the CEM process to assess the rigidity of our core matching variables. The ultimate matching of samples in a smaller overall number of observations ultimately provides weights in which the "better" match is regressed to add robustness to results (Hsu, 2006).

In our study, we arrived at a "better" sample of matched observations of n=576, which dropped 38 observations from the full sample analysis. As suggested by Azoulay et al. (2010) the selection of covariates ought to center on a relatively small group. In the case of our study, we sought to identify a series of observable measures on which startups may be considered, regardless of the program (accelerator or angel group) they enter. In so doing, the key observables establish the balance between the sample groups. For this study, those variables were industry, location of the startup, and education of the founders. This group of covariates is consistent with how our initial sampling design was structured.

4.4. Identification of outcomes

We use multiple sources to determine outcomes and timing, including the dates of founding, exit by acquisition, successive rounds and amounts of funding, and quitting. Triangulation was particularly necessary in the determination of quitting and the timing of that exit. We collected all events to the day level of analysis. For cases in which only the month was given, we defaulted to the first day of the month.

For exit by acquisition and funding data, we started with *VentureXpert* as the core source of data. We then augmented this information from the other sources above; this strategy was particularly effective in the absence of records from *VentureXpert.* We delved into the ecosystem of technology blogs to confirm existing details and fill in gaps (e.g., a founder may have neglected to include a second degree on his/her *LinkedIn* profile, but may have mentioned it in an interview with a blog).

Unlike the founding of a startup, quitting is often not announced to the public. We carried out a series of crosschecks to establish a distinction between quitting and a simple lack of ongoing public activity. To conduct these checks, we relied on accelerator/angel group, firm, and founder level sources. At the accelerator/angel group level, we used a combination of the websites of the accelerators/angel groups themselves, as well as *Crunchbase*. In some cases, the exact status of the startup is listed, such as those on TechStars' website. At the firm level, we used a comprehensive process to establish the ongoing efforts of the firm. An active company website indicated an active firm, while dated posts and updates provided clues as its last known efforts. A discontinued website indicated a shuttered firm, but not the timing of *when* it was shut down. Further clues came from the startups' social media networks, such as *Facebook*, *Twitter*, or *LinkedIn*. A *Twitter* account with regular posts up until a specific date, along with a company website no longer updated after that date, gave stronger clues as to the timing of quitting.

Triangulating from the founder level of analysis provided more concrete evidence to the clues above. Using founder work histories on *LinkedIn*, we could pinpoint the dates at which founders moved on to other jobs. On its own this data may not suggest startup failure; founders often leave startups to pursue other ventures (In some cases, founders actually state that the startup was shut down on a particular date). However, the combination of a job move with startup inactivity may suggest quitting. This process is one consistent with how quitting is described in accelerator programs, where "death" is a gradual process "*...starting with a long stretch in which the product goes without updates. The founders leave to do something else. The Web site might remain live but no one is at home*." (Stross, 2012: 219).

4.5. Identification of founder data

We collect founder data using a similar regimen of triangulating processes. We start with the founders listed under the company listings on *VentureXpert*, and supplemented with *Crunchbase.* This served to provide details on the number and names of founders. Then, to establish the education histories of the founders, we turned again to *LinkedIn.* We further cross-checked the *LinkedIn* profiles of founders against other sources, such as founder biography sections of startup websites, *Business Week* magazine founder profiles, profiles on other social media networks (such as *Twitter*), and technology blog posts. (*LinkedIn* was overwhelmingly the most complete source of data available.)

We identified the name of the school each founder attended using the education history. Many founders had more than one university degree, and the number of schools listed in the data reflects this possibility, even when accounting for the same school.[8]

5. Econometric analysis

5.1. Measures and variables

5.1.1. Exit and Funding Outcomes

Discrete Outcomes. As described above, we identified five distinct potential outcomes for each startup: *ExitByAcquisition* (successful exit through acquisition)[9], *ExitByQuitting* (exit by quitting), *Alive* (received initial round of funding and remained active), *VC Round1* (receive first round of follow-up funding from VCs), and *VC Round*2+ (receive second or further rounds of follow-up funding from VCs).

Outcome Timing. As a result of the processes above, our data contains information on successful exit via acquisition, exit by quitting, and each successive round of funding. For each of the outcomes of interest, we construct measures of the time it takes from startup founding to each outcome (measured in months). Specifically, *TimeToExit,* measures the number of months from founding to an exit through acquisition; *TimeToQuit* measures the number of months from founding to quitting, and *TimeToVCRound1,* and *TimeToVCRound2+*, measure the number of months until VC funding is received, in either the next or subsequent round of financing received after getting initial financing from the accelerator or angel group, respectively.

5.1.2. Independent variables

Accelerator. Our main independent variable is a dichotomous variable equal to 1 if the startup receives financing from an accelerator and equal to 0 if the startup received its initial financing from a top angel group.

Top Degrees Per Founder. The variable *TopDegreePerFounder* is the ratio of the total number of high status degrees held by all of the founders of a given startup relative to the total number of founders.

[8] E.g., one founder that went to Stanford for both bachelors and masters degrees would have Stanford listed twice.
[9] Given the early stage of firms in our sample there were no IPO exits.

The status of the founder's education may signal the quality of the founder and the peer effects associated with coming from a highly ranked institution (Pollock, Chen, Jackson and Hambrick, 2010). We determine the prestige of an educational institution from the *U.S. News* Top 400 World University Rankings. We use the *U.S. News* measure of academic reputation in its overall survey to sort schools outside of other measures (such as International Students and Faculty To Student Ratio). [10] For our classification of high status schools, we selected the top 13 U.S. schools as an initial group and added several additional schools.[11] This is consistent with other studies controlling for elite education (see, e.g., Cohen, Frazzini, and Malloy (2010) and Kacperzyck (2013)). Founders with degrees from schools in our list received a code of 1 for each degree.

5.1.3. Control variables

Silicon Valley Location. We controlled specifically for the effect of Silicon Valley as the startup location in our analysis (*LocSV)*. Our sample was selected to represent a series of pockets of innovation across the United States and is matched across angel groups and accelerators. However, there are may be strong regional innovation effect from Silicon Valley (Saxenian, 1994), and with many sample firms located in the area we sought to capture this in a control.

Number of Founders. From the startup unit of analysis, we assembled career and education histories of each founder. We coded the number of founders per startup at the time of founding as *NumFounders*.

Cohort. Firms that proceed through accelerator programs do so in cohorts. These cohorts allow us to control for the clustering that exists between firms in time, but also the progression of firms over time. Therefore, we have created a variable called *Cohort*, which matches Y Combinator or TechStars startups to the specific cohort in which they entered (e.g., Spring 2010).

Funding. We control for the total funding the startup has received as ln(1+*ToFundAllRounds)*.

Industry. While portfolio firms were sampled on the basis of a broad technology definition, the specific industries, ranging from social media websites to payment technologies have been coded into six different categories. 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).

5.2. Empirical strategy

We are interested in both the likelihood and the timing of distinct outcomes. The alternative

[10] *U.S. News Top 400 World University Rankings, 2012.* Accessed at http://www.usnews.com/education/worlds-best-universities-rankings/top-400-universities-in-the-world?page=2 on Apr 1, 2013.

[11] The initial list of top schools were: Harvard, Princeton, Yale, Columbia, University of Pennsylvania, Cornell, Stanford, University of Chicago, UCLA, Berkeley, Stanford, University of Michigan, and MIT. This group was supplemented by the Oxford, Cambridge, Brown, Dartmouth, and Duke universities.

outcomes consist of: *ExitByAcquisition*, *ExitByQuitting*, *VC Round1,* and *VCRound2+* (which includes all further rounds of financing). The baseline outcome is remaining *Alive*, in which startups receive only the initial round of either accelerator or angel-group funding and continue to operate. We estimate the likelihood of each of the alternative outcomes using multinomial logit regression (Greene, 2008).

Turning next to the timing of distinct outcomes, we estimate competing risks survival models to determine the hazard rate of each alternative outcome from the time of first starting in the accelerator program or receiving the first round of angel group finance. Specifically, we estimate the relative hazard rates of: *TimeToExit, TimeToQuit, TimeToVCRound1*, and *TimeToVCRound2+*. Competing risks analysis allows us to discern differences across each of these destination states (Wooldridge, 2002).

Overall, our analysis highlights the necessity of finding an appropriate counterfactual: *what would the trajectory of a given startup in an accelerator have been if that same startup instead had not participated in the accelerator program?* In addition to comparison to our matched sample of startups that instead receive angel group backing, we employ a coarsened exact matching (CEM) process to balance the treatment (accelerator-backed startups) and control (angel group-backed startups) groups on the basis of selection into study sample. We also examine robustness using an Inverse Probability of Treatment Weighting (IPTW) propensity score based weighting scheme. As an additional (unreported) check, we also consider a two-stage Heckman correction to take into account the probability of selection into an accelerator in the first stage.

5.3. Univariate statistics

Variables in the full sample are summarized in **Table 1**. A basic correlation matrix can be found in **Appendix Table 1**. In order to facilitate comparison between the accelerator and angel group samples, we provide a breakdown of each group separately.

Table 2a presents a series of summary statistics for our baseline data. Of the 389 accelerator-backed firms, 15% successfully exited during the sample period, while 23% quit. In comparison, 14% of the 225 angel-backed startups exited, while 8% quit. For accelerator-backed firms, 9% receive a first round of VC funding, compared to 20% of angel group-funded startups. Accelerator-backed firms also had higher average time to outcomes. Their average time from founding to a successful exit was 27 months while the angel-backed firms averaged 58 months. Time to quitting was even more divergent between the two groups. Accelerator-backed firms quit in about 20 months while the angel-backed firms averaged 48 months from founding to exit by quitting.

In a t-test of means of our matching criteria of geography and industry, there were no significant differences in several characteristics such as the industries of Payment/Commerce, Web Business, and Media/Music/Gaming, and the locations of California, New York City and Boston, and in foreign locations. Significant differences did exist between the accelerator and angel-backed startups in other characteristics such as Industry: Underlying Technology, Industry: Other and locations in Colorado and the remainder of North America. However, coarsened exact matching (discussed) weights on industry and location take these differences into account. **Table 2b** displays the CEM-matched data, consisting of n=357 accelerator-backed firms and n=219 angel group-backed firms. The patterns of firm egress remain generally consistent with the slightly smaller matched groups.

6. Results

6.1. Analysis of full sample

6.1.1. Results from multinomial logit analysis

As hypothesized, we expect accelerator-backed startups to have different likelihood of alternative outcomes relative to angel-group backed startups. Results of our multinomial logit regressions are presented in **Table 3** in the format of a relative risk ratio.

The results in **Table 3** provide strong support for Hypothesis 1a and 1b: Startups that participate in accelerator programs are more likely to *ExitByAcquistion* and are more likely to *ExitByQuitting* relative to angel-group backed startups. All else equal, the relative risk of exiting through acquisition is 5.6 times greater for accelerator-backed startups (p <0.001) (Column1) and the relative risk of quitting is 16.0 times greater for accelerator-backed startups (p<0.001) (Column 3). Thus, as hypothesized, participation in the accelerator program appears to increase the likelihood of exit through multiple channels, i.e., through both acquisitions and through quitting operations. When we take into account the interaction between accelerator participation and educational status (*Accelerator*TopDegreePerFounder)*, we find that these results are strengthened. The relative likelihood of *ExitByAcquisition* (Column 2) and *ExitByQuitting* (Column 4) increase compared to Column 1 and Column 3, respectively, and both remain highly statistically significant (p<0.001). Finally, Hypothesis 1c does not receive support here: the coefficients on *VC Round1* and *VC Round2* are not statistically significant at conventional levels.

The results in **Table 3** also support Hypothesis 2: Higher status educational background of the founders is associated with a greater likelihood of exit by acquisition, exit by quitting and receiving subsequent financing from VCs. When we take into account the interactive effect, the effect of *TopDegreePerFounder* becomes statistically significant in Column 2 and Column 4, indicating that higher status educational backgrounds of founders is associated with similar (roughly 2.5 times) greater risk of *ExitByAcquisition* (Column 2, p<0.001) and of *ExitByQuitting* (Column 4, p<0.001). However, the magnitude of the effect of educational background is far smaller than that associated with accelerator backing for both exit outcomes. In Column 5, the relative risk of receiving follow-on *VC Round1* is 1.6 times greater (p<0.10); this effect increases in both magnitude and significance (2.5, p<0.01) when we take into account the interactive term (Column 2). This effect appears to diminish with subsequent rounds of financing, *VCRound2+* (Columns 6 and 7).

Interpreting the interactive term requires additional care. Simple inspection of the coefficients on the interaction term *Accelerator*TopDegreePerFounder* in Table 3 is not sufficient to determine the magnitude or significance of the interactive effect, as the cross-partial terms in the derivative of a non-linear specification (such as multinomial logit) depend on the value of both of the component terms (Ai and Norton, 2003, Zelner, 2009). In order to give meaningful interpretation to Hypothesis 3, we use a simulation-based approach to examine these interactive effects. Briefly, based on the matrix of estimated coefficients and their covariance matrix, we simulate (n=10,000 draws) the distribution of outcomes for the full range of parameters. This allows us to numerically determine the upper and lower bounds of the confidence intervals as well as the magnitude of the combined effect.[12]

Figure 1a-d (Panel A) show these results plotted across the full range of *TopDegreePerFounder* and other variables set to their mean values. The dotted lines represent the upper and lower bounds, respectively, of the 95% confidence interval derived from 10,000 simulations. (The intuition here is that the interaction of *Accelerator*TopDegreePerFounder* is statistically significant when the upper and lower bounds of the confidence interval do not include zero, i.e., we can reject the null hypothesis that they are not statistically different from zero). In looking at these plots, we observe that the interactive effect is significant across nearly the full range of *TopDegreePerFounder* for *ExitByAcquisition* (Figure 1a) and across the full range of *TopDegreePerFounder* for *ExitByQuitting* (Figure 1b). The funding outcomes are more ambiguous: we see that the interaction is significant across nearly the full range of *TopDegreePerFounder* for the likelihood of receiving *VC Round1 (*Figure 1c), but the interaction effect is clearly insignificant with respect to the likelihood of receiving subsequent rounds of VC investment (*VC Round2+)* (Figure 1d).

6.1.2. Results from competing risks proportional hazard regressions

Implicitly and explicitly, accelerator programs purport to influence the speed with which various outcomes occur. Thus, we estimate the hazard of each alternative outcome, i.e. the time from first receipt of either accelerator or angel group backing to the occurrence of the given outcome. As noted above, we consider the competing hazards of alternative outcomes occurring: *TimeToExit, TimeToQuit, TimeToVCRound1*, and *TimeToVCRound2+*. Competing risks analysis allows us to consider the cumulative incidence function for the hazard of each competing outcome given that each startup is "at risk" of multiple outcomes (Fine and Gray, 1999). **Table 4** presents results from the baseline competing risks estimation. Again, the baseline risk is remaining alive. We report results in terms of hazard ratios for ease of interpretation.

[12] We develop and code a simulation-based approach to deriving confidence intervals on interactive terms in non-linear models (e.g., the multinomial logit and competing risks model we employ) that is similar to Zelner (2009). This encompasses a wider variety of models and outcomes than permitted in the program *Clarify*.

Overall, the results from the hazard analysis are substantively similar to those presented in our multinomial logit analysis above. The results in **Table 4** provide strong support for Hypothesis 1a: Accelerator-backed startups have a greater hazard of *TimeToExitByAcquistion* relative to angel-group backed startups, i.e. *ExitByAcquisition* occurs more quickly than for angel-group backed startups. As shown in Column 1, all else equal, the hazard of exiting through acquisition is 2.6 times greater for accelerator-backed startups ($p < 0.001$). Likewise, Hypotheses 1b also receives strong support: Startups that participate in accelerator programs have a greater hazard of *TimeToExitByQuitting* relative to angel-group backed startups. As shown in Column 3, the hazard of quitting is 12.2 times greater for accelerator-backed startups ($p<0.001$). Thus, as hypothesized, participation in the accelerator program appears to increase the speed of exit through multiple channels, i.e., through both acquisitions and through quitting operations.

The results in **Table 4** also provide support for Hypothesis 1c: Accelerator-backed startups appear to have a *lower hazard* of receiving either *VCRound1* or *VCRound2+* financing relative to angel-group backed startups. The hazard of *TimeToVCRound1* financing is just over one-third as high (0.385) for accelerator-backed startups relative to those that are angel-group backed (Column 5, $p<0.001$). This effect is slightly diminished for subsequent VC financing, with the hazard rate of *TimeToVCRound2+* for accelerator-backed startups almost half that of angel-backed startups (Column 7, $p<0.05$). When we take into account the interactive term, the hazard of *TimeToExitByAcquisition* (Column 2) and *TimeToExitByQuitting* (Column 4) both increase (i.e., occur more quickly) compared to Column 1 and Column 3, respectively, and both remain highly statistically significant ($p<0.001$).

Hypothesis 2 also receives support from the competing risk regressions: greater status of founders' educational institutions is associated with quicker time to multiple outcomes. When we take into account the interactive effect, the effect of *TopDegreePerFounder* becomes statistically significant ($p<0.01$) in Column 2 and Column 4, indicating that higher status educational backgrounds of founders is associated with similar approximately 1.4 times greater hazard of *TimeToExitbyAcquisition* (Column 2, $p<0.001$) and 1.3 times greater hazard of *ExitByQuitting* (Column 4, $p<0.001$). However, the magnitude of the effect of educational background is far smaller than that associated with accelerator backing for both exit outcomes. As well, higher educational status increases the hazard of both *TimeToVCRound1* (Column 6, $p<0.001$) and *TimeToVCRound2+* (Column 8, $p<0.001$).

Again, the non-linearity of the competing risks regression complicates interpretation of the interactive term. Thus, we turn to our simulation-based approach to give meaningful interpretations to these interactions and assess Hypothesis 3: that accelerator participation and high status educational background serve as substitutes. Looking at **Figure 2a-d** (**Panel A)** we see that the interaction is significant at the 95% level for lower values of *TopDegreePerFounder*, but becomes insignificant at higher values for *ExitByAcquisition* (Figure 2a). The interactive effect is significant across the full range of *TopDegreePerFounder* values for *ExitByQuitting* (Figure 2b). The interaction term is significant across the full range for *VCRound1* (Figure 2c) and across nearly the full range for *VCRound2+* (Figure 2d). In each case, the graphs are downward sloping across the range of significance as expected if the two effects serve as partial substitutes for one another.

In sum, the results of the multinomial logit analysis and the competing risks analysis strongly suggest that startups backed by accelerators had a higher likelihood of exit by acquisition and of exit by quitting (relative to the baseline "alive" outcome) than did angel group-backed startups, and that they achieve these outcomes with greater speed. As well, the results suggest that accelerator participation actually increases the length of time until VC funding is received. As hypothesized, higher status educational background of founders increases the likelihood and speed of exits through acquisition and through quitting and of receiving follow-on VC financing. Finally, the results suggest that these effects—accelerator participation and high-status educational background—may be partial substitutes.

6.2. Analysis of CEM sample

6.2.1. Multinomial logit analysis with CEM sample

The multinomial logit and competing risks models are presented with CEM weights in **Table 5** and **Table 6,** respectively. Naturally, the final number of observations is smaller in each of the CEM matched analyses, due to the observations that are pruned during coarsening and matching. The results in **Table 5** provide further support for our hypotheses and largely magnify the results from our full sample analysis. All results are presented in terms of relative risk ratios.

The results in **Table 5** support Hypotheses 1a and 1b: Accelerator-backed startups are substantially more likely to exit by both acquisition (Column 2) and by Quitting (Column 4). In the CEM matched sample, accelerator-backed startups face a 6.8 times greater relative risk of *ExitByAcquisition* compared to similar angel-group backed startups (Column 2, $p<0.001$). The matching algorithm particularly strengthens the likelihood of *ExitByQuitting* (Column 4, $p<0.001$). Hypothesis 1c receives little empirical support: The coefficients on likelihood of subsequent VC financing, *VCRound1* (Column 7) and *VC Round2+* (Column 8) remain statistically insignificant.

Similarly, Hypothesis 2 is further supported in the CEM matched sample. As we see in **Table 5** higher prestige educational institutions *(TopDegreePerFounder*) is associated with a greater likelihood of each of the alternative outcomes, relative to the baseline of remaining alive. Likewise, the simulation-based plots (**Figure 1a-d, Panel B**) provide similar support for Hypothesis 3 as above.

6.2.2. Competing risk hazard analysis with CEM sample

Table 6 presents the results from competing risk analysis on the CEM sample. As with the competing risk analysis of the full sample, results are presented in the hazard of each potential and competing outcome.

Consistent with the multinomial logit estimations, the main results of the competing risk analysis are congruent to those derived using the full sample. Hypotheses 1a and 1b retain support, with accelerator-backed firms showing higher hazard ratios of *TimeToExitByAcquisition* and *TimeToExitByQuitting* than that of angel group-backed firms. **Table 6** also shows continued support for Hypothesis 1c, with accelerator-backed startups showing a lower hazard ratio of *TimeToVCRound1*. The support for *TimeToVCRound2+* decreases with the CEM weights relative to the results in the full sample.

Similar to the results in the full sample, Hypothesis 2 also receives consistent support in the CEM sample. The role of high status education remains statistically significant in Table 6, with *TopDegreePerFounder* showing increasing hazard of of *TimeToExitByAcquisition* (p<.01), *TimeToExitByQuitting* (p<.01), *TimeToVCRound1* (p<.01), and *TimeToVCRound2* (p<.05) Finally, .our simulation-based plots (**Figure 2a-d, Panel B**) show similar patterns as presented earlier in support of Hypothesis 3 that *Accelerator* and *TopDegreePerFounder* are partial substitutes.

6.3. Robustness checks

6.3.1. Alternative matching methodology

We carry out a number of robustness checks. First, we consider the appropriateness of an alternative matching methodology, Inverse Probability Treatment Weighting (IPTW), which draws on the principles of propensity score matching. Results based on the IPTW weights applied to our full sample regressions are substantively similar to those previously described (available from authors). We also employ a two-stage Heckman correction model to take into account the probability of selection into an accelerator in the first stage. This approach allows us to correct for potential possibility of selection bias by incorporating a Heckman correction (Heckman, 1979, Lee, 1983). Again, these results are substantively similar to the results above (available from authors).

6.3.2. Robustness to specification

We explore the robustness of our results to alternative treatment of the cohort variable. Unlike startups in the accelerator programs, startups that instead receive backing from angel groups are not organized in a formal cohort. In order to take this into account, we construct an alternative "cohort" grouping in which each startup is assigned to a cohort based on having the same funder in the same year of entry. The magnitude and direction of the findings remain fairly consistent when compared to the earlier results (available from authors). We also conduct robustness checks on our independent variables. Results are robust to inclusion of controls for additional headquarters locations besides Silicon Valley, to coarser industry definitions, and to whether founders attended the same educational institutions as one another. None of these substantively impact the findings. As well, we explored robustness using the startup founding date as the origin instead of the date of entry into the accelerator or angel-group. Again, results were qualitatively similar.

7. Conclusion and Discussion

7.1. Conclusion

In this paper, we identify the entrepreneurial accelerator as emerging type source of very early stage entrepreneurial finance. At the outset, we asked: *What is the impact of receiving financing from a top accelerator on subsequent outcomes-i.e., being acquired, deciding to quit, or obtaining follow-on funding from formal venture capitalists (VCs)?* We bring to bear unique data and find that accelerators contribute to substantial differences in each of these outcomes relative to startups that receive formal angel group financing. Specifically, we find that participation in a top accelerator program increases the likelihood of exit through multiple channels: accelerators increase the likelihood of exit by acquisition as well as exit by quitting. Second, we find that accelerator participation on its own does not have a statistically significant effect on the likelihood of attaining follow-on financing from formal venture capitalists. In parallel results we examine the effect of accelerator participation on the time to reaching each of these outcomes. Again, we find that accelerator participation increases the time to exit through multiple channels, i.e. both exit by acquisition and exit by quitting occur more quickly in accelerator-backed startups relative to those that are backed by angel groups. By contrast, we find that receipt of follow-on funding from VCs occurs more slowly for startups participating in an accelerator relative to those with angel group financing.

We further investigate the role of high status educational background on these outcomes. We find that high status educational background increases the likelihood and time to exit by acquisition and exit by quitting, but with significantly smaller magnitude than the effect of accelerator participation. By contrast, we find that educational background increases the likelihood and time to follow-on VC funding. Finally, we find that high status educational background in conjunction with accelerator participation diminishes the effect of being in an accelerator on the outcomes of interest, suggesting that accelerator participation and high status educational background may serve as substitutes.

7.2. Discussion

Overall, we demonstrate a potentially important role for these accelerators in shaping the trajectory of startups through in the earliest stages of the entrepreneurial landscape. Our contribution to the literature is several-fold. We examine the full population of startups that have gone through the top two accelerators and follow them through to their final outcome (at the end of our sample period in June 2013). Likewise, our angel sample is matched based on characteristics at time of funding, and are followed through the same range of outcomes over the same period of time. To our knowledge, this is the first comprehensive study of a large sample of startups from first round of formal accelerator finance through current outcomes that is not censored on outcomes, such as receipt of VC backing. We thus provide invaluable evidence of a significant and growing phenomenon.

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 the top accelerators have demonstrably distinct impacts on a multitude of entrepreneurial outcomes: To echo our title, accelerator-backed startups are quicker to be “home runs” (acquisitions) or “strikeouts” (quitting) relative to angel-group backed startups, yet these accelerator-backed startups are slower to simply get “on base” (obtain subsequent rounds of VC financing) relative to their angel-backed counterparts.

Important as the phenomenon may turn out to be, our contribution to the literature extends beyond the descriptive. We provide careful theoretical predictions about the relationship between the type of earliest formal financing—accelerator or angel group—and the founders’ prior background. In particular, we show that high status educational effects play a moderating role in the trajectory of the startup. In particular, we find that top accelerators and high status educational background of the founder(s) may be partial substitutes. In doing so, we contribute to theory that suggests that multiple signals of status are substitutes rather than complements (Ozmel, Reuer and Gulati, 2012, Pollock, Chen, Jackson and Hambrick, 2010). Furthermore, we build on recent papers that focus on the importance of learning to fail quickly (Arora and Nandkumar, 2011, Lerner and Malmendier, 2013). Finally, we contribute to a rich and vast literature on the importance of early financial and human capital resources on new venture performance.

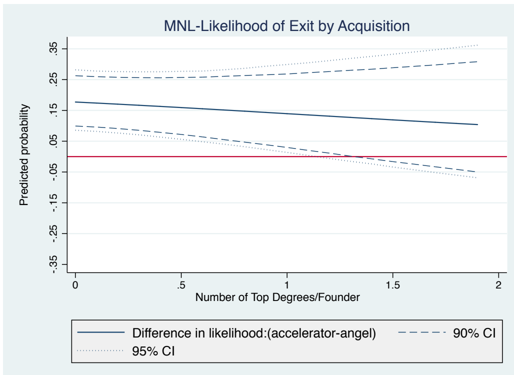
Our study, of course, is not without its limitations. Foremost, we have intentionally studied two of the most well known and longest established accelerators (and thus compared them to established angel groups). However, our study does not include the many other accelerators that are in existence. Our results suggest that *top accelerators* influence the trajectory and outcomes of the entrepreneurs and startups whom they mentor/select to work with. We cannot comment on the role of less established or lesser-ranked accelerators; instead, we leave that to future research.

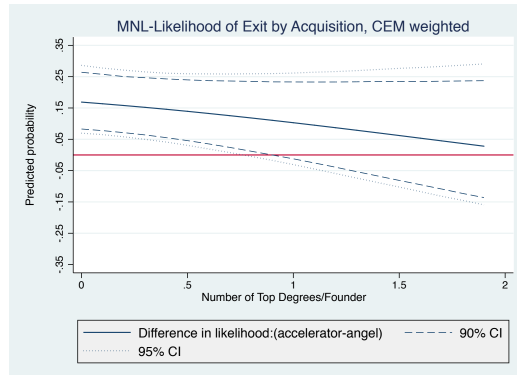
A related limitation is that the top accelerators most certainly do not randomly choose the participating entrepreneurs and startups. This selection bias of course will have consequences for understanding the true effect of the accelerator separate from the selection itself. To the best of our econometric ability we have sought to take this into account through creation of a matched sample and matching techniques based on observable characteristics. However, we cannot address the role of unobservables, nor do we know about the entrepreneurs that applied but were not accepted into these top programs. Again, future research might provide data and insight into the selection process itself.

Figure 1. Multinomial Logit Regressions, Probability of Outcomes (Simulation derived confidence intervals)

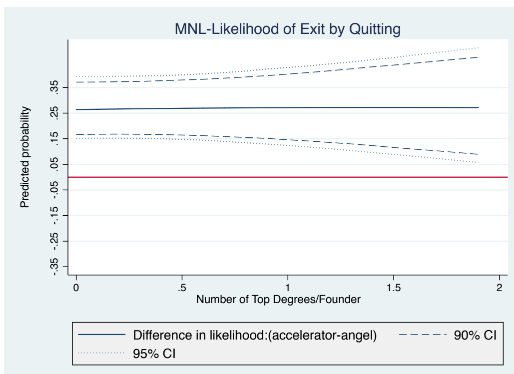
Panel A: Full Sample *Panel B: CEM Weighted*

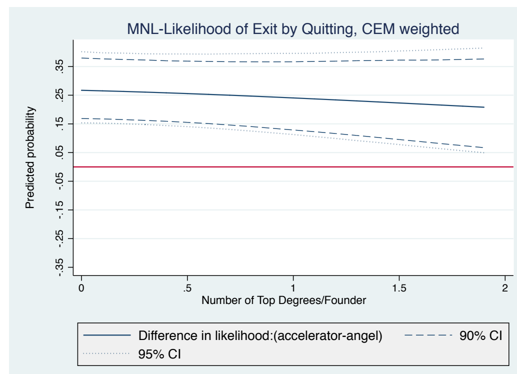
(1a.)



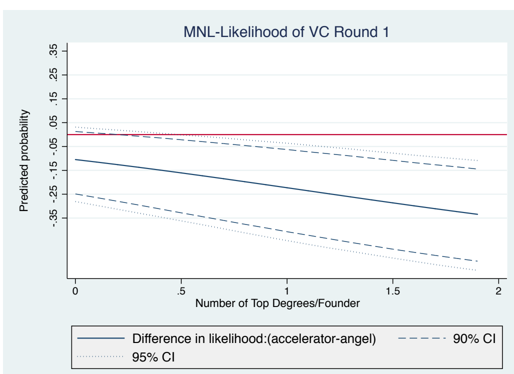


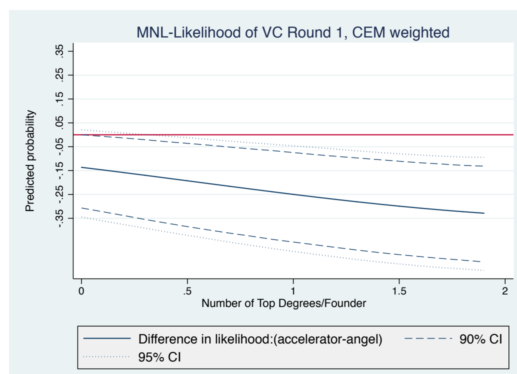
(1b.)



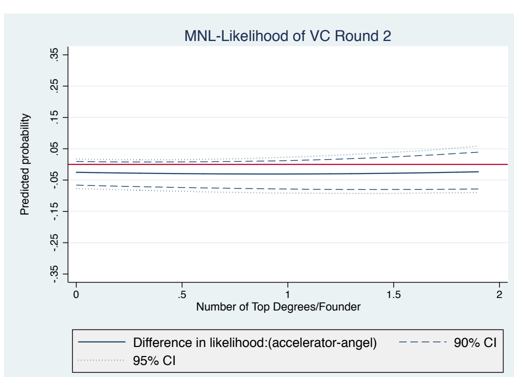


(1c.)





(1d.)



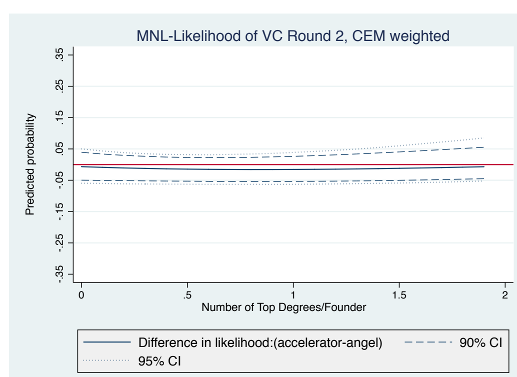
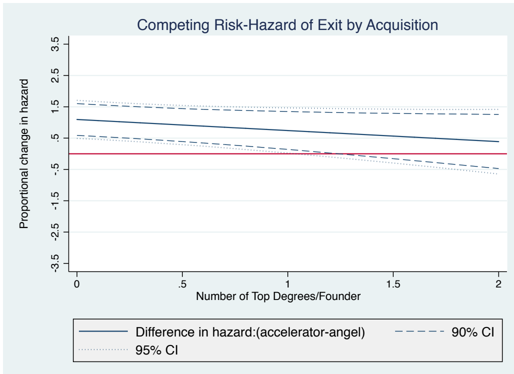
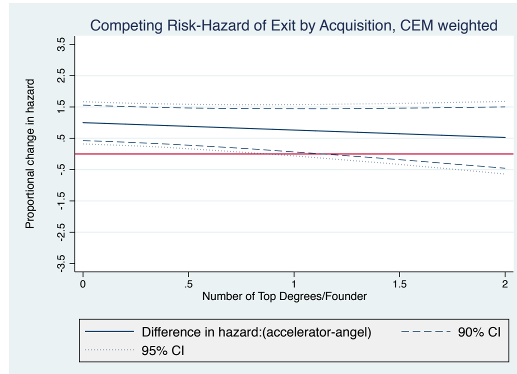


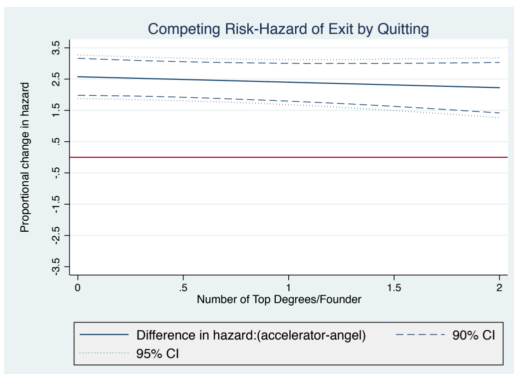
Figure 2. Competing Risks Regressions, Proportional Change in Hazard of Event For a Change in Number of Top Degrees Per Founder (Simulation derived confidence intervals)

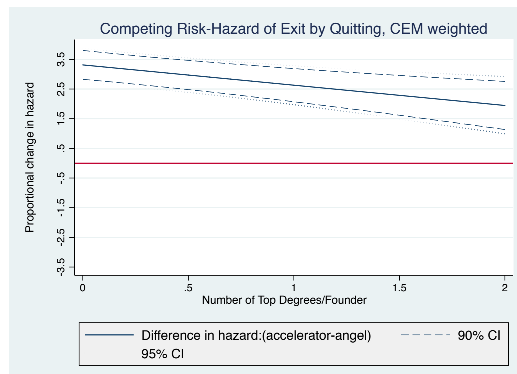
Panel A: Full Sample *Panel B: CEM Weighted*



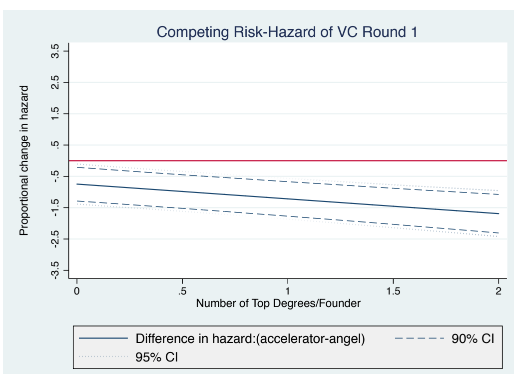


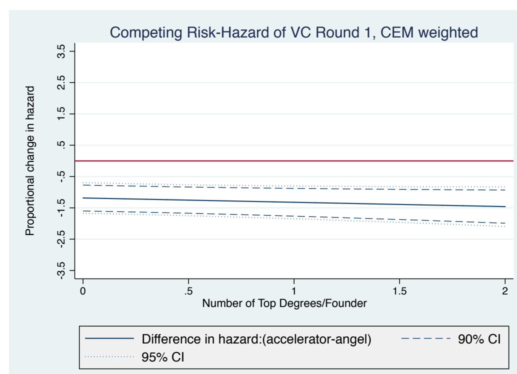
(2a.)



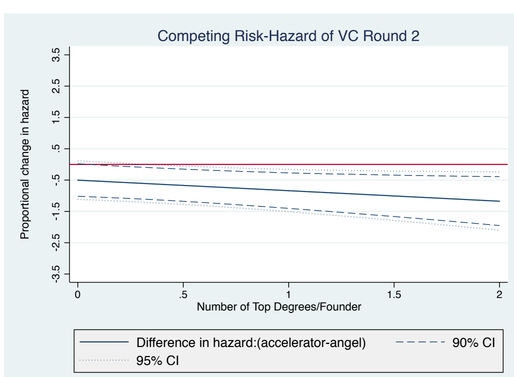


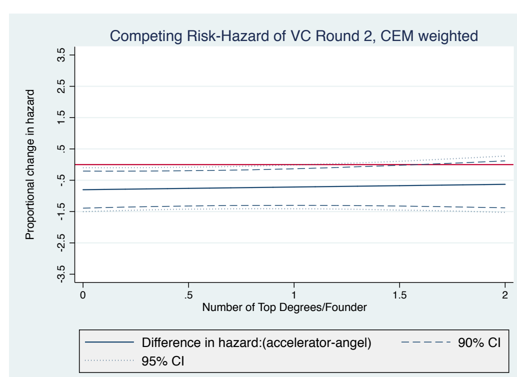
(2b.)





(2c.)





(2d.)

Table 1. Variables, Definitions, and Summary Statistics

Variable Name	*Description*	*Full Sample (n=614)*			
		Mean	*SD*	*Min*	*Max*
Accelerator	*Startup Backed By An Accelerator (Dummy)*	0.6335	0.4822	0	1
ExitByAcquisition	*Startup Exit via Acquisition or IPO (Dummy)*	0.1482	0.3555	0	1
ExitByQuitting	*Startup Exit by Quitting (Dummy)*	0.1726	0.3782	0	1
Alive	*Alive (Baseline Dummy)*	0.4023	0.4907	0	1
VCRound1	*2nd Round Funding (Dummy)*	0.1319	0.3386	0	1
VCRound2+	*3rd to 8th Round Funding (Dummy)*	0.1449	0.3523	0	1
TimeToExitByAcquisition (Months)	*Time from startup founding date to date of successful exit.*	36.5794	22.5510	5	102
TimeToExitByQuitting (Months)	*Time from startup founding date to date of exit by quitting.*	24.3619	20.1928	2	105
TimeToVCRound1 (Months)	*Time from startup founding date to close date of first round VC funding.*	21.1281	15.8930	2	89
TimeToVCRound2+ (Months)	*Time from startup founding date to close date of second round VC funding.*	33.9056	16.7932	7	101
Cohort	*The cohort that with whom each startup passes through, if accelerator-backed. Ranked chronologically.*	8.6335	8.3561	0	25
NumFounders	*Number of Founders Per Startup*	1.9691	0.7836	1	5
TopDegreePerFounder	*Number of degrees from high status institutions, per founder, per startup*	0.4041	0.4916	0	2
LocSV	*Startup HQ in Silicon Valley (Dummy)*	0.4935	0.5004	0	1
Ln_TotFundAllRounds	*Total Venture Funding Received by Startup ($s, All Rounds, log)*	13.0564	2.4314	9.2104	19.3654
Industry (Music, Gaming, Media)	*Startup in Music, Gaming, Media Industries (Dummy)*	0.1335	0.3404	0	1
Industry (Social, Location, Mobile Apps)	*Startup in Social, Location, Mobile App Industries (Dummy)*	0.2638	0.4411	0	1
Industry (Payment/Commerce)	*Startup in Payment/Commerce Technology Industries (Dummy)*	0.1661	0.3725	0	1
Industry (Web Business)	*Startup in Web Business Industry (Dummy)*	0.1710	0.3768	0	1
Industry (Underlying Tech)	*Startup in Platform/Underlying Technology Industries (Dummy)*	0.1775	0.3824	0	1
Industry (Other)	*Startup in Miscellaneous Industries (Dummy)*	0.0863	0.2810	0	1
HQ Location: California	*Startup HQ Location: California*	0.5162	0.5001	0	1
HQ Location: NYC/Boston	*Startup HQ Location: NYC/Boston*	0.1921	0.3943	0	1
HQ Location: Colorado	*Startup HQ Location: Colorado*	0.0619	0.2411	0	1
HQ Location: Other N/A	*Startup HQ Location: Other N/A*	0.2084	0.4065	0	1
HQ Location: Foreign	*Startup HQ Location: Foreign*	0.0179	0.1328	0	1

Table 2a. Summary Statistics of Accelerator and Angel-Group Backed Startups (Full Sample)

	Panel A: Accelerator Backed Firms (n=389)				*Panel B: Angel Backed Firms (n=225)*			
Funding Outcomes	*Mean*	*SD*	*Min*	*Max*	*Mean*	*SD*	*Min*	*Max*
ExitByAcquisition	0.1542	0.3615	0	1	0.1378	0.3454	0	1
ExitByQuitting	0.2287	0.4205	0	1	0.0756	0.2649	0	1
Alive	0.4653	0.4994	0	1	0.2933	0.4563	0	1
VCRound1	0.0925	0.2902	0	1	0.2000	0.4009	0	1
VCRound2+	0.0591	0.2361	0	1	0.2933	0.4563	0	1
Outcome Timing	*Mean*	*SD*	*Min*	*Max*	*Mean*	*SD*	*Min*	*Max*
TimeToExitByAcquisition (Months)	27.3467	16.7061	5	81	58.2189	19.5724	25	102
TimeToExitByQuitting (Months)	19.7386	12.0816	2	65	48.2941	33.6243	8	105
TimeToVCRound1 (Months)	13.7891	10.1116	2	56	31.1852	16.8719	2	89
TimeToVCRound2+ (Months)	25.8378	13.0124	7	65	40.9294	16.6145	12	101
Startup Characteristics	*Mean*	*SD*	*Min*	*Max*	*Mean*	*SD*	*Min*	*Max*
Cohort	13.6273	6.4877	1	25	-	-	-	-
NumFounders	2.2287	0.7506	1	5	1.5200	0.6202	1	4
TopDegreePerFounder	0.4328	0.5021	0	2	0.3544	0.4698	0	2
LocSV	0.6041	0.4896	0	1	0.3022	0.4602	0	1
Ln_TotFundAllRounds	12.1977	2.4466	9.2104	19.3654	13.9027	3.4484	10.8198	18.5985
Industry (Music, Gaming, Media)	0.1362	0.3435	0	1	0.1288	0.3358	0	1
Industry (Social, Location, Mobile Apps)	0.2956	0.4569	0	1	0.2089	0.4074	0	1
Industry (Payment/Commerce)	0.1825	0.3867	0	1	0.1378	0.3454	0	1
Industry (Web Business)	0.1697	0.3758	0	1	0.1733	0.3793	0	1
Industry (Underlying Tech)	0.1619	0.3689	0	1	0.2044	0.4042	0	1
Industry (Other)	0.0540	0.2263	0	1	0.1422	0.3500	0	1
HQ Location: California	0.5372	0.4993	0	1	0.4800	0.5007	0	1
HQ Location: NYC/Boston	0.1928	0.3950	0	1	0.1911	0.3941	0	1
HQ Location: Colorado	0.0979	0.2976	0	1	0	0	0	1
HQ Location: Other N/A	0.1440	0.3515	0	1	0.3200	0.4675	0	1
HQ Location: Foreign	0.0257	0.1585	0	1	0.0044	0.0667	0	1

Table 2b. Summary Statistics of Accelerator and Angel-Group Backed Startups (CEM Sample)

	Panel A: Accelerator Backed Firms (n=357)				*Panel B: Angel Backed Firms (n=219)*			
Funding Outcomes	*Mean*	*SD*	*Min*	*Max*	*Mean*	*SD*	*Min*	*Max*
ExitByAcquisition	0.1540	0.3615	0	1	0.1369	0.3446	0	1
ExitByQuitting	0.2240	0.4175	0	1	0.0731	0.2608	0	1
Alive	0.4762	0.5001	0	1	0.2968	0.4579	0	1
VCRound1	0.0924	0.2900	0	1	0.2009	0.4579	0	1
VCRound2+	0.0532	0.2248	0	1	0.2922	0.4016	0	1
Outcome Timing	*Mean*	*SD*	*Min*	*Max*	*Mean*	*SD*	*Min*	*Max*
TimeToExitByAcquisition (Months)	27.0145	16.9137	5	81	58.6129	19.7664	25	102
TimeToExitByQuitting (Months)	19.2405	12.4542	2	65	47.5000	34.5620	8	105
TimeToVCRound1 (Months)	13.7485	9.9866	2	56	31.0385	17.0349	2	89
TimeToVCRound2+ (Months)	26.6418	13.2170	7	65	40.9259	16.8039	12	101
Startup Characteristics	*Mean*	*SD*	*Min*	*Max*	*Mean*	*SD*	*Min*	*Max*
Cohort	13.4479	6.3942	1	25	-	-	-	-
NumFounders	2.1972	0.7291	1	4	1.4977	0.5933	1	3
TopDegreePerFounder	0.3683	0.4442	0	1.5	0.3349	0.4512	0	2
LocSV	0.6190	0.4863	0	1	0.3014	0.4599	0	1
Ln_TotFundAllRounds	0.4328	0.5021	0	2	14.6008	1.4262	10.8198	18.05985
Industry (Music, Gaming, Media)	0.1344	0.3416	0	1	0.1142	0.3187	0	1
Industry (Social, Location, Mobile Apps)	0.3025	0.4599	0	1	0.2100	0.4083	0	1
Industry (Payment/Commerce)	0.1933	0.3954	0	1	0.1416	0.3494	0	1
Industry (Web Business)	0.1709	0.3769	0	1	0.1781	0.3835	0	1
Industry (Underlying Tech)	0.1540	0.3615	0	1	0.2100	0.4083	0	1
Industry (Other)	0.0448	0.2071	0	1	0.1415	0.3495	0	1
HQ Location: California	0.5490	0.4982	0	1	0.4886	0.5010	0	1
HQ Location: NYC/Boston	0.1877	0.3910	0	1	0.1735	0.3795	0	1
HQ Location: Colorado	0.0980	0.2977	0	1	0	0	0	1
HQ Location: Other N/A	0.1344	0.3416	0	1	0.3288	0.4708	0	1
HQ Location: Foreign	0.0252	0.1569	0	1	0.0046	0.0676	0	0

Table 3. Multinomial Logit Analysis (Full Sample)
(Baseline = Alive, Standard Errors Clustered on Cohort)

VARIABLES	***Exit By Acquisition*** *(1)*	***Exit By Acquisition*** *(2)*	***Exit By Quitting*** *(3)*	***Exit By Quitting*** *(4)*	**VC Round 1** *(5)*	**VC Round 1** *(6)*	**VC Round 2+** *(7)*	**VC Round 2+** *(8)*
Accelerator	5.559***	7.363***	16.012***	20.578***	0.565	0.727	0.930	1.008
	(3.95)	(4.77)	(5.66)	(6.01)	(-0.80)	(-0.44)	(-0.14)	(0.02)
TopDegreePerFounder	1.425	2.466***	1.434	2.528***	1.568*	2.504***	1.215	1.622***
	(1.36)	(25.77)	(1.58)	(23.54)	(1.75)	(17.83)	(0.98)	(9.08)
Accelerator*TopDeg.PerFounder		0.460**		0.489***		0.490***		0.740
		(-2.40)		(-2.81)		(-2.70)		(-0.79)
LocSV	0.864	0.867	0.599*	0.602*	0.583*	0.584*	0.602***	0.601***
	(-0.65)	(-0.63)	(-1.84)	(-1.83)	(-1.79)	(-1.78)	(-2.84)	(-2.86)
NumFounders	1.469**	1.468**	1.033	1.032	1.207	1.200	0.932	0.926
	(2.49)	(2.48)	(0.19)	(0.19)	(0.99)	(0.97)	(-0.59)	(-0.65)
Cohort	0.839***	0.840***	0.863***	0.863***	0.984	0.985	0.918**	0.918**
	(-7.98)	(-7.99)	(-5.01)	(-5.04)	(-0.46)	(-0.44)	(-2.38)	(-2.37)
Ln_TotFundAllRounds	1.072*	1.071*	0.857*	0.857*	1.543***	1.543***	2.330***	2.326***
	(1.66)	(1.67)	(-1.71)	(-1.71)	(2.77)	(2.77)	(4.39)	(4.39)
Industry	Y	Y	Y	Y	Y	Y	Y	Y
Observations	614	614	614	614	614	614	614	614
log pseudolikelihood	-737.4	-736.0	-737.4	-736.0	-737.4	-736.0	-737.4	-736.0

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.10

Table 4: Competing Risk Cox Hazard Model, Base Regressions
(Origin Date: Startup First Round of Funding; Standard Errors Clustered on Cohort)

VARIABLES	*TimeToExitByAcquisition* (1)	*TimeToExitByAcquisition* (2)	*TimeToExitByQuitting* (3)	*TimeToExitByQuitting* (4)	*TimeToVCRound1* (5)	*TimeToVCRound1* (6)	*TimeToVCRound2+* (7)	*TimeToVCRound2+* (8)
Accelerator	2.585***	2.994***	12.224***	13.135***	0.385***	0.473**	0.525**	0.605
	(2.97)	(3.55)	(7.30)	(7.23)	(-2.83)	(-2.28)	(-2.06)	(-1.60)
TopDegreePerFounder	1.102	1.422***	1.133	1.311***	1.227	1.619***	1.151	1.358***
	(0.58)	(9.88)	(0.76)	(7.02)	(1.42)	(16.22)	(1.01)	(12.84)
Accelerator*TopDeg.PerFounder		0.702		0.841		0.624***		0.714
		(-1.55)		(-0.79)		(-4.26)		(-1.62)
LocSV	1.022	1.028	0.840	0.841	0.584***	0.587***	0.622**	0.626*
	(0.10)	(0.12)	(-0.70)	(-0.70)	(-3.17)	(-3.17)	(-1.96)	(-1.94)
NumFounders	1.356***	1.359***	0.836	0.836	1.221***	1.220***	1.046	1.048
	(3.02)	(3.00)	(-1.45)	(-1.45)	(3.62)	(3.59)	(0.58)	(0.60)
Cohort	0.935***	0.935***	0.914***	0.914***	1.054***	1.054***	0.999	0.998
	(-3.83)	(-3.86)	(-4.29)	(-4.30)	(3.33)	(3.37)	(-0.06)	(-0.08)
Industry	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,226	1,226	1,231	1,231	618	618	935	935
Log pseudolikelihood	-654.7	-654.3	-636.0	-635.9	-1924	-1922	-981.3	-980.7

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.10

Table 5: Outcomes, Multinomial Logit Regression, Coarsened Exact Matching (CEM)
(Baseline = Alive, Standard Errors Clustered on Cohort)

VARIABLES	***Exit By Acquisition*** *(1)*	***Exit By Acquisition*** *(2)*	***Exit By Quitting*** *(3)*	***Exit By Quitting*** *(4)*	**VC Round 1** *(5)*	**VC Round 1** *(6)*	**VC Round 2+** *(7)*	**VC Round 2+** *(8)*
Accelerator	4.372***	6.756***	15.754***	23.160***	0.488	0.627	1.189	1.546
	(3.42)	(4.30)	(6.00)	(6.71)	(-1.01)	(-0.63)	(0.34)	(0.80)
TopDegreePerFounder	1.441	3.066***	1.204	2.635***	1.546	2.495***	0.807	1.281**
	(1.04)	(14.74)	(0.67)	(19.79)	(1.55)	(10.72)	(-0.71)	(2.49)
Accelerator*TopDeg.PerFounder		0.316***		0.358***		0.497*		0.468
		(-2.84)		(-4.05)		(-1.88)		(-1.21)
LocSV	1.081	1.099	0.724	0.742	0.643	0.654	0.685**	0.697**
	(0.31)	(0.36)	(-1.05)	(-0.97)	(-1.44)	(-1.36)	(-2.09)	(-1.99)
NumFounders	1.286	1.315	0.889	0.900	1.042	1.052	0.851	0.858
	(1.53)	(1.57)	(-0.57)	(-0.51)	(0.22)	(0.26)	(-1.47)	(-1.35)
Cohort	0.840***	0.839***	0.870***	0.869***	0.986	0.985	0.888***	0.887***
	(-7.40)	(-7.47)	(-4.52)	(-4.56)	(-0.37)	(-0.39)	(-2.93)	(-2.94)
Ln_TotFundAllRounds	1.065*	1.067*	0.869	0.871	1.481***	1.485***	2.155***	2.161***
	(1.72)	(1.78)	(-1.55)	(-1.52)	(2.67)	(2.70)	(4.63)	(4.65)
Industry	Y	Y	Y	Y	Y	Y	Y	Y
Observations	576	576	576	576	576	576	576	576
Log pseudolikelihood	-687.0	-684.9	-687.0	-684.9	-687.0	-684.9	-687.0	-684.9

Robust z-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table 6: Competing Risk Cox Hazard Model, Coarsened Exact Matching (CEM)
(Origin Date: Startup First Round of Funding; Standard Errors Clustered on Cohort)

VARIABLES	***TimeToExitByAcquisition*** (1)	***TimeToExitByAcquisition*** (2)	***TimeToExitByQuitting*** (3)	***TimeToExitByQuitting*** (4)	***TimeToVC Round1*** (5)	***TimeToVC Round1*** (6)	***TimeToVC Round2+*** (7)	***TimeToVC Round2+*** (8)
Accelerator	2.479**	2.714***	12.279***	15.720***	0.410***	0.521**	0.773	0.752
	(2.55)	(2.89)	(8.27)	(8.85)	(-2.87)	(-2.11)	(-0.85)	(-0.92)
TopDegreePerFounder	1.205	1.418***	1.064	1.734***	1.262	1.736***	0.857	0.826**
	(0.98)	(5.79)	(0.34)	(8.12)	(1.24)	(8.82)	(-1.19)	(-2.02)
Accelerator*TopDeg.PerFounder		0.790		0.558***		0.553***		1.080
		(-0.94)		(-2.82)		(-3.47)		(0.31)
LocSV	1.118	1.122	0.852	0.854	0.624**	0.642**	0.655*	0.654*
	(0.43)	(0.44)	(-0.63)	(-0.63)	(-2.47)	(-2.27)	(-1.78)	(-1.77)
NumFounders	1.307**	1.311**	0.785	0.788	1.116	1.117	0.922	0.921
	(2.07)	(2.07)	(-1.59)	(-1.59)	(0.97)	(0.99)	(-0.60)	(-0.61)
Cohort	0.936***	0.936***	0.923***	0.922***	1.050***	1.048***	0.980	0.981
	(-3.57)	(-3.60)	(-3.89)	(-3.93)	(3.03)	(3.01)	(-0.83)	(-0.82)
Industry	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,144	1,144	1,148	1,148	577	577	871	871
log pseudolikelihood	-613.6	-613.5	-567.2	-566.7	-1780	-1777	-855.4	-855.3

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.10

Appendix Table 1. Correlation Matrix

Variable		(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)	(m)	(n)	(o)	(p)	(q)
Accelerator	(a)	1.00																
ExitByAcquisition	(b)	0.03	1.00															
Exit By Quitting	(c)	0.20	-0.19	1.00														
Alive	(d)	0.18	-0.34	-0.37	1.00													
VC Round 1	(e)	-0.17	-0.16	-0.18	-0.32	1.00												
VC Round 2+	(f)	-0.33	-0.17	-0.19	-0.34	-0.16	1.00											
Cohort	(g)	0.78	-0.11	0.00	0.31	-0.07	-0.27	1.00										
NumFounders	(h)	0.43	0.10	0.06	0.02	-0.04	-0.16	0.31	1.00									
TopDegreePerFounder	(i)	0.08	0.04	0.04	-0.07	0.04	-0.01	0.05	0.12	1.00								
LocSV	(j)	0.29	0.04	0.04	0.11	-0.11	-0.13	0.17	0.18	0.12	1.00							
Ln_TotFundAllRounds	(k)	-0.48	-0.01	-0.43	-0.13	0.23	0.43	-0.24	-0.15	-0.00	-0.17	1.00						
Industry (Media, Music, Gaming))	(l)	0.01	-0.01	0.04	0.00	-0.07	0.02	-0.03	0.03	-0.00	-0.02	-0.03	1.00					
Industry (Social, Location, Mobile Apps)	(m)	0.10	0.05	0.02	0.01	-0.00	-0.06	0.07	-0.01	-0.00	0.06	-0.07	-0.23	1.00				
Industry (Payment/Commerce)	(n)	0.05	-0.05	-0.00	0.04	0.01	-0.01	0.07	0.07	0.04	0.10	-0.01	-0.18	-0.27	1.00			
Industry (Web Business)	(o)	-0.02	-0.00	-0.01	-0.06	0.01	0.10	-0.02	-0.05	-0.09	-0.11	-0.01	-0.18	-0.27	-0.21	1.00		
Industry (Underlying Tech)	(p)	-0.04	0.02	-0.02	-0.00	0.04	-0.03	-0.05	0.01	0.05	-0.09	0.04	-0.18	-0.27	-0.21	-0.21	1.00	
Industry (Other)	(q)	-0.16	-0.03	-0.02	0.03	0.02	-0.01	-0.06	-0.06	0.02	0.05	0.10	-0.12	-0.18	-0.14	-0.14	-0.14	1.00

Appendix Table 2. Angel Groups, Name and Location

Angel Group	Location	Angel Group	Location
Tech Coast Angels	San Diego, CA	Keiretsu Forum	Lafayette, CA
Band of Angels	Menlo Park, CA	Launchpad Ventures	Boston, MA
CommonAngels	Boston, MA	Nashville Capital Network	Franklin, TN
Alliance of Angels	Seattle, WA	North Coast Angel Fund	Cleveland, OH
The Angels' Forum LLC	Mountain View, CA	Pasadena Angels	Altadena, CA
Atlanta Technology Angels	Atlanta, GA	Queen City Angels	Cincinnati, OH
eCoast Angels	Portsmouth, NH	Robin Hood Ventures	Philadelphia, PA
Golden Seeds LLC	Cos Cob, CT	Sand Hill Angels	Redwood City, CA
Hub Angels	Cambridge, MA	TechColumbus	Columbus, OH
Hyde Park Angels	Chicago, IL		

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